Diagnosing uncertainties in global biomass burning emission inventories and their impact on modeled air pollutants

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Abstract

~~Biomass burning (BB) emission inventories are often used to understand the interactions of aerosols with weather and climate. However, large~~ Large uncertainties ~~exist among~~persist within current Biomass burning (BB) inventories, ~~so~~ and the choice of these inventories can ~~greatly~~ substantially ~~affect~~ impact model results when assessing the influence of BB aerosols on weather and climate. ~~To quantify the differences among BB emission inventories and reveal their reasons, we~~ We evaluated discrepancies among BB emission inventories by ~~compared~~ comparing carbon monoxide (CO) and organic carbon (OC) emissions from seven major BB regions globally ~~from~~ between 2013 ~~to~~ and 2016. ~~The current inventories are based on two basic approaches: (1) bottom-up approach, which establishes inventories based on observed surface data, and (2) top-down approach, which based on the release rate of radiative energy from vegetation burning. In this study, we selected~~ M~~m~~ainstream bottom-up inventories, including Fire INventory from NCAR 1.5 (FINN1.5) and Global Fire Emissions Database version 4s (GFED4s), ~~and~~ along with~~the~~ top-down inventories Quick Fire Emissions Dataset 2.5 (QFED2.5) and VIIRS-based Fire Emission Inventory version 0 (VFEI0), were selected for this study.

~~We find that~~ G~~the total g~~lobal CO emissions ~~fluctuate between~~range from 252 ~~and~~ to 336 Tg, ~~and the~~with regional ~~bias is even larger, which can be up to~~disparities reaching up to a sixfold difference~~times~~. Dry matter is ~~responsible~~ the primary contributor ~~for most of~~to the regional variation in CO emissions (50-80%), with emission factors accounting for the remaining 20-50%. Uncertainties in dry matter often ~~come~~ arise from biases in ~~the~~ calculati~~on~~ng ~~of~~ bottom fuel consumption and burned area, ~~which are closely related to~~influenced by vegetation classification methods and fire detection products. In the tropics, peatlands contribute more fuel loads and higher emission factors than grasslands. At high latitudes, ~~as~~increased cloud fraction ~~increases,~~amplifies the ~~bias~~ discrepancy in ~~between~~ estimated burned area (or fire radiative power) ~~increases~~ by 20%. ~~In addition, due to the corrected emission factors in QFED2.5, global BB OC emissions have higher variability, fluctuating between~~The global OC emissions range from 14.9 ~~and~~ to 42.9 Tg, exhibiting higher variability than CO emissions due to the corrected emission factors in QFED2.5, with regional disparities reaching a factor of 8.7.~~.~~

~~Finally~~Additionally, we applied ~~the four sets of~~these BB emission inventories to the Community Atmosphere Model version 6 (CAM6) and ~~compared~~ assessed the model ~~results~~ performance ~~with~~ against observations. Our results suggest that the simulations based on the GFED4s agree best with the MOPITT-retrieved CO. ~~We also~~While ~~compared~~ comparing the simulation ~~results~~ with ~~satellite or ground-based measurments, such as~~ Moderate Resolution Imaging Spectroradiometer (MODIS)~~)~~ ~~AOD and~~ and AErosol RObotic NETwork (AERONET) aerosol optical depth (AOD)~~.~~, o~~O~~ur results reveal that there is no global optimal choice for ~~the~~ BB inventories~~,~~. In the high latitudes of the Northern Hemisphere, using GFED4s and QFED2.5 can better capture the AOD magnitude and diurnal variation. In equatorial Asia, GFED4s outperform others in representing day-to-day changes, particularly during intense burning. In Southeast Asia, we recommend using the OC emission magnitude from FINN1.5 combined with daily variability from QFED2.5. In the Southern Hemisphere, the latest VFEI0 has performed relatively well. ~~but we give certain inventory recommendations based on different study areas and spatiotemporal scales.~~ This study has implications for reducing the uncertainties in emissions or improving BB emission inventories in further studies.

1 Introduction

In recent years, extreme wildfire events have occurred frequently around the world (Balshi et al., 2009; Knorr et al., 2016; Yang et al., 2019; Junghenn Noyes et al., 2022). The size of the fire has consistently broken records over the last decades (Westerling et al., 2006; Westerling and Bryant, 2008; Brando et al., 2020), threatened lives and infrastructure, and continuously jeopardized the global economy. Wildfires are also one of the most important sources of biomass burning (BB) emissions, which can emit loads of gaseous and particulate pollutants (Ferek et al., 1998; Adams et al., 2019), detrimental to regional air quality and human health (Reid et al., 2005, Reid and Mooney, 2016). Additionally, BB aerosols, predominantly black carbon (BC) and organic carbon (OC) can affect regional climate by absorbing/scattering solar radiation, acting as cloud condensation nuclei, and altering cloud albedo (Spracklen et al., 2011; Boucher et al. 2013). Recent studies have shown that aerosols produced by biomass burning can significantly affect changes in temperature, cloud fraction, precipitation, and even the circulation structure (Christian et al., 2019; Yang et al., 2019; Yu et al., 2019; Carter et al., 2020; Jiang et al.,2020; Ding et al., 2021; Huang et al., 2023). However, these changes in meteorology are sensitive to the choice of BB emission inventory.

~~Recent studies have shown that aerosols produced by biomass burning can significantly affect changes in temperature, cloud fraction, precipitation, and even the circulation structure (Christian et al., 2019; Yang et al., 2019; Yu et al., 2019; Carter et al., 2020; Jiang et al.,2020; Ding et al., 2021; Huang et al., 2023). Jiang et al. (2020) used the Community Earth System Model version 1.2 (CESM1.2) to investigate the impact of BB aerosols on global climate change. They pointed out that BB aerosols reduce the annual mean surface air temperature and precipitation by 0.64 K and 0.06 mm day^{-1}, respectively. Based on 16 years of simulation from the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem), Ding et al. (2021) reported that BB aerosols increased low cloud coverage by 20% in areas downwind of wildfires in Southeast Asia in March and Southern Africa in August. A recent study also reported that the radiative effects of BB aerosols alter the local circulation structure, leading to dry air on the West Coast of the United States, or less precipitation in Southeast Asia, thus intensifying fires and exacerbating air pollution (Huang et al., 2023). However, these simulated results are sensitive to the amount of BB pollutants (Liu et al., 2020a).~~

Previous studies often found that there is a significant deviation between the gaseous or particulate pollutants simulated by the model and the satellite retrieval value (Bian et al., 2007; Chen et al., 2009; Carter et al., 2020), one of the most important reasons comes from the uncertainties in emission inventories. For example, Bian et al. (2007) applied six different BB emission inventories, GFED1 and GFED2 (Global Fire Emissions Database version 1 and 2) (GFED1 and GFED2), Arellano1, Arellano2, Duncan1, and Duncan2, to the Unified Chemistry Transport Model (UCTM). They reported that although the total global CO of the six BB emission inventories was within 30% of each other, the model results suggested that regional deviations can be much higher, by as much as 2-5 times, especially in the Southern Hemisphere. Bias in emission inventories can therefore often have a significant impact on the direct and indirect effects of models on aerosol assessments (Liu et al., 2018; Liu et al., 2020a; Ramnarine et al., 2019; Carter et al., 2020). Carter et al. (2020) compared the simulated black carbon (BC) and organic carbon (OC) concentrations with measurements from IMPROVE (Interagency Monitoring of Protected Visual Environments) observation network from May to September. They suggested that using the

FINN1.5 inventory (Fire INventory from NCAR 1.5) improves model results in eastern North America, while using GFED4s, QFED2.4 (Quick Fire Emissions Dataset 2.4), and GFAS1.2 (Global Fire Assimilation System 1.2) inventories shows better agreement with observations in western North America. They also noted that population-weighted BB $PM_{2.5}$ concentrations in Canada and the adjacent United States could vary between 0.5 and 1.6 $\mu g\ m^{-3}$ in 2012 by using different BB emissions. Liu et al. (2018) used the global model CAM5 (The Community Atmosphere Model 5) and three different BB emission inventories to analyze the uncertainties in the aerosol radiative effects in the Northeastern United States in early April 2009. They found that aerosols exhibited a stronger cooling effect when CAM5 used the QFED2.4 inventory than the GFED3.1 and GFED4s inventories, with additional cooling of -0.7 W m^{-2} and -1.2 W m^{-2} through aerosol direct radiative effect and the aerosol-cloud radiative effect, respectively. On a global basis, Ramnarine et al. (2019) used the global model GEOS-Chem-TOMAS (GEOS-Chem-TwO-Moment Aerosol Sectional), and found that the direct radiative effects and indirect effects of aerosols driven by the FINN1.5 emission inventory in 2010 were 70% and 10% lower than those driven by GFED4, respectively. Therefore, to better estimate regional aerosol-radiation/aerosol-cloud interactions in wildfire regions, it is necessary to understand the differences in emission inventories from biomass combustion and the main drivers of uncertainties.

In general, BB emission inventories are based on bottom-up or top-down methods to infer the emission source intensity. The bottom-up approach, also known as the fire detection and/or burned area method, estimates emissions based on surface data such as fuel loading, active fire counts, and/or burned area. Currently, the widely used BB inventories based on the bottom-up approach include Duncan (Duncan, 2003), GFED (van der Werf et al., 2006, 2010a, 2010b, 2017), FINN (Wiedingmyer et al., 2011), Global Inventory for Chemistry-Climate Studies-GFED4S (G-G) (Mieville et al., 2010). The top-down approach uses satellite observations of fire radiative power (FPR), a method to measure the radiative energy release rate of burning vegetation, to estimate emissions by fuel consumption. The BB inventories based on the top-down method include Arellano (Arellano Jr et al., 2004; Arellano Jr and Hess, 2006), GFAS (Kaiser et al., 2012), Fire Energetics and Emission Research (FEER) (Ichoku and Ellison, 2014), QFED (Darmenov et al., 2015), the Fire Emissions Estimate Via Aerosol Optical Depth (FEEV-AOD) (Paton-Walsh et al., 2012) and the recently released VIIRS-based Fire Emission Inventory version 0 (VFEI0) (Ferrada et al., 2022). On a global scale, the average annual BB emissions of CO and OC can differ by a factor of 3 to 4, with the global emissions fluctuating in the range of 280-580 Tg yr^{-1} and 13-50 Tg yr^{-1} respectively. The bias may be even greater when focusing on emissions in specific regions (Bian et al., 2007; Liousse et al., 2010; Williams et al., 2012; Carter et al., 2020; Lin et al., 2020b; Liu et al., 2020b). For example, the estimated CO emission of Arellano inventory in South America during the burning peak season of September 2000 is four times greater than that of GFED1 inventory (Bian et al., 2007). A recent study even found that since 2008, OC emissions from QFED2.5 in the Middle East are approximately 50 times larger than those from GFED3 and GFED4 (Pan et al., 2020).

Several previous studies have analyzed the reason for the huge emission bias. According to Darmenov et al. (2015), the emissions E_i (mass of pollutant i) is the sum of the products of the emission factor ($EF_{\cancel{b}}$) and the dry matter ($DM_{\cancel{b}}$) for each biome~~:~~

$$\cancel{E_i = \sum_B EF_B \times DM_B \qquad (1)}$$

. While earlier studies suggested that the uncertainty in BB emissions arises mainly from differences in emission factors (e.g., Alvarado et al., 2010; Akagi et al., 2011; Urbanski et al., 2011), more recent studies point out that uncertainty in dry matter also plays an important role ~~in differences in BB emissions~~ (Paton-Walsh et al., 2010; 2012; Carter et al., 2020). For example, Paton-Walsh et al. (2012) assessed the difference in CO emissions from the February 2009 Australian fire and found that total CO emissions in GFED3.1 were roughly three times higher than that in FINN1, with DM contributing up to 80%. Carter et al. (2020) evaluated emissions from various North American BB inventories over the period 2004-2016 and found that changes in DM ~~was~~ were very close to the emission trend, suggesting that uncertainty in potential DM across ~~the~~ North America~~n~~ was the primary factor, rather than EF.

The accuracy of BB inventories is influenced by l~~EF.~~

~~To analyze the root causes of the differences in EFs and DM among BB inventories, equation (1) is further decomposed. According to the bottom-up method, the emission for each species i can be further summarized as:~~

~~$E_i = \sum_b (EF_b \times BA(x,t) \times FC_b) = \sum_b (EF_b \times BA(x,t) \times FL_b \times FB_b)$ (2)~~

~~where BA(x,t) is burned area at location x and time t, which can be obtained from the fire detection products. For each biome, fuel consumption (FC_b) is the product of fuel loadings (FL_b) and the fraction of biomass burned (FB_b), which can be obtained with reference to static biomass density or using a biological models.~~

~~Similarly, the top-down inventories can be further divided into:~~

~~$E_i = \sum_b$ (3)~~

~~where A is the area of unit pixel observed by satellite, and FRP/A represents the FRP density, which is proportional to E_i. For the emission E_i of a substance i, the empirical coefficient α_b is used to convert the fire radiative energy (i.e., the time-integrated FRP) of each biome into DM (also can be considered as converting FRP density into emission fluxes).~~

~~Therefore, l~~and cover and land use (LULC) data, ~~associated with vegetation types can influence the BB inventory by~~impacting both ~~affecting~~ EFs and ~~EFs, fuel loads, and the FB for bottom-up approach, or by affecting EFs and empirical coefficient α for top-down approach~~ DM (Wiedinmyer et al., 2006; Ferrada et al., 2022). In a study by ~~For example,~~ Wiedinmyer et al. (2006), ~~used~~ three ~~different~~ distinct LULC products were employed to drive a regional ~~model of~~ BB emissions model. ~~and found that~~The variations in~~ying~~ LULC products ~~drive~~ led ~~through~~ to discrepancies in fuel consumption, ~~ultimately leading to~~resulting in an annual bias of up to 26% in North and Central America. ~~Furthermore~~Moreover, ~~since~~ EFs are ~~highly dependent~~closely tied ~~on~~ to ~~various~~ different biomes, ~~different biome classifications will~~ introducing~~e~~ uncertainty into BB emission inventories with varied biome classifications (Ferrada et al., 2022). In addition to LULC products, uncertainties are introduced by fire detection products (such as FRP and burned area products) ~~that are~~, affected by factors such as satellite transit time and cloud obscuration ~~also bring uncertainty to BB emission inventories~~. For example, Paton-Walsh et al. (2012) found that in an Australian fire called "Black Friday" in February 2009, the burned areas of FINN1 were barely half of that of GFED3.1. Liu et al. (2020b) reported that compared with the active fire area used in FINN1.5, the burned area product selected by GFED4s is less sensitive to the satellite overpass time and cloud obscuration. These results indicate that LULC and fire detection products are key factors leading to bias in BB emission estimation.

Although previous work has generated biomass burning emission inventories and attempted to reduce their uncertainties (Duncan, 2003; Arellano Jr et al., 2004; Arellano Jr and Hess, 2006; van der Werf et al., 2006, 2010a, 2010b, 2017; Bian et al., 2007; Mieville et al., 2010; Wiedingmyer et al., 2011; Kaiser et al., 2012; Paton-Walsh et al., 2012; Ichoku and Ellison, 2014; Darmenov et al., 2015; Liu et al., 2018; Ramnarine et al., 2019; Carter et al., 2020; Lin et al., 2020b; Liu et al., 2020b; Pan et al., 2020; Zhang et al., 2020; Ferrada et al., 2022), they did not analyze the reasons why DM and EF exhibited large differences among various emission inventories, which may vary over time and location. Here, this study aims to explore the underlying reasons for the differences in BB emission inventories in major combustion regions around the world, thereby attempting to reduce the uncertainties of the impact of BB emission inventories on model results. To minimize the interference of anthropogenic emissions on model results, we selected combustion regions satisfying the following conditions: (1) regional BB CO emissions above 20 Tg yr^{-1}; (2) BB CO emissions contribute more than 70% of the total. We ultimately selected seven major burning areas as shown in Fig. 1, including Boreal North America (BONA), Southern Hemispheric South America (SHSA), Northern Hemispheric Africa (NHAF), Southern Hemispheric Africa (SHAF), Boreal Asia (BOAS), Southeast Asia and India (SEAS), and Equatorial Asia (EQAS).

~~Due to the abundance of published BB inventories, in this study~~In this study, we compare several widely used datasets~~ we selected several datasets that are widely used~~ (FINN1.5, GFED4s, and QFED2.5) and the ~~latest~~ recently released VFEI0. ~~for comparison, with t~~The former two ~~of them~~datasets are based on the bottom-up method, ~~and~~ while the latter two~~others~~ are based on the top-down method. Specific details of these BB inventories~~ will be~~ are described in Section 2. In section 3~~.1~~, we ~~will discuss~~explore the differences ~~of~~ in CO and OC emissions among the four inventories,~~ along with~~ examining the contributions of DM and EFs to these differences, respectively. For the first time, we ~~have~~ evaluate~~d~~ the biases of CO column concentrations and AOD driven by BB inventories in the CESM2-CAM6 model~~,~~. Based on our findings, ~~and given~~we provide recommendations~~ suggestions~~ on ~~what~~ which inventory should be adopted across various regions. ~~(Section 3.2).~~ Section 4 presents t~~T~~he conclusion and discussion~~ are presented in section 4~~, and our research is ~~anticipated~~ expected to ~~provide some~~offer insights ~~for~~ into reducing the uncertainties ~~of~~ with BB emission datasets.

2 Data and Methodology

2.1 Biomass Burning emission inventories

We simultaneously diagnosed the differences ~~among~~ between two bottom-up approach inventories and two top-down approach inventories, including FINN1.5, GFED4s, and QFED2.5, which are commonly used in the current atmospheric model, as well as the recently released VFEI0. Details about the emission inventories and the satellite products they use are listed in Table 1 and Text S1 in supplementary.~~.~~

Bottom-up (Burned Area) inventories

I~~Among the four BB emission inventories selected i~~n this study, both FINN1.5 and GFED4s ~~both use~~adopt ~~the~~ a bottom-up ~~method~~approach ~~, also known as the~~(also called the Burned Area method), and the~~.~~ ~~As shown~~details are shown in Table 1.~~,~~ FINN1.5 uses the MODIS (Moderate Resolution Imaging Spectroradiometer) product MCD14DL ~~to~~ for ~~calculate the~~ burned area ~~,~~calculations. ~~which can monitor fire points with an area larger than 0.05 km^2. Since the MCD14DL is an~~ This active fire detection product monitors real-time fire points larger than 0.05 km^2~~that reflects real-time fire point detectio~~. However, it is important to note that~~n,~~ if a fire occurs ~~but~~ when the satellite is not in transit or is obscured by clouds ~~while the satellite is in~~during transit, ~~the fire~~it will not be detected (Firms, 2017). Additionally, ~~considering that MODIS on polar-orbiting satellites cannot provide daily coverage products in the tropics (30°N-30°S),~~ FINN1.5 ~~makes some smoothing assumptions for fire detection in this region. It~~ assumes that every fire detected at the equator (30°N-30°S) will ~~continue~~ persist the next day at half the size of the previous day (Table 1~~),~~). ~~and~~ However, this assumption ~~obviously raises some questions~~may not accurately reflect real-world conditions (Wiedinmyer et al., 2011; Pan et al., 2020). ~~Meanwhile, t~~The land cover classification ~~of land cover types~~ in FINN1.5 is based on MCD12Q1 (IGBP, version 2005). According to the IGBP land cover classification, each fire is initially assigned to one of 16 land use/land cover (LULC) classes, and then lumped into six generic categories including tropical forest, temperate forest, boreal forest, savanna and grasslands, woody savannas and shrublands, and cropland (Fig. S1, Wiedingmyer et al., 2011). ~~The amount of usable biomass that can be burned per fire (fuel loadings) for each generic LULC according to Hoelzemann et al. (2004). The FB for each fire is specified as a function of vegetation cover (MODIS Vegetation Continuous Fields (VCF) product), as described by Wiedinmyer et al. (2006; 2011).~~ Emission factors (EFs) for various gaseous and particulate species are determined from a dataset compiled by Akagi et al. (2011) and Andreae and Merlet (2001), ~~and~~ with these EFs varying for different LULC types. Currently, FINN1.5 provides ~~the~~ daily global emissions from biomass burning since 2002, including 41 species, with a spatial resolution of 1 km^2 (Table 1).

~~The main difference between FINN1.5 and~~ GFED4s differs in that it primarily ~~is that the latter mainly~~ uses the MCD64A1 Collection 5.1 burned area product (Giglio et al., 2013; Randerson et al., 2018), ~~which can only~~capable of detecting fires ~~with a size~~ larger than 500 m × 500 m. For small fire ~~burning~~ areas, GFED4s ~~additionally~~ incorporate active fire detection products (MOD14A1 and MYD14A1), ~~and by comparing the difference normalized burned area (dNBR) of active fire products observed inside and outside the 500 m burning area, which~~ compensatinges to some extent for the ~~bias caused by the~~ lower spatial resolution of the original product MCD64A1 (van der Werf et al., 2017). ~~Note that, according to van der Werf et al. (2017), only small or moderate angel fire point detections are retained in order to reduce uncertainty in geolocation.~~ In general, burned area products reduce uncertainty in fire detection due to satellite non-transit and cloud/smoke obscuration when a burn occurs by identifying day-to-day surface variations, such as charcoal and ash deposition, vegetation migration, and changes in vegetation structure (Boschetti et al., 2019). Similar to FINN1.5, each fire in GFED4s is initially assigned to one of 16 LULC subcategories and then lumped into six categories, with the inclusion of an additional biome, peatland (Fig. S1).~~According to the annual MODIS MCD12C1 version 5.1 land cover type product and University of Maryland (UMD) classification scheme (Friedl et al., 2010), each fire is also initially assigned to one of 16 LULC subcategories and then lumped into six categories: tropical forest, temperate forest, boreal forest, savanna, cropland (agriculture), and peatland as shown in Fig. S1. While GFED4s combines the "savanna and grasslands" and "woody savannas and shrublands" in FINN1.5 into one biome, it has an additional biome "peatland". GFED4s generate the fuel loadings and the fraction of biomass burned for each category by combining the burned area and vegetation morality in a modified Carnegie-Ames-Stanford Approach (CASA) model, which is driven by the data of temperature, precipitation, solar radiation, NDVI, and vegetation types (Schaefer et al., 2008; van der Werf et al., 2010; 2017). Additionally,~~ EFs for various ~~gaseous and particulate~~ species follow Akagi et al. (2011) and Andreae and Merlet (2001), ~~also~~ var~~y~~ying across ~~with~~ different biome categories. Currently, GFED4s provide~~s~~ ~~the~~ daily global emissions from biomass burning since 1997, including 27 species, with a spatial resolution of 0.25° × 0.25° (Table 1). However, since 2017, the DM provided by GFED4s is derived from a linear relationship between past emissions and MODIS FRP data for the period 2003-2016.

Top-down (Fire Radiative Power) inventories

~~The other two emission inventories selected for~~In this study, both QFED2.5 and VFEI0~~,~~ use a top-down approach~~, also~~ known as the Fire Radiative Power (FRP) method. ~~Unlike~~ In contrast to the bottom-up approach, the top-down approach ~~is not based~~ relies on satellite products detecting fire-radiated power rather than ~~on~~ fire point detection.~~,~~ ~~but on satellite products that detected fire radiated power.~~ QFED2.5 uses MODIS Collection 6 MOD14/MYD14 level 2 products to estimate ~~the~~ fire radiative power~~,~~ and pinpoint fire locations using~~e~~ MOD03/MYD03 ~~to pinpoint the location of the fire~~ (Darmenov and Silva 2015; Liu et al., 2020b). ~~Since MOD14 and MYD14 products are strongly influenced by clouds, missing FRPs are corrected using the "sequential approach" combining current observations and predicted values (Darmenov and da Silva, 2015).~~ The FRPs are ~~then~~ integrated ~~in~~ over time to obtain ~~the~~ fire radiative energy (FRE), which is ~~detected and~~ converted to DM ~~by~~ using an empirical coefficient α. The initial ~~value of~~ α values ~~in QFED2.5 is~~are ~~taken~~ obtained from Kaiser et al. (2009) and ~~subsequently~~ are adjusted monthly based on global emissions of GFED2 in 2003–2007~~, resulting in two sets of empirical coefficients: $\alpha_{MOD14} = 1.89 \times 10^{-6}$ kg (DM) J^{-1} and $\alpha_{MYD14} = 0.644 \times 10^{-6}$ kg (DM) J^{-1}~~. ~~In~~ QFED2.5 classifies land cover using~~,~~ the International Geosphere-Biosphere Programme (IGBP-INPE) dataset~~,~~ ~~classes are used to~~ aggregat~~e~~ing 17 land cover classes into four broad vegetation types~~, including tropical forest, extra-tropical forest (forest classes that exclude tropical forest), savanna, and grassland~~ (Fig. S1, Darmenov and da Silva 2015). Initially, EFs for various species in QFED2.5 also follow Akagi et al. (2011) and Andreae and Merlet (2001)~~The EFs of particulate or trace gas species are from previous studies (Andreae and Merlet, 2001; Akagi et al., 2011)~~. But for certain species, including organic carbon (OC), black carbon (BC), ammonia (NH_3), sulfur dioxide (SO_2), and particulate matter diameter < 2.5μm ($PM_{2.5}$), QFED2.5 incorporates a scaling factor to enhance the EFs. QFED2.5 provides daily global BB emissions since 2000, including 17 species, with a spatial resolution of 0.1° × 0.1° (Table 1).

~~It is important to note that QFED2.5 scales up the EFs for emissions associated with the particulate phase, such as organic carbon (OC), black carbon (BC), ammonia (NH_3), sulfur dioxide (SO_2), and particulate matter diameter < 2.5μm ($PM_{2.5}$), so emissions of these species are greater in QFED2.5 than in other inventories. The QFED2.5 product covers daily emission inventories from 2000 to the present, and contains 17 emission species with a spatial resolution of up to 0.1° × 0.1°.~~

VFEI0 also adopts the top-down method but uses VNP14IMG.001 FRP product from VIIRS I-band (Visible Infrared Imaging Radiometer~~),~~). This product has a higher resolution (375 m at nadir) compared to MODIS (1 km resolution at nadir), enabling the detection of ~~which can detect~~ smaller and colder flames ~~than MODIS (1 km resolution at nadir), since it has a resolution of 375 m at nadir~~ (Ferrada et al., 2022). ~~Unlike QFED2.5,~~ VFEI0 ~~has no cloud calibration, but it will be supplemented in future versions. It also~~ uses ~~the~~ an empirical coefficient α derived from the linear regression of GFED3.1 DM and VIIRS FRP to convert ~~the~~ detected FRE into DM~~, but α is derived from the linear regression of GFED3.1DM and VIIRS FRP~~. ~~Additionally,~~VFEI0 uses MCD12C1 (IGBP, version

2015) ~~is~~ as the underlying LULC data, ~~which is further~~ supplemented by Köppen climate classification (Beck et al., 2018), ~~to~~ defining~~e~~ ten subcategories in VFEI0 (~~i.e., Tropical forest, Savanna, Temperate forest, Temperate Savanna, Boreal forest, Boreal Savanna, Grass, Agriculture, Peatland and Desertic areas~~Fig. S1). VFEI0 ~~then~~ groups~~ed~~ ~~the previous ten~~these subcategories into six biomes ~~(Fig. S1)~~, corresponding to ~~the emission factors~~EFs provided by Andreae (2019)~~, to calculate the BB emission inventory~~. ~~Among the four BB emission inventories~~Currently, VFEI0 ~~provides~~ offers ~~the shortest inventory time coverage (~~daily BB emission ~~fluxes from~~ since 20 January 2012~~ to the present)~~, ~~but it provides the largest number of emitted species at~~ covering 46 emitted species with~~and the highest~~ a horizontal resolution of 0.005° × 0.005° (Table 1).

2.2 The calculation for EFs and DMs

To calculate regional EFs and DMs, we adopt the approach outlined by Carter (2020). Initially, we divide CO emissions per grid by the EF applied to each biome, yielding DM:

$$DM_{b,x} = CO_{b,x}/EF_b \quad (1)$$

where b represents one of the seven biomes in Fig. S1, and x represents the location grid. This calculation of DM using CO is reasonably representative, given that the inventories are not adjusted for CO emission factors. After calculating $DM_{b,x}$ for each grid, we derive a regional average emission factor by dividing total CO emissions by total DM for each major BB region:

$$EF_{CO} = \sum_{b,x} CO \,/\, \sum_{b,x} DM \quad (2)$$

These calculations enable us to discern the influence of LULC classification on BB emission inventories. For a specific biome type within a given region, we calculate EF by dividing the CO emissions of that particular biome classification by the sum of the value from each biome in the respective region:

$$EF_b = CO_b/\sum_b DM \quad (3)$$

where b represents one of the seven biome classifications in this study (Fig. S1).

Furthermore, for the two bottom-up inventories, we invert the fuel consumption for each vegetation biome b within a given area:

$$FC_b = DM_b/BA \quad (4)$$

Here, the DM corresponding to each biome in FINN1.5 and GFED4s is obtained using equation (1), and BA represents the total burned area derived from the emission inventory.

2.~~2~~ 3 Quantitative statistical methods

As described in section 2.1, fire detection is greatly affected by cloud/smoke obscuration in the bottom-up approach. For example, if there are clouds/smoke at high altitudes while fire occurs on the ground, the MCD14DL active fire detection product used in FINN1.5 may miss these fire points. In addition, ~~for~~ the combustion that is too small in size and too low in temperature,~~ it~~ cannot be effectively monitored due to the low brightness temperature contrast with the surrounding environment. In contrast, the burned area product (mainly MCD64A1) used by GFED4s determines the burning information based on the changes such as surface albedo, and is, therefore less affected by clouds/smoke. For inventories based on the top-down approach, the emission inventories also differ to a large extent due to the cloud/smoke obscuration, since QFED2.5 uses a "sequential method" to correct for missing FRPs during cloud/smoke obscuration, whereas VFEI0 does not. Thus, in this study, the symmetrical mean absolute percentage error (SMAPE) and Pearson's R are used to ~~access~~ assess the difference in sensitivity to clouds/smoke between the two BB products based on the bottom-up (or top-down) approach. The specific algorithm is as follows:

$$\mathrm{SMAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|X-Y|}{(|X|+|Y|)/2}, \qquad (\cancel{4}5)$$

$$R = \frac{\sum_{i=1}^{N}|(X-\bar{X})\cdot(Y-\bar{Y})|}{\sqrt{\sum_{i=1}^{N}(X-\bar{X})^2\cdot\sum_{i=1}^{N}(Y-\bar{Y})^2}}, \qquad (\cancel{5}6)$$

where X and Y are fire detection data from two different datasets (e.g. burned area from FINN1.5 and GFED4s or FRP from VFEI0 and QFED2.5). We divided these fire detection data into three groups according to the cloud fractions less than 0.4, 0.4-0.7, and greater than 0.7, and the number n represents valid samples in different cloud fraction groups. SMAPE ranges from 0% to 200%, with smaller values indicating smaller differences, while Pearson's R ranges from 0 to 1, with smaller values implying less correlation.

In order to quantify the effect of cloud obscuration on BB datasets, we selected the most intensely burning regions in BONA in July for this study. For consistency, we re-interpolated the fire detection data used in the four BB datasets, as well as the MODIS MCD06 cloud fraction data, to the same horizontal resolution (0.25° × 0.25°). Considering the continuity of combustion, we took every 5° × 5° as a sample area in the northern U.S. to ensure that if a large burn occurred, the area would be detected to some extent, avoiding errors due to differences between the inventories. At the same time, we excluded the samples ~~in~~ at the same time and location, where the emissions are all zero. Finally, a total of 1888 samples were obtained for the burned area group, with 534, 541, and 813 samples for low (<0.4), medium (0.4-0.7), and high (>0.7) cloud fraction, respectively. A total of 1,682 samples were obtained for the FRP group, with 860, 390, and 432 samples under low, medium, and high cloud fraction, respectively. It is worth noting that we use the average FRP of MOD and MYD for QFED2.5 since the VFEI0 FRP is the average between day and nighttime observations. Moreover, our approach cannot rule out the case of missing measurements when two sets of BB inventories are both obscured by the cloud. However, the main goal of this paper is to explore the causes of uncertainties in emission inventories, the specific case of omission due to cloud obscuration depends on the development of satellite detection technology and is not part of the purpose of this study.

2.~~3~~ 4 CESM2-CAM6 model

The Community Earth System Model version 2.1 (CESM2) is a new generation of the coupled climate/Earth system models developed by National Center for Atmospheric Research (NCAR). In this study, we used the global Community Atmosphere Model version 6 (CAM6) (Danabasoglu et al., 2020). Gas-phase chemistry was represented by the Model for Ozone and Related chemical Tracers tropospheric chemistry (MOZART-T1, Emmons et al., 2020). The wet deposition of soluble gaseous compounds in CAM6-Chem is based on the scheme of Neu and Prather (2012), which describes the process of in-cloud cleaning and under-cloud cleaning. The formation of secondary organic aerosols (SOA) is from a volatility basis set (VBS) approach developed by Tilmes (2019). Properties and processes of aerosol species of black carbon (BC), primary organic aerosols (POA), SOA, sulfate, dust, and sea salt are calculated by Modal Aerosol Module (MAM4) described by Liu (2016). CAM6 uses a horizontal resolution of nominal 1° (1.25° × 0.9°~~-~~, longitude by latitude) and 32 vertical levels from the surface to 2.26 hPa (~40 km).

In this study, four BB emission inventories (FINN1.5, GFED4s, QFED2.5, and VFEI0) are re-gridded to a horizontal resolution of 1.25° (longitude) × 0.9° (latitude), and then applied to the model. All simulations were performed for five years, while horizontal winds and temperature ~~are~~ were nudged toward the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) reanalysis data (GMAO, 2015) for every 6 h. Simulations are conducted for 2012-2016, with the first year used for initialization and model spin-up. Daily BB emissions were applied in this study, whereas the vertical distribution of fire emissions was followed Freitas et al. (2006, 2010). Anthropogenic and biogenic emissions in this study are from the Community Emissions Data System (CEDS) and Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGANv2.1), respectively, at 2010 levels (Guenther et al.,2012; Hoesly et al., 2018).

2.~~4~~ 5 Measurement data

The Tropospheric Pollution Measurement Instrument (MOPITT) is aboard the Earth Observing System (EOS)/Terra satellite launched by NASA (Warner, et al., 2001). MOPITT is the first instrument to observe the global concentration and currently provides column concentration and volume mixing ratio of global carbon monoxide (CO) since 1999. We used MOPITT CO gridded monthly means (Near and Thermal Infrared Radiances) V009 (MOP03JM_9; NASA Langley Atmospheric Science Data Center DAAC, retrieved from https://doi.org/10.5067/TERRA/MOPITT/MOP03JM.009), which has a horizontal resolution of 1° × 1°. It should be noted that ~~in order~~ to compare the CO column concentration simulated by CESM2-CAM6 with MOPITT CO, we calculated the simulated CO column concentrations by cumulative integration from 900 hPa to 100 hPa isobaric height (Deeter et al., 2022). We also used the daily AOD (550 nm) and cloud fraction data from MODIS products MOD08_D3 (MODIS/Terra Aerosol Cloud Water Vapor Ozone Daily L3; Platnick et al. 2015) and MCD06COSP (MODIS (Aqua/Terra) Cloud Properties Level 3 daily, Webb et al., 2017), respectively.

The observations of AERONET (http://AERONET.gsfc.nasa.gov/; Holben et al., 1998) from 12 sites are used in this study. These AERONET stations were selected since they are close to BB source regions. As marked in Figure 1b, these sites include sites in BONA (Yellowknife_Aurora (62.5°N, 114.4°W), Pickle Lake (51.4°N, 90.2°W)), BOAS (Tiksi (71.6°N, 128.9°E), Yakutsk (61.7°N, 129.4°E)), SHAF (Namibe (15.2°S, 12.2°E), Mongu Inn (15.3°S, 23.1°E)), SHSA (Alta Floresta (9.9°S, 56.1°W), Rio Branco (9.9°S, 67.9°W)), EQAS (Palangkaraya (2.2°S, 113.9°E), Jambi (1.6°S, 103.6°E)), SEAS (Omkoi (17.8°N, 98.4°E), Ubon Ratchathani (15.2°N, 104.9°E)).

All observed AOD represent real atmospheric conditions and therefore, in addition to BB aerosols, biogenic aerosols, anthropogenic aerosols, dust, and sea salts are also integrated in MODIS and AERONET datasets.

3 Comparative analysis of emission inventories

CO and OC are the main species emitted from biomass burning (Westerling et al., 2010; van der Werf et al., 2010b; Carter et al., 2020) but emissions vary widely. In this study, we compare the differences in CO and OC emissions (representing gaseous and particulate pollutants, respectively) in four BB inventories, and investigate in detail the key reasons for the differences in emission inventories.

3.1 The contribution of dry matter and emission factors to the difference in CO emission

The total global CO emissions from the four BB emission inventories selected for this study are in the range of 252-336 Tg, with GFED4s being the highest and FINN1.5 the lowest. ~~In order t~~To quantify the differences in CO emissions among four datasets, we use the standard deviation (SD) to characterize the absolute difference, and the coefficient of variation (cv, calculated as the ratio of SD to the mean) to characterize the relative differences (Fig. 2a). The larger the cv, the greater the difference between emission inventories. We have ranked the major seven BB regions in the world according to the differences in CO emissions between the four sets of inventories, with the differences being, in descending order, EQAS, BONA, SEAS, SHAF, NHAF, BOAS, and SHSA.

This study points to a high variability of different BB emission inventories in EQAS, which is inconsistent with previous studies (Liu et al., 2020b; Pan et al., 2020). Previous studies mainly focused on emission differences of particulate pollutants, such as BC and OC (Bian et al., 2007; Paton-Walsh et al., 2012; Carter et al., 2020; Lin et al., 2020b; Pan et al., 2020), thus assuming that the inventory differences in Equatorial Asia are smaller than those in Southern Hemispheric Africa and Northern Hemispheric Africa. In contrast, this study analyzes the differences between particulate and gaseous pollutant emissions separately when comparing the differences in BB emission inventories. For example, GFED4s classify a large portion of EQAS land cover as peatland (Kasischke and Bruhwiler, 2002; Stockwell et al., 2016; van der Werf et al., 2006, 2010a, 2010b, 2017) and suggest that this organic matter-rich soil emits a large amount of CO when burned. The other three inventories either do not include peatland (FINN1.5 and QFED2.5) or only consider peatlands as a small fraction of the burned area in EQAS (VFEI0), thus estimating CO emissions much smaller than GFED4s. In addition, the extent of peatland fires in EQAS increased significantly during the strong El Niño event (Page et al., 2002). Considering that a strong El Niño event also occurred in 2015-2016, these increases in peatland fires further amplify the discrepancy between GFED4s and other emission inventories on CO estimates.

~~According to Eq. (1), we split the difference in CO emission into the difference in EFs and DM (Fig. 2b and c). Since only GFED4s provides DM information in its dataset, we follow Carter (2020) to divide CO emissions per grid by the EF applied to each biome to obtain DM:~~

$$\cancel{DM_{b,x} = CO_{b,x}/EF_b} \qquad \cancel{(6)}$$

~~where b represents one of the seven biomes in Fig. S1, and x represents the location grid. The calculation of DM by CO is somewhat representative, since all inventories are not corrected for CO emission factors. After calculating the~~ ~~$DM_{b,x}$~~ ~~for each grid, we obtained a regional average emission factor by dividing the total CO emissions by the total DM for each major BB region:~~

$$\cancel{EF_{CO} = \sum_{b,x} CO \,/\, \sum_{b,x} DM} \qquad \cancel{(7)}$$

~~Such calculations allow us to distinguish the impact of LULC classification on BB emission inventories.~~

As shown in Fig. 2, the distribution pattern of DM differences is very similar to that of CO emission differences, indicating that DM is the main reason for dominating the difference in the four emission inventories. In comparison, the difference in DM contributes 50-80% to the regional CO emission differences, and the comprehensive EFs contributes the remaining 20-50%. However, in EQAS, BONA, and BOAS, the contribution of comprehensive EFs to BB emission differences in four datasets is comparable to that of DM (Fig. 2). In the following sections, we will further analyze the main causes of the differences for DM and EFs.

3.2 Primary causes of DM inconsistency in the bottom-up inventories

To investigate the underlying causes of the differences in DM, we first compared DM between emission inventories produced by the bottom-up and up-down approaches. The difference in DM estimated by the top-down method is small, and the DM ratio of QFED2.5 to VFEI0 does not exceed two times in different regions. However, DM estimated by the bottom-up approach varied widely, with DM ratio as high as 4.7 in BONA for GFED4s and FINN1.5 during the 2013-2016 fire season. Therefore, we need to focus on the main reasons for DM variance in emission inventories based on bottom-up approach.

According to Eq. (2), DM equals the product of the burned area, fuel load, and FB in the bottom-up inventories, with the product of the last two terms being fuel consumption. Fig. 3 compares the burned area and fuel consumption of GFED4s and FINN1.5 emission inventories for the seven largest BB regions. The ratio GFED4s/FINN1.5 represents the relative difference in burned area or fuel consumption between the two emission inventories. In general, the difference in burned area between the two inventories varies greatly with latitude, and the ratio of GFED4s to FINN1.5 fluctuates in the range of 0.28-1.94. In contrast, differences in fuel consumption between the two inventories were more consistent, with GFED4s consistently having higher fuel consumption than FINN1.5 in all regions except SEAS. In the next sections, we discuss the main reasons for the differences in burned area and fuel consumption between the two datasets.

3.2.1 Effect of land cover on burned area

As shown in Fig. 3a, the differences in the burned area between the bottom-up emission inventories ~~is~~ are highly variable. At high latitudes, the burned area of GFED4s is significantly higher than that of FINN1.5, especially in BONA, where the burned area of GFED4s is twice that of FINN1.5. In contrast, the burned area of GFED4s in the equatorial region is much lower than that of FINN1.5, and even 60% smaller in EQAS. This is a result of the difference in fire detection between the two datasets. As shown in Table 1, FINN1.5 uses the MCD14 DL fire point product, while GFED4s uses the hybrid burned area product, mainly using MCD64A1 combined with fire point products MOD14A1/MYD14A1 to enhance the detection of small fires.

These two sets of products have their ~~own~~ advantages in detection ability under different vegetation type conditions. The hybrid burned area product detects burned areas over a period of time (up to days), while the fire point product detects burned areas primarily in near ~~real~~ real-time (Roy et al., 2008). In addition, the burned area used in GFED4s (hybrid burned area product) is not affected by the vegetation canopy when the leaf area index (LAI) is less than 5. Therefore, a higher burned area is estimated in GFED4s in BONA and BOAS than in FINN1.5. However, in areas with more broadleaf forests and grasslands such as EQAS, SEAS, and SHSA (Fig. S2), the MCD14DL fire point product used in FINN1.5 performed better in capturing understory fires that occurred in closed canopies (Cochrane and Laurance, 2002; Cochrane, 2003; Alencar et al., 2005; Roy et al., 2008). It also has an advantage in capturing sporadic and fragmented small fires in grasslands and agricultural fields due to its high resolution (Liu et al., 2020b). Furthermore, FINN1.5 assumes that each detected fire in the equatorial region will continue to burn for 2 days, and that the next day's fire will continue to be half the size of the previous day (Table 1). Thus, the burned area of FINN1.5 in the tropical zone is 2.6 times higher than ~~those~~ that of GFED4s, which is consistent with previous studies (Wiedinmyer et al., 2011; Pan et al., 2020). At the equator, the burned area in grassland/agricultural fields and forests estimated by FINN1.5 is 1-3 and 4-6 times higher than in GFED4s, respectively (not shown).

It is worth noting that in Africa (NHAF and SHAF), although the dominant burnable vegetation is grassland (Fig. S2), unlike the sporadic small fires that occur in grassland in the other five regions, large continuous fires often occur in African Savannas (Liu et al., 2020b). Therefore, the hybrid burned area product used in GFED4s is more effective in detecting all fire events occurring over ~~a period of~~ time, with 10-20% higher burned area than FINN1.5.

3.2.2 Effect of cloud obscuration on burned area

In addition to the vegetation, cloud occlusion can likewise bias the satellite detection of burned area. Figure S3 shows the time series of AOD measured by satellite or ground-based data at the Pickle Lack site of BONA from June to August 2013. In contrast to the high AOD values observed for the AERONET network, MODIS AOD ~~is~~ often in missing measurements when the MODIS cloud fraction is larger than 0.5. Furthermore, AERONET AOD varies dramatically over a short period ~~of time~~, suggesting that different detection principles (such as detecting fire points in near real-time during satellite overpass time, or estimating the accumulation of burned area over time through changes in surface albedo over multiple satellite overpass times) can significantly affect the burned area product under high cloud fraction/smoke conditions (Paton-Walsh et al., 2012; Liu et al., 2020b; Pan et al., 2020). Although some assumptions are made in FINN1.5 in the equatorial regions as described above to improve the effect of cloud obscuration on burned area detection, these assumptions are not used for mid- and high-latitudes. GFED4s uses a hybrid burned area product and is relatively unaffected by cloud obscuration. By fusing the MCD64A1 with MOD14A1/MYD14A1 products with multi-temporal satellite data, GFED4s is able to determine the approximate date and extent of fires through post-fire ash deposition, vegetation migration, and land surface changes (van der Werf et al., 2017; Boschetti et al., 2015, 2019).

To quantitatively assess the impact of cloud obscuration on different emission inventory estimates, we perform ~~analyzes~~ analyses in areas with high cloud fraction (Fig. S4), intense biomass burning, and unaffected by the smoothing hypothesis used in FINN1.5. We selected the regions of North America with the most intense biomass burning (Alberta and Saskatchewan, Canada, 50°-70°E, 100°-130°W, Fig. S5), and analyzed the relationship between the burned area and cloud fraction for bottom-up inventories during July from 2013 to 2016 (Fig. S6). As shown in Fig. 4, with the increase in cloud fraction, the SMAPE of the two bottom-up emission inventories increases from 150% to 180%, while the Pearson correlation declines from 0.85 to around 0.75. These results demonstrate that the uncertainty in the burned area for two bottom-up emission inventories increases by ~20% during high cloud fraction compared to low cloud fraction conditions.

3.2.3 Causes of Fuel Consumption differences

Fuel consumption is another factor that affects DM differences between two BB emission inventories. As shown in Fig. 3b, the fuel consumption of GFED4s is 30-75% higher than that of FINN1.5 in almost all BB areas except SEAS. The difference in fuel consumption between the two emission inventories is larger in the tropics than in the high latitudes. ~~In this study, we invert the fuel consumption for each vegetation biome b in a given area as follows:~~

$$\cancel{FC_b = DM_b / BA} \qquad \cancel{(8)}$$

~~The DM corresponding to each biome in FINN1.5 and GFED4s has been obtained according to equation (6), and BA is the total burned area obtained from the emission inventory.~~ As shown in Fig. 5, at high latitudes (e.g., BONA and BOAS), and in the equatorial region (such as EQAS), relatively high fuel consumption comes from peatlands in GFED4s. According to previous studies, peatlands, a type of soil rich in organic matter, store large amounts of carbon underground (van der Werf et al., 2010b, 2017; Gibson et al., 2018; Kiely et al., 2021; Vetrita et al., 2021), and emit large amounts of CO when burned. Peatlands contribute 30-60% of the total fuel consumption in BONA, BOAS, and EQAS (Fig. 5a-c).

Besides peatlands, GFED4s tends to have higher fuel consumption than FINN1.5 due to forest contributions. Forests (including tropical, temperate, and boreal forests) account for more than 50% of the fuel consumption in all burning regions except EQAS, where peatlands dominate the fuel consumption. Moreover, forest fuel consumption in GFED4s is generally much higher than in FINN1.5 except in BOAS and SEAS (Fig. 5). Since fuel consumption is equal to the product of fuel load and FB (the percentage of specific plants that can be adequately burned, Eq. 2), different vegetation classifications may be responsible for large differences in fuel consumption between emission inventories. For example, for woody vegetation such as forests, GFED4s assumes a range of FB between 40-60% for temperate and tropical forests and 20-40% for boreal forests, while FINN1.5 assumes that all woody vegetation burns no more than 30% (van der Werf et al., 2010; Wiedinmyer et al., 2011). Thus, in terms of FB alone, the forest fuel consumption of GFED4s is therefore 0.67-1.3 times greater than that of FINN1.5, which is one of the main reasons for the difference in fuel consumption.

3.3 Primary causes of DM inconsistency in the top-down approach

We also analyze the causes of the difference in DM between BB emission inventories estimated by the top-down method. According to Eq. (3), it is evident that the empirical factor and the radiative energy of the fire are the key factors that cause the discrepancy in the top-down emission inventories. The QFED2.5 and VFEI0 inventories we have chosen use different satellites for the fire detection products. For example, for the fire radiative power product, QFED2.5 is based on the Moderate Resolution Imaging Spectroradiometer (MODIS) inversion of the NASA Terra and Aqua combined satellites, while VFEI0 is based on the Visible Infrared Imaging Radiometer (VIIRS) inversion of the combined ~~polar~~ polar-orbiting satellites Suomi NPP and NOAA-20, although the algorithms are similar. However, there are systematic deviations due to different satellites, specific tests and metadata, and resolutions. The VIIRS 375 m fire product used by VFEI0 has a finer resolution and is more advantageous for small fire spot detection than other coarser resolution (1 km) fire spot detection products. The FRP density used in VFEI0 is much higher than that of QFED2.5 due to the fine horizontal resolution.

The estimations of FRP and DM are ~~highly dependent on~~strongly influenced by the horizontal resolution of satellite products. For example, in the BONA region during~~in~~ July (the month with the most intense burning at the position of 50°-70°N, 100°-130°W), the total QFED FRP (average FRP measured by MOD and MYD) is 1.5 times higher than VFEI0 (Fig. S7~~),~~). Additionally, the differing α values between QFED2.5 and VFEI0 in BONA can potentially result in higher DM in QFED2.5 compared to VFEI0 by a factor of 1.3-3.8. However, the actual ~~but~~ DM in the QFED2.5 inventory is 30% lower than in VFEI0. The relatively high FRP density used in VFEI0 (Fig. S8) results in a higher DM than in QFED2.5 due to its ~~higher~~ superior horizontal resolution, enabling ~~which~~

~~facilitates capturin~~the~~g~~ precise ~~areas~~ delineation of fire areas. It is important to n~~N~~ote that while the empirical factor also ~~has an impact~~influences ~~on~~ the amount of DM, ~~but it~~its impact should not be as significant as the difference caused by the horizontal resolution of satellite products (Kaiser et al., 2012; Darmenov et al., 2015; Ferrada et al. 2022).

Previous studies have shown that cloud occlusion also causes bias in FRP detection (Liu et al., 2020b). We also take BONA as a pilot region to analyze the influence of cloud fraction on FRP in QFED2.5 and VFEI0. According to Fig. 5c-d, the SMAPE of the two emission inventories rises as the cloud fraction increases, and the Pearson correlation is noticeably low under the maximum cloud fraction. While QFED2.5 uses the "sequential approach" (section 2.1) to correct for the missing FRP in cloud-obscured fires, this correction is not considered in VFEI0. Therefore, although the two top-down emission inventories use similar algorithms, significant bias occurs under high cloud fraction conditions, with QFED2.5 estimating DM much higher than VFEI0.

3.4 Primary causes of EF inconsistencies

Although DM differences dominate the inconsistencies of CO emissions across major BB regions, the contribution of EFs is still not negligible in some regions. For example, in EQAS, BONA, and BOAS, the contribution of EFs is up to 50%, which is comparable to that of DM. ~~Considering that EF is closely related to vegetation types, we calculated the emission factor of a single biome type in a given region as follows:~~

$$\cancel{EF_b = CO_b/\sum_b DM} \qquad \cancel{(8)}$$

~~where b represents one of the seven biome classifications in this study (Fig. S1), and DM here is the sum of the value from each biome in a certain region.~~

The comprehensive EFs of GFED4s are higher in BONA, BOAS, and EQAS regions than in other inventories, with vegetation classification being one of the most important factors (Fig. 6). For example, in EQAS at low latitudes, peatlands in GFED4s account for 65% of the regional comprehensive EF. In contrast to GFED4s, FINN1.5, and QFED2.5 do not consider this organic matter-rich land as a source of burning, and they classify this category of land cover type as savanna or grass. The CO emission factor for peatlands is four times higher than the CO emission factor for savanna or grass (Table 2), ultimately making the comprehensive EF for GFED4s 60-70% higher than that of the other three datasets. It is worth noting that although the classification of Peatland exists in VFEI0 (Ferrada et al., 2022), due to differences in terrestrial ecological divisions (Olson et al., 2001; http://www.worldwildlife.org/science/data/item1875.html), peatlands identification areas are much smaller than GFED4s inventory. Therefore CO emissions from peatlands in GFED4s are much higher than in the VFEI0 inventory (Figure 3-9a; Ferrada et al., 2022).

In both BONA and BOAS, we find that the comprehensive EFs in the four datasets are ranked as follows: GFED4s>FINN1.5>QFED2.5>VFEI0, where the EF of GFED4s is about 1.5 times higher than that of VFEI0. Unlike the low-latitude regions, the classification of forests in different emission inventories is the main reason for the difference in comprehensive EF in high-latitude regions. At high latitudes (50° - 70°N), GFED4s, QFED2.5, and FINN1.5 identify more forests than VFEI0 (Fig. S1) because the former three classify some shrubs (e.g., closed shrublands and woody savanna) as forests, while the latter classify them as grassland. Forests contribute to 70% ~~and~~ or more of the comprehensive EFs at high latitudes in the first three emission inventories, but only 8% to the comprehensive EF in VFEI0. The remaining gap in the absolute contribution of forests is caused by the difference in the selected emission factors and the horizontal resolution of the satellite products.

3.5 Contribution of DM and EFs to differences in OC emissions

The above analysis completes the comparison of gaseous pollutant CO among different emission inventories. In this section, we will take OC as an example to compare the emission differences of particulate pollutants. As shown in Fig. 7, the global OC emissions of four datasets range from 14.9 to 42.9Tg, with the highest emissions from QFED2.5, which is consistent with previous studies (Carter et al., 2020; Pan et al., 2020). According to the statistical method in section 3.1, we quantified the magnitude of OC emission differences between regions and ranked them as follows: BONA>BOAS>NHAF>SHAF>SEAS>SHSA>EQAS. Compared to the CO emission differences (Fig. 2), the difference in OC emissions becomes larger for BOAS and smaller for low latitude regions of SEAS and EQAS. Since DM should be consistent in the same emission inventories for a given time and area, the magnitude of emissions for different species depends on changes in emission factors. Considering that the emission factors of aerosol-related emission species such as OC, BC, NH_3, SO_2, and $PM_{2.5}$ have been corrected based on the satellite retrieved AOD of the QFED2.5 emission inventory (Table 2), the EFs of OC in QFED2.5 are much higher than that of the other three emission inventories (Fig. 7b). As a result, the OC EFs in the QFED2.5 emission inventory were enlarged by a factor of 1.8-4.5 times through the correction of BOAS, SEAS and EQAS (Table 2). In contrast, the other three emission inventories were not corrected for OC EFs.

Unlike the CO EFs, the OC EFs of GFED4s in equatorial regions are largely consistent with the FINN1.5 and VFEI0 emission inventories. Although burning organic matter-rich soil substrates is generally thought to release large amounts of CO, their ability to release OC is similar to that of vegetation such as sh~~u~~rubs and some forests. Thus, despite CO emissions bias in EQAS being largely affected by peatlands, differences in OC emissions among the four inventories are not significant.

Compared with Pan et al. (2020), it is obvious that the top-down approach will not lead to an increase in emission deviation of the particulate-phase species. The correction of EFs, however, is the root cause of the increased bias in OC emissions. Pan et al. (2020) reported that QFED2.5 and FEER1.0 had the highest global OC emissions, while GFAS1.2 had much lower OC emissions. In this study, the largest OC emission also appears in QFED2.5, but the global total OC emissions of the recently released VFEI0 are relatively low.

4 Model evaluation based on emission inventories application

4.1 Comparison of simulations with MOPITT CO

One of the main goals of this study is to provide a confidence assessment of the BB emission inventories by comparing model simulations with observations. A comparison between model simulations using different emission inventories and ground-based/~~satellite~~ satellite-retrieved data for the respective fire seasons (Table 3) of the main BB regions is explored below. In this study, we compared the model results with measurements from two perspectives: the spatial distribution of BB pollutants, and the time-varying characteristics of BB pollutants.

Figure 8 depicts the spatial distribution of CO column burdens in SHSA and SHAF during the fire seasons. In SHSA, the simulated CO column burdens using different emission inventories are all consistent with the spatial distribution pattern of MOPITT CO column burden, with the peak value located in the Amazon rainforest. However, the central value of MOPITT CO column burden is as high as 2.8×10^{18} molecules cm^{-2}, which is slightly higher than the simulated results. Among the four sets of emission inventories, the peak amplitude and spatial distribution of simulated CO column burdens are closest to the ~~satellite~~ satellite-retrieved data after applying the GFED4s and VFEI0. In SHAF, however, the model underestimated the peak CO column burden after applying all emission inventories except VFEI0.

In addition to SHSA and SHAF, a comparison of regionally averaged CO column burdens between our simulations and MOPITT CO in major BB regions is also shown in Table 3. In the Northern Hemisphere, our simulations are significantly underestimated compared to MOPITT CO, while those in the Southern Hemisphere are consistent with satellite retrievals. Surprisingly, the simulated spatial distributions and magnitudes of CO in the Southern Hemisphere using the recently released VFEI0 agree very well with observations. In contrast, the underestimation of CO concentrations in the Northern Hemisphere is partly due to uncertainty in anthropogenic emissions, as we assume anthropogenic emissions at 2010 levels, which are lower than those during the 2013-2016 period.

Note that simulated CO concentrations are 30-40% lower than MOPITT CO at high latitudes. Besides the impact of emission inventories, there are also large uncertainties in satellite-retrieved CO concentrations (Lin et al., 2020a; Pan et al., 2020). In addition, OH loss, long-range transport, and photochemical reactions involved in the CESM2-CAM6 model simulations also lead to uncertainties in simulated CO. For example, MOZART-4x contains an additional OH oxidation pathway for CO, which may lead to lower CO concentrations (Lamarque et al., 2012; He and Zhang, 2014; Barré et al., 2015; Brown-Steiner et al., 2018; Emmons et al., 2020). In comparison, the simulated CO by using GFED4s is closest to the MOPITT CO value in terms of spatial distribution and peak magnitude at high latitudes in the Northern Hemisphere, which is superior to other emission inventories.

4.2 Comparison of simulations with MODIS AOD

We compared MODIS-derived aerosol optical depth (AOD) data with simulated AOD in major BB areas. Figure 9 shows the spatial distribution of AOD in SHSA and SHAF during their fire seasons. The simulated AOD is significantly higher than the MODIS AOD in SHSA. Note that primary organic aerosols (POA) associated with BB account for only 15-23% of the total AOD in Amazon, while secondary organic aerosols (SOA) account for approximately 50% of the total AOD. Furthermore, overestimation of simulated AOD occurs throughout the year, not just during the fire season. Considering the high biogenic emissions in this region, the overestimation of AOD could be attributed to the formation of biogenic SOA (He et al., 2015; Tilmes et al., 2019). In SHAF, the spatial distribution and magnitude of simulated AOD using GFED4s and VFEI0 are close to those of the MODIS AOD. In comparison, our results show that AOD is significantly underestimated using FINN1.5, but largely overestimated using QFED2.5.

Table 4 shows the mean values of model-simulated AOD and satellite measurements for each region during its fire season. The influence of the BB emission inventory has little effect on the simulated AOD value in the Southern Hemisphere, and the regional average AOD deviation is within 20%. In contrast, the average deviation of simulated AOD driven by four BB inventories can be as high as 40% in the high latitudes of the Northern Hemisphere. Comparatively, GFED4s and QFED2.5 are more suited for high latitudes in the northern hemisphere, whereas the VFEI0 is most suitable for the southern hemisphere for AOD simulations. In Africa, QFED2.5 is not recommended due to its considerable overestimation.

4.3 Comparison of simulations with ground-based measurements

In the above sections, we merely discussed the spatial distribution and the magnitude of pollutants during fire seasons. To further analyze whether each dataset can effectively capture the instantaneous combustion of BB, we compared the value of simulated daily AOD with that of ground-based observation (Fig. 10). ~~In order t~~To be more representative, we selected stations in each BB region with a large amount of data during fire season, allowing a comprehensive assessment of the global BB emission inventories. The specific locations of the selected 12 AERONET sites are shown as red triangles in Fig. 1b.

At EQAS sites such as Palangkaraya and Jambi, the observed AOD from September to November ~~in~~ 2014/2015 is generally higher than 1, with peaks exceeding 5, reflecting the intense BB events (Fig. 10a-b). Only simulations using GFED4s are consistent with observed AOD during strong BB events, with a slight underestimation of 33-38%, while none of the other simulations could capture the BB process. Considering the significant contribution of peatlands to BB emissions in EQAS in GFED4s, our results suggest that it is important to include the burning of organic matter-rich soils in BB emission inventories. At SEAS sites such as Omkoi and Ubon Ratchathani, the peak AOD occurs from February to April at a value of about 2, and all simulations applying the four emission inventories capture the observed changes in AOD (Fig 10c-d). However, due to the uncertainty of anthropogenic emissions, the simulated AOD is usually smaller than the actual observed value in EQAS. Note that simulations using QFED2.5 are most consistent with observed AOD during intense biomass burning events.

At the Namibe station of SHAF (Fig. 10e), the simulated AOD agrees best with the measured results after using FINN1.5 and GFED2.5, with NMB values within ±8%, indicating these two emission inventories can characterize the day-to-day variability of the intense BB process. However, Namibe is located downwind of the dust source, and dust aerosols contribute more than 50% to the total AOD in this area. To better evaluate the performance of the four BB emission inventories in SHAF, we chose another site, Mongu Inn, located in the interior of Southern Hemispheric Africa, where dust and sea salt accounted for 20-30% of the total AOD. At Mongu Inn, all simulations underestimate AOD by 46-71%, and only QFED2.5 and VFEI0 emission inventories ~~are able to~~can capture a few peaks during intense biomass burning events (Fig. 10f). In SHSA, while Figures 9 and 10h show an overall overestimation of simulated AOD compared to MODIS AOD, at the Brazilian Alta Floresta site east of the Amazon, simulated AOD agrees very well with the ground-based observations (Fig. 10g). In general, the simulations using the VFEI0 emission inventory for the Southern Hemisphere are close to the measurements.

At high latitudes, simulations driven by GFED4s and QFED2.5 better capture the observed peak AOD, with regional NMB values of less than 40% (Fig. 10i-l), suggesting that these two simulations can reproduce the intense BB process. In contrast, FINN1.5 and VFEI0 are obviously not suitable for describing the BB process in these sites, and the simulated AOD is underestimated by 60-80%.

5 Conclusion and Discussion

~~The establishment of BB emission inventories follows two basic approaches, one is a "bottom-~~

~~up" approach, which usually establishes inventory information based on observed surface data (such as detected fire points, burned area, and vegetation types). The other one is a "top-down" approach, that is, the vegetation consumption is inversely calculated from the radiative energy release rate of vegetation burning observed by satellite, and the vegetation type information is superimposed to establish the inventory.~~ In this study, we examine four commonly used BB emission inventories (two bottom-up inventories (GFED4s and FINN1.5) and two top-down inventories (QFED2.5 and VFEI0)) ~~are chosen~~ to better understand the ~~uncertainty~~ uncertainties ~~of~~ associated with BB emissions. ~~, two of which are bottom-up inventories (GFED4s and FINN1.5), and two are top-down inventories (QFED2.5 and VFEI0).~~ We analyze ~~the difference~~variations in CO and OC emissions across~~from these inventories for~~ seven major BB regions ~~-around the world~~worldwide from 2013 to 2016. We explore the differences between gaseous and particulate emission inventories, ~~and~~ quantifying the impact of vegetation classification, cloud cover, and emission factors on ~~emission~~ inventory bias. Additionally, w~~W~~e ~~also~~ apply~~ied the fou~~these~~r BB emission~~ inventories to the global model CESM2-CAM6 to assess the model~~'s~~ ~~ability~~ performance ~~to~~ in simulating~~e~~ pollutants~~, by comparing the simulations with measurements from~~ against satellite ~~products or~~and ground-based observations.

The total global CO emissions exhibit significant variability ~~in~~ among the four inventories ~~vary greatly~~, with ~~their~~ annual average ~~values~~s ~~fluctuating~~ ranging ~~between~~ from 252~~-~~ to 336 Tg, and ~~the~~ a maximum deviation rate exceeding~~s~~ 30%. In ~~some~~ certain regions such as BONA~~s~~, changes in CO emissions are even larger~~.~~, ~~For example,~~ GFED4s ~~in BONA~~ emits 5.8 times more CO ~~emissions~~ than FINN1.5~~, while the coefficient variation of the four emission inventories in EQAS is as high as 0.67~~. ~~Overall, CO emissions from GFED4s are higher than those from VFEI0 and QFED2.5 inventories in all regions, with the lowest CO emissions in FINN1.5 inventory.~~ DM is ~~dominates~~ identified as the primary contributor to ~~the~~ variance among BB emission inventories, accounting for 50-80% of ~~the~~ regional bias, while comprehensive EFs ~~account for~~contribute the remaining 20-50%. ~~Notably~~Interestingly, the contributions of DM and comprehensive EFs to ~~the~~ emission inventory differences ~~in BB emission inventories~~ are comparable across equatorial regions and Northern Hemisphere high latitudes.

T~~here is a large~~he uncertainty in DM ~~due to~~arises from ~~the calculation of~~ underlying fuel consumption and burned area, ~~which in turn is related~~linked to ~~the~~ vegetation classification ~~method~~, fire detection product algorithm, and cloud/smoke masking ~~used in the emission inventory~~. ~~First, the~~ V~~v~~egetation classification ~~method~~ significantly impacts~~affects~~ fuel loading and the Fraction of Biomass burned~~.~~, with discrepancies contributing to biases in fuel consumption. ~~At~~ In regions at both low and high latitudes (except Southeast Asia), ~~the fuel consumption term of~~ FINN1.5 ~~is~~ exhibits a fuel consumption term that is less than 50% of ~~that of~~ GFED4s,~~,~~ ~~where~~ with the vegetation classification methodology ~~contributes~~ contributing ~~significantly~~ primarily to this bias. ~~For example, in EQAS, while GFED4s classifies a significant protion of the area as peatland, FINN1.5 identifies it as grassland, resulting in 37% lower fuel consumption for FINN1.5 than GFED4s in this region. In addition, GFED4s assumes that the FB of tropical forest is 40-60%, while FINN1.5 assumes that the FB of forests does not exceed 30%, so the FB of forests in FINN1.5 is 25-50% lower than GFED4s. Similarly, the fuel consumption of FINN1.5 in high latitudes is also lower than that of GFED4s, with a deviation of up to 50% or more. The classification of peatlands, the amount of forest burnable (fuel load) and burning percentage of the forest remain the main contributions.~~ ~~Second, d~~Different fire detection products ~~can also cause~~introduce bias in ~~the~~

estimated burned area, ~~leading to~~affecting uncertainty in DM. ~~For example, the MCD14DL used in FINN1.5 identifies fire points based on brightness temperature, which can effectively detect understory burns in tropical rainforests, and can easily capture small area burns in agricultural fields. Furthermore, combined with the smoothing assumptions for equatorial regions, the estimated burned area in FINN1.5 is generally larger than that in GFED4s at low latitudes. Last but not least, s~~Satellite transit/cloud obscuration ~~can similarly affect~~ influences DM ~~between emission inventories~~ by ~~influencing~~ affecting ~~the~~ burned area/fire radiative energy~~identification of burned area/fire radiative energy~~. ~~In the Africa grasslands where fires develop rapidly, due to the fast fuel consumption, the burned area often has a large difference in a short period of time. If the fire point monitoring product based on brightness temperature data identification is used, there may be missed detections of fire that occur during the satellite transit/cloud occlusion, but fire area product indentified based on surface albedo changes can better avoid missed detections caused by satellite transit/cloud occlusion.~~ Cloud cover at high latitudes substantially ~~has a significant~~ impacts ~~on the uncertainty of~~ emission ~~inventories~~uncertainty~~.~~, with ~~According to our results, the~~ bias ~~between bottom-up (or top-down) emission inventories in BONA~~ increasing~~ed~~ by 20% in July in BONA ~~with~~ under ~~increased~~ higher cloud fraction.

We extend our analysis to ~~In addition to gaseous emissions, we also analyzed the differences in emissions of~~ particulate pollutants, ~~among emission inventories~~ using OC emissions as an example. ~~The four sets of BB emission inventories fluctuate between 14.9 and 42.9 Tg of g~~Global average annual OC emissions vary widely among the four inventories, ranging from 14.9 to 42.9 Tg, ~~a greater variation than the gaseous species~~demonstrating greater variability than gaseous species like CO. ~~Similar to the results for CO emission variability, current BB emission inventories have large variability at high northern latitudes. Unlike differences in CO emissions, there is less variability in comprehensive EFs over the equator. In particular, the QFED2.5 inventory adjusted emission factors using satellite aerosol optical thickness (AOD) to enhance emissions of particulate matter including OC. In addition, peatlands only have comparable OC emission capacity to the shrub, which makes the impact of vegetation classification differences on OC EFs less significant, ultimately resulting in lower variability in particle-phase emissions in equatorial regions.~~ BB OC emissions exhibit large variability at high latitudes in the Northern Hemisphere, with QFED2.5 adjusting emission factors based on satellite aerosol optical thickness (AOD) to enhance particulate matter emissions.

~~We a~~Applying~~ied~~ four ~~sets of~~ BB emission inventories to CESM2-CAM6, ~~and~~ we compare~~d the~~ model-simulated CO column concentrations with the MOPITT satellite inversion CO column concentrations. According to our simulations, CO simulated using GFED4s is closest to satellite observations in almost all regions except southern Asia and Africa. We also compared model results with AOD retrieved from MODIS satellites or measured by AERONET. Simulated AOD at high northern latitudes is often underestimated when using current mainstream BB emission inventories. For example, the simulated regional average AOD is 8-46% lower than MODIS in North America. Unlike the high latitudes, the simulated AOD is significantly overestimated at the equator, and the regional average AOD simulated by the model in Northern Hemispheric Africa is 66-91% higher than MODIS. In addition, comparing model simulated AOD with AERONET ground-based observations, we find that GFED4s performs best in EQAS for daily variability during intense burning. In SEAS, although FINN1.5 can better represent the magnitude of the overall OC emissions in the BB season, QFED2.5 can capture the day-to-day variation characteristics of intense combustion. In the Southern Hemisphere, the latest VFEI0 emission inventory performs well, and the simulated AOD is able to capture the BB processes.

Our study assesses the global applicability of BB emission inventories and has some implications for future studies~~y~~. Overall, GFED4s and QFED2.5 inventories for the northern high latitudes capture the magnitude and daily variation of OC emitted throughout the BB season. These two emission inventories outperformed the others when applied to studies of interactions between BB aerosol and weather/climate. In the Southern Hemisphere, the spatial distribution and daily variation characteristics of CO and AOD simulated by the model are closest to the observed values when the latest VFEI0 emission inventory is applied. For the equator, the situation is more complicated, and we recommend combining emission inventories according to the research objectives. For example, GFED4s performs best in day-to-day changes during intense burning in equatorial Asia. In Southeast Asia, combining OC magnitude in FINN1.5 and daily variation in QFED2.5 is the optimal choice.

It is worth noting that emission factors (as listed in Table 2) significantly contribute to the differences in BB emissions. However, actual emission factors vary widely depending on the different states of combustion (Pokhrel et al., 2021). Further study is needed to understand the impact of combustion efficiency on the BB EFs and optimize them.

Data availability. The biomass burning emission datasets used in this work are available from http://www.globalfifiredata.org (GFED4s), https://www.acom.ucar.edu/Data/fire/ (FINN1.5), https://portal.nccs.nasa.gov/datashare/iesa/aerosol/emissions/QFED/v2.5r1/ (QFED2.5), and http://bio.cgrer.uiowa.edu/VFEI/DOWNLOAD/ (VFEI0). AOD and cloud fraction from MODIS dataset can be obtained from https://ladsweb.modaps.eosdis.nasa.gov/search/. MOPITT CO can be obtained from https://doi.org/10.5067/TERRA/MOPITT/MOP03JM.009. AERONET AOD is avaiable from https://aeronet.gsfc.nasa.gov/new_web/download_all_v3_aod.html. The Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) reanalysis data is available from https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/. All data analyzed during the current study are included in this published article and its supplementary information. Raw model simulations are available from the corresponding author on reasonable request.

Author contributions. S. L. and A. D. designed the research, W. H. and S. L. conducted the data analysis and model simulations, W. H. and S. L. took the lead in writing the manuscript, with contributions from all authors.

Competing interests. The authors declare that they have no conflict of interest.

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Table 1. Brief introduction of four BB inventories

Inventory	"Bottom-up"		"Top-down"	
	FINN1.5	GFED4s	QFED2.5	VFEI0
Temporal range	2002- (NRT) [a]	1997-2022[b]	2000- (NRT) [a]	2012- (NRT) [a]
Spatio-temporal resolution	1km, daily	0.25°, monthly (daily fraction)	0.1°, daily (0.25° × 0.375°, NRT [a])	500m, daily
Primary satellite fire input	MCD14DL C5 active fire area (1km)	MCD64A1 C5.1 burned area (500m)	MOD14/MYD14 C6 FRP (1km)	VNP14IMG FRP (1km)
Statistical boosts/Adjustion	Smooth assumption in tropics [c]	Small fire boost (MOD14A1/MYD14A1)	Cloud-gap adjusted FRP density	
Primary land use/land cover (LULC)	MCD12Q1 (IGBP), 2005	MCD12Q1 (UMD), 2001-2012	IGBP-INPE	MCD12C1(IGBP) + The Köppen Climate Classification
Peatland fire	×	Olson et al. (2001)	×	Ferrada et al. (2022)
Conversion to dry matter	Hoelzemann et al. (2004)	CASA biogeochemical model (van der Werf et al., 2010)	QFED FRP vs GFED2 dry matter global calibration	VFEI FRP vs GFED3.1 dry matter global calibration
Emission factors	Akagi et al. (2011), Andreae and Merlet (2001)	Akagi et al. (2011) + updates from Andreae et al. (2013)	Andreae and Merlet (2001), Akagi et al. (2011) [d]	Akagi et al. (2019)
Speciation	41 species	27 species	17 species	46 species
References	Wiedinmyer et al. (2011)	van der Werf et al. (2017)	Darmenov and da Silva (2015)	Ferrada et al. (2022)

a: NRT = near real time; b: 2017-2022 are beta version releases;

c: In equatorial region (30°N-30°S), each detected fire will be counted as 2-day, assuming the second day's fire will continue to be half the size of the previous day;

d: Particulate matter-related emissions from biomass burning (e.g. BC, OC, NH_3, SO_2, and $PM_{2.5}$) were corrected from emission factors based on MODIS AOD.

Table 2. CO and OC emission factors used in the four biomass burning emission inventories.

	Emission factors across inventories and vegetation types (g species per kg dry matter)							
Types	CO				OC			
	FINN1.5	GFED4s	QFED2.5	VFEI0	FINN1.5	GFED4s	QFED2.5	VFEI0
Temperate forest	108[Ak]	88[Ak]	107[AM]	113[An]	6.97[AR]	9.6[AM]	41.09*	10.9[An]
Boreal forest	118[Ak]	127[Ak]	107[AM]	121[An]	7.31[Mc]	9.6[AM]	41.09*	5.9.[An]
Savanna and Grass, shrub	59[Ak]/68[Ak]	63[Ak]	65[AM]	69[An]	2.6[Ak]/6.61[Mc]	2.62[Ak]	6.12*	3[An]
Tropical forest	92[Ak]	93[Ak]	104[AM]	104[An]	4.77[Ak]	4.71[Ak]	13*	4.4[An]
Agricultural	111[Ak]	102[Ak]	/	76[An]	3.3[AM]	2.3[Ak]	/	4.9[An]
Peatlands	/	210[#]	/	260[An]	/	6.02[#]	/	14.2[An]

Ak: Akagi et al. (2011); AM: Andreae and Merlet (2001); An: Andreae (2019); AR: Andreae and Rosenfeld (2008); Mc: McMeeking et al. (2009)

*: QFED2.5 PM-related emission factors are obtained by multiplying the base EF multiplied by its biome-specific enhancement factor

#: Emission factors for peatland is the average of lab measurements of Yokelson et al. (1997) and Christian et al. (2003)

Table 3. Comparison of CESM-CAM6 simulated CO column averages and satellite retrieved CO column averages during the fire season.

		Satellite	CESM2-CAM6			
Regions	Fire-Season	MOPITT	FINN1.5	GFED4s	QFED2.5	VFEI0
EQAS	Jan.-Apr.	1.88	1.66	*1.69*	1.61	1.47
BONA	Apr.-Aug.	2.03	1.29	*1.47*	1.30	1.32
SEAS	Feb.-Apr.	2.40	*2.10*	1.94	1.89	1.95
SHAF	May.-Nov.	2.31	1.75	2.04	1.99	*2.19*
NHAF	Jan.-May.	2.66	1.96	2.02	2.05	*2.10*
BOAS	Mar.-Nov.	2.05	1.31	*1.42*	1.33	1.34
SHSA	July.-Dec.	1.77	*1.75*	*1.80*	*1.76*	*1.80*

Table 4. Same as Table 3 but for AOD

	Satellite	CESM2-CAM6			
Regions	MODIS	FINN1.5	GFED4s	QFED2.5	VFEI0
EQAS	0.23	*0.22*	*0.25*	*0.23*	*0.21*
BONA	0.13	0.07	*0.12*	*0.11*	0.07
SEAS	0.30	0.35	*0.30*	0.36	*0.30*
SHAF	0.33	*0.31*	*0.37*	0.53	*0.40*
NHAF	0.32	*0.53*	0.54	0.61	0.55
BOAS	0.15	0.11	*0.13*	*0.16*	0.11
SHSA	0.14	0.30	0.31	0.34	*0.29*

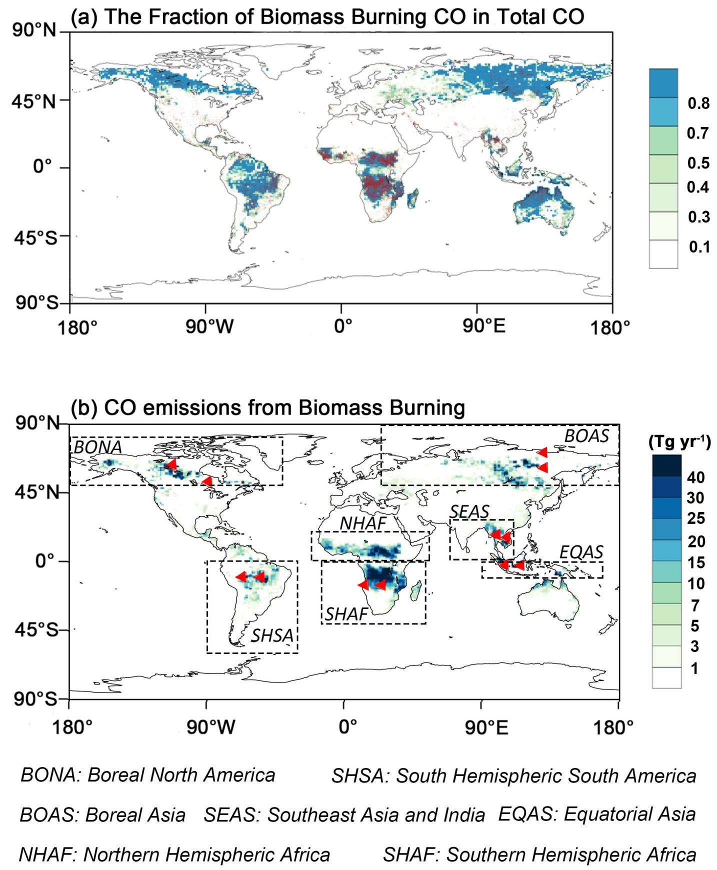

Figure 1. (a) The fraction of BB CO emissions to the sum of anthropogenic and BB CO emissions (CO_BB/CO_Total) during 2013-2016 and (b) the spatial distribution of CO emissions (FINN1.5 was used as an example). The red dots in Fig. 1(a) are the fire points from the MCD14DL satellite product. In Fig. 1(b), seven regions with high BB emissions taken from those applied by van der Werf et al. (2006, 2010) are marked with black boxes, and the red triangles represent 12 AERONET stations. In this study, seven major BB regions includes Boreal North America (BONA), Boreal Asia (BOAS), Southeast Asia (SEAS), Equatorial Asia (EQAS), North Hemisphere Africa (NHAF), South Hemisphere Africa (SHAF), and South Hemisphere South America (SHSA).

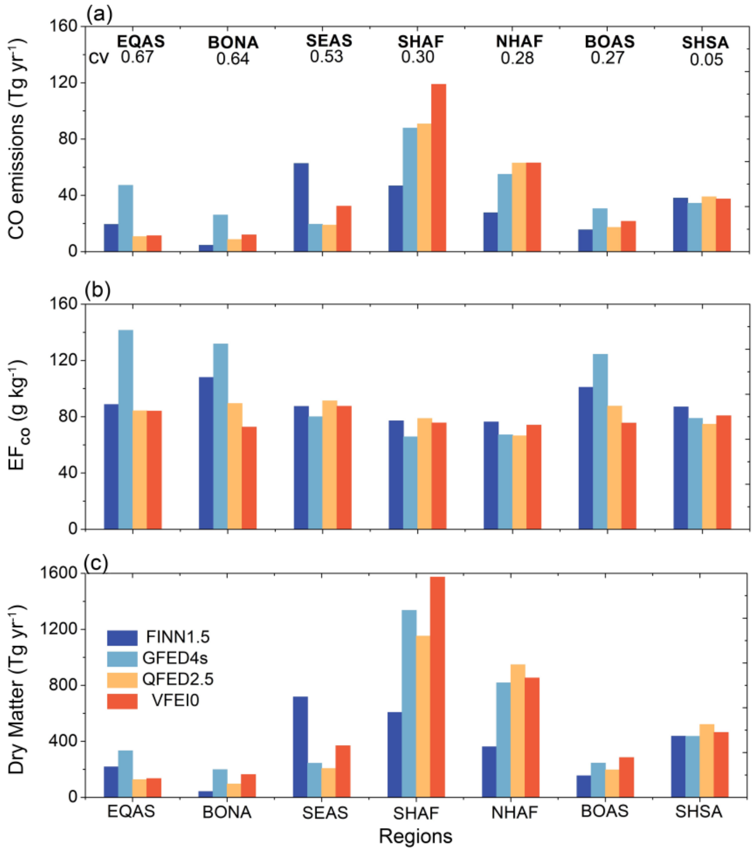

Figure 2. (a) Average annual CO emissions of four biomass burning emission inventories across seven major BB regions during 2013-2016. The cv, defined as the ratio of the standard deviation to the mean, is the coefficient of variation among the emissions of four datasets. (b) and (c) are the same as (a), but for the emission factor of CO (EF_{CO}) and Dry Matter.

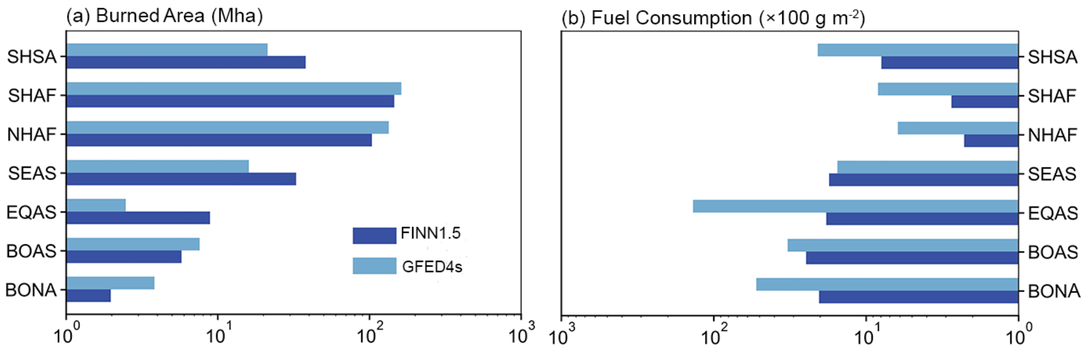

Figure 3. Annual burned area (a) and fuel consumption (b) of two bottom-up datasets (FINN1.5 and GFED4s) across seven regions from 2013 to 2016.

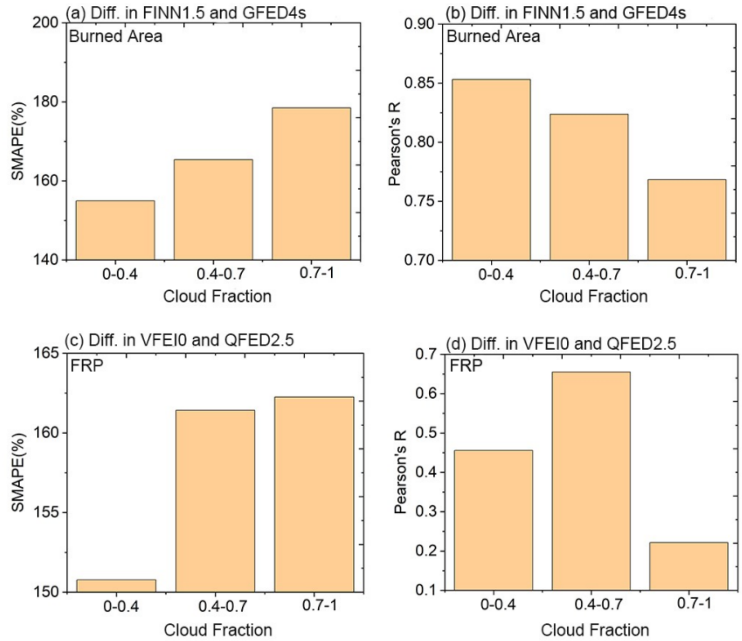

Figure 4. The differences in (a-b) burned areas and (c-d) total FRP detected by two inventories under different cloud fraction in a pilot region of BONA. These differences are quantified by two indicators: SMAPE and Pearson's R. Could fraction data is calculated from MODIS product MCD06COSP.

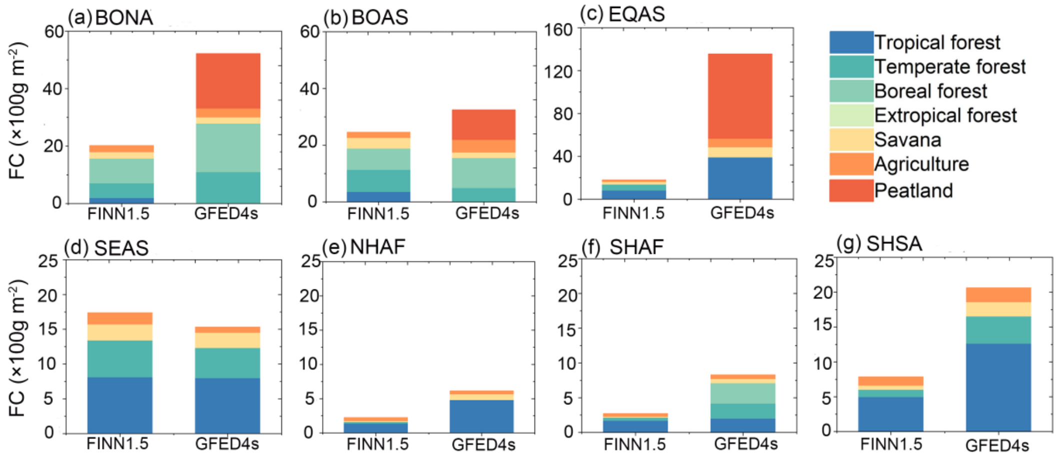

Figure 5. Annual average fuel consumption of two bottom-up datasets (FINN1.5 and GFED4s) across seven regions from 2013 to 2016. The contributions of the seven biomes are shown in different colors.

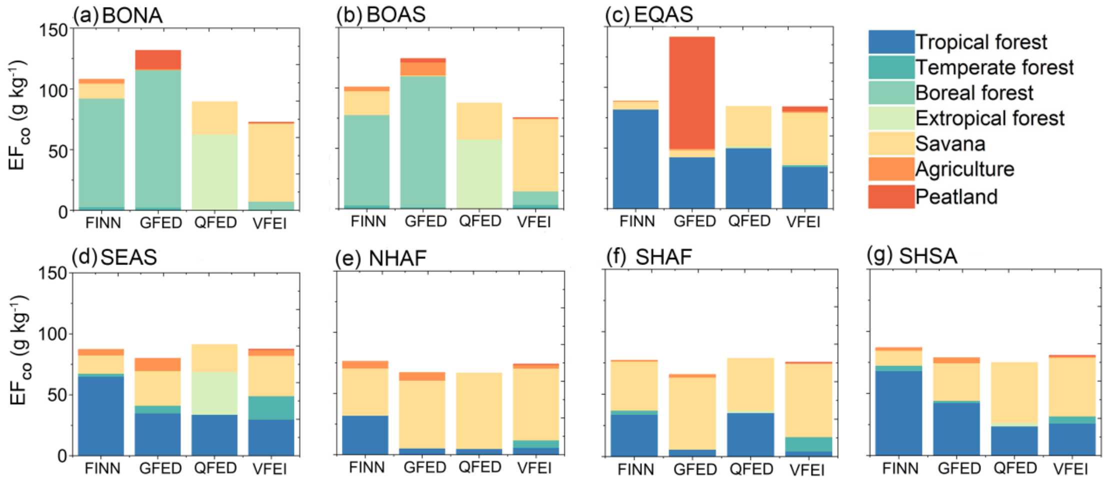

Figure 6. Regional comprehensive emission factors for four datasets (FINN1.5, GFED4s, QFED2.5, and VFEI0) in seven regions from 2013 to 2016. The contributions of the seven biomes are shown in different colors.

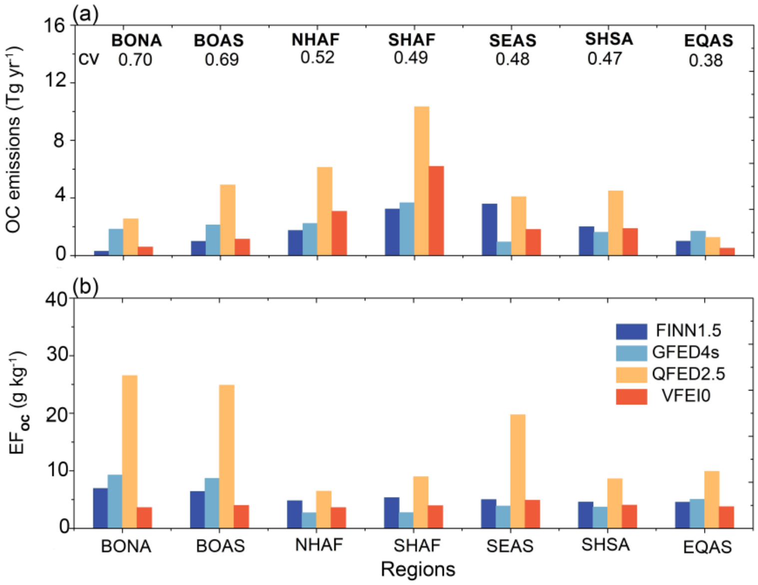

Figure 7. (a) Average annual OC emissions of four biomass burning emissions inventories across seven major BB regions during 2013-2016. The cv, defined as the ratio of the standard deviation to the mean, is the coefficient of variation among the emissions of four datasets. (b) is the same as (a) but for the emission factor of OC (EF_{oc}).

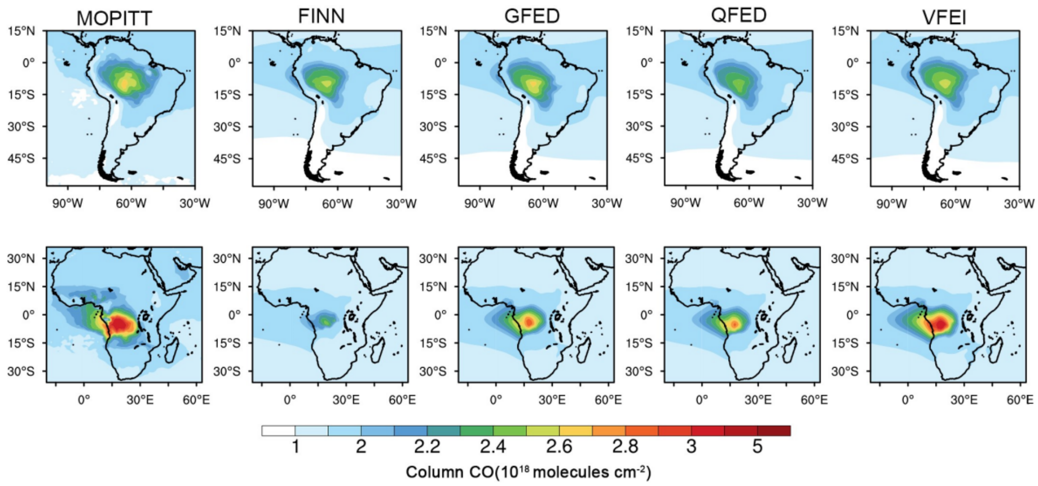

Figure 8. Spatial distribution of CO column burdens from MOPITT and CESM2-CAM6 simulations during the fire season (Table 3). The text above each plot identifies the name of the satellite inversion dataset or emission inventory dataset applied by the model, namely FINN1.5, GFED4s, QFED2.5, and VFEI0.

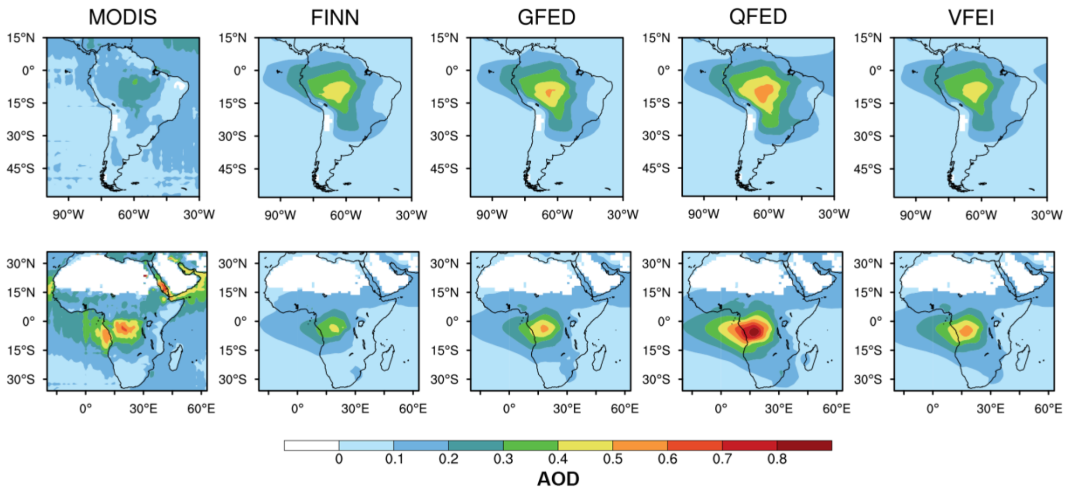

Figure 9. The same as figure 8 but for AOD.

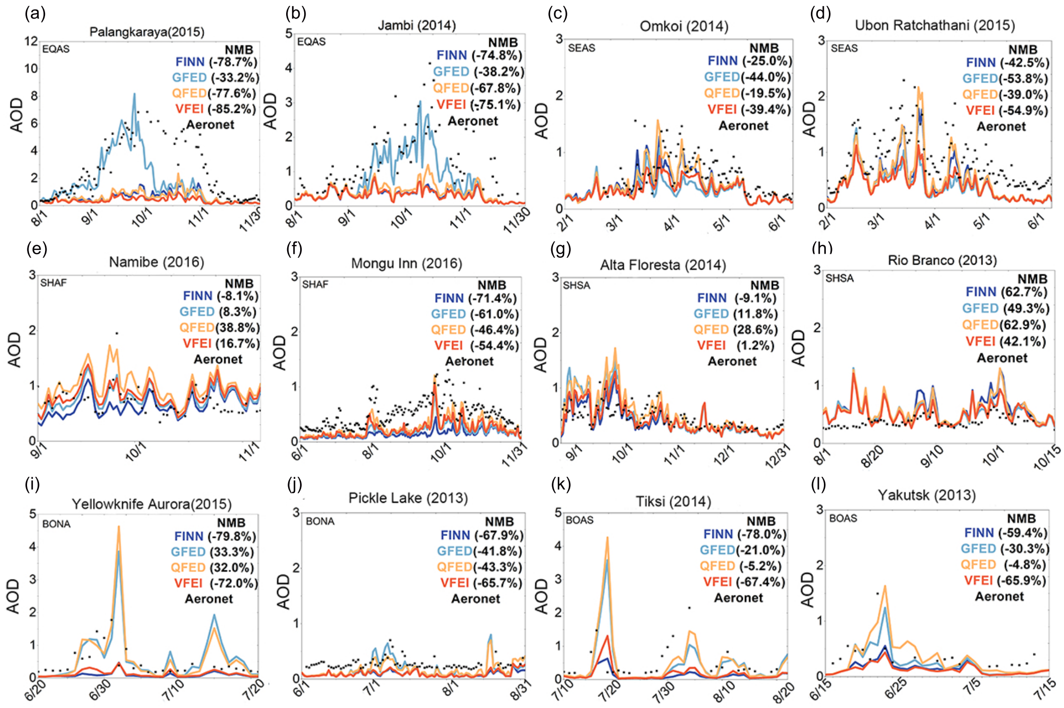

Figure 10. Comparison between AOD simulated by CESM2-CAM6 using the four datasets (FINN1.5, GFED4s, QFED2.5, and VFEI0) and AERONET ground-based observations during fire seasons. These AERONET sites are: (a) Palangkaraya (2.2°S, 113.9°E), (b) Jambi (1.6°S, 103.6°E), (c) Omkoi (17.8°N, 98.4°E), (d) Ubon Ratchathani (15.2°N, 104.9°E), (e) Namibe (15.2°S, 12.2°E), (f) Mongu Inn (15.3°S, 23.1°E), (g) Alta Floresta (9.9°S, 56.1°W), (h) Rio Branco (9.9°S, 67.9°W), (i) Yellowknife_Aurora (62.5°N, 114.4°W), (j) Pickle Lake (51.4°N, 90.2°W), (k) Tiksi (71.6°N, 128.9°E), (l) Yakutsk (61.7°N, 129.4°E).