Global wildfire plume-rise dataset and parameterizations for climate model applications

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Abstract

The fire plume height (smoke injection height) is an important parameter for calculating the transport and lifetime of smoke particles, which can significantly affect regional and global air quality and atmospheric radiation budget. To develop an observation-based global fire plume-rise dataset, a modified one-dimensional plume-rise model was used with observation-based fire size and Maximum Fire Radiative Power (MFRP) data, which are derived from satellite fire hotspot measurements. The resulting dataset captured well the observed plume height distribution derived from the Multi-angle Imaging SpectroRadiometer (MISR) measurements. The fraction of fire plumes penetrating above the boundary layer is relatively low at 20% at the time of MISR observation (10:30 am LT) but increases to an average of ~55% in the late afternoon implying a sampling bias in MISR measurements, which requires corrections through dynamic modeling or parameterization of fire plume height as a function of meteorological and fire conditions when the dataset is applied in climate model simulations. We conducted sensitivity simulations using the Community Atmospheric Models version 5 (CAM5). Model results show that the incorporation of fire plume rise in the model tends to significantly increase fire aerosol impacted regions. We applied the offline plume rise data to develop an online fire plume height parameterization, allowing for simulating the feedbacks of climate/weather on fire plume rise in climate models.

1 Introduction

Wildfires release large amounts of greenhouse gases, carbonaceous aerosols, and other pollutants, therefore having complex impacts on the earth climate, local weather, and air quality. CO_2 released from fires (2-4 Pg C yr^{-1}) is up to half of that from fossil-fuel combustion (7 Pg C yr^{-1}) (e.g., Browman et al., 2009; van der Werf et al., 2006). In addition to greenhouse gases, carbonaceous aerosols (organic and black carbon) released from fires modulate atmospheric radiative balance directly through scattering and absorbing solar radiation and indirectly through changing cloud properties (e.g., Bauer & Menon, 2012; Boucher et al., 2013; Jiang et al., 2016). Climate model experiments indicated that organic carbonaceous aerosols generally increase the Aerosol Optical Depth (AOD) and reduce surface temperature, while black carbon aerosols enhance heat absorption in the troposphere and increase air temperature; the resulting atmospheric stability changes could potentially suppress atmospheric convection and subsequently affect atmospheric circulations (e.g., Liu, 2005a and b; Bauer and Menon, 2012; Tosca et al., 2013a). In the tropics, previous studies highlighted the role of black carbon in changing the Hadley circulation and precipitation patterns (Allen et al., 2012; Hodnebrog et al., 2016; Tosca et al., 2015). At the middle to high latitudes, previous studies indicated potential impacts of smoke emissions on regional climate and weather patterns (e.g., Grell et al., 2011; Liu, 2004; Madden et al., 2015), and severe weather evens (Saide et al., 2016). Additionally, evidence was found for the effects of high latitude wildfires on the Arctic air quality during spring and summer (Evangeliou et al., 2016; Monks et al., 2012; Winiger et al., 2016) and for potential impacts on Greenland ice shelves melting (Keegan et al., 2014).

In order to accurately simulate the impacts of wildfire emissions, a crucial parameter is fire plume height or injection height, defined as the highest altitude in the atmosphere the smoke can reach. This parameter affects the transport of smoke particles and thereby influences climate and air quality in the downwind regions. Generally, if the plume heights are above the Atmospheric Boundary Layer (ABL), the smoke particles can be transported far away from a fire site because of higher wind speed in the free troposphere than the ABL. In contrast, the impacts of smoke particles within the ABL are restricted to smaller regions (e.g., Liu et al., 2014; Paugam et al., 2016).

The reported fire plume heights range from completely within the ABL (Trentmann et al., 2002), to the free troposphere (de Gouw et al., 2006), even the stratosphere (Dirksen et al., 2009; Ditas et al., 2018; Yu et al., 2019). The fire plume heights derived from the Multi-angle Imaging SpectroRadiometer (MISR) stereo imaging developed by Kahn et al. (2007) were widely used to evaluate model simulated plume height data (e.g., Kahn et al., 2008; Tosca et al., 2011; val Martin et al., 2009) with a resolution of 500 m in the vertical and 1.1 km in the horizontal (Kahn et al., 2007). The global MISR wildfire plume height dataset is available at https://www-misr.jpl.nasa.gov/getData/accessData/MisrMinxPlumes/.

A somewhat surprising result of the MISR fire plume height data is that the fraction of fire plume height above the ABL is relatively low, ~10% over North America (Kahn et al., 2008; val Martin et al., 2009) and only 4% in Southeast Asia (Tosca et al., 2011). However, the MISR instrument is onboard the sun-synchronous Terra satellite; its local equatorial crossing time is approximately 10:30 a.m. Hence MISR data only represented fire plume heights in the late morning and likely missed the daily maximum fire plume heights that would occur in the late afternoon due to the diurnal variation of wildfires intensity (Ellicott et al., 2009) and unstable ABL conditions (Sofiev et al., 2012). Therefore, a fire plume height dataset that captures the diurnal variation on a global scale is needed in order to improve the understanding of the temporal and spatial variability of fire plume heights and their impacts. In the same vein, a dynamic model or online parameterization is required to simulate the feedbacks of climate/weather on fire intensity and atmospheric stability and their effects on fire plume rise in climate models.

val Martin et al. (2012) applied 1-D plume-rise model, which is a physics based dynamic model developed by Freitas et al. (2007, 2010), with Moderate Resolution Imaging Spectroradiometer (MODIS) Fire Radiative Power (FRP) and assimilated GEOS meteorology data to calculate the wildfire plume heights over North America for the 2002 and 2004-2007 fire seasons, and compared the results with the MISR plume heights. They suggested that the plume-rise model tends to underestimate the observed plume heights, but did not account for the diurnal variation of wildfire plume heights. The relatively coarse spatial (2^{o}x2.5^{o}) and temporal (6 hrs) resolutions of meteorological data may have contributed to the estimated model biases due to the sensitivity of wildfire plume height to ambient meteorological conditions (Sofiev et al., 2012).

In this work, we attempt to develop a global hourly smoke plume height dataset based on observations, and formulate a corresponding online parameterization for use in climate model applications based on the 1-D plume-rise model by Freitas et al. (2007, 2010). Using assimilated high-resolution meteorological reanalysis and satellite observations, we improved upon previous studies to develop an observation-based (offline) global fire plume height dataset from 2002 to 2010 that account for diurnal variability in wildfire intensity and meteorological data. This dataset is then applied to formulate an online parameterization of fire plume height for use in climate model simulations. The observation and assimilated meteorological data, modifications and application of the 1-D dynamic fire plume height model, the online parameterization of fire plume height, and climate simulations are described in section 2. The evaluation of the global fire plume height dataset with observations and climate model simulations and evaluations using the prescribed global fire plume height dataset or the online fire plume height parameterization are discussed in section 3. Conclusions are given in section 4.

2 Data, Models, and Methods

2.1 Offline global fire plume height calculation and evaluation

In this study, we calculated hourly global smoke plume heights from 2002 to 2010 on the basis of available observation data. Several The input data for simulating smoke plume rise using the 1-D model by Freitas et al. (2007, 2010) are descriebd in Fig. 1. To improve the accuracy of the calculations, we made use of satellite observations and assimilated meteorological data to provide the model input data. We describe the methods for data processing in the following sections, including (1) meteorological data, fire region, and plant function type (PFT), (2) computing the total fire energy and the fire size data, (3) the 1-D fire plume-rise model modifications, and (4) fire plume height diurnal variation. We then describe the MISR fire plume height and MODIS AOD data for model evaluations.

2.1.1 Meteorology data, fire regions, and plant functional types (PFTs)

The meteorology fields from 2002 to 2010 were obtained from the Climate Forecast System Reanalysis (CFSR) hourly forecast data, with a 0.5^o x 0.5^o horizontal resolution and 37 vertical layers (Saha et al., 2014). We used four meteorology variables, the temperature, geopotential height, specific humidity and wind, from land surface to the top of troposphere. The hourly and high spatial resolution assimilated CSFR meteorological data are needed for the fire plume height modeling due to the high sensitivity of fire plume rise to atmospheric conditions (Sofiev et al., 2012).

To further improve the 1-D fire plume modeling, we derived fire characteristics (next section and Fig. 1) as a function of region and PFT type. Fifteen wildfire regions were used in this study (Figure S1 and Table S1 in the Supplement), same as the 14 Global Fire Emissions

Database (GFED) regions (Giglio et al., 2013) except that the GFED Temperate North America was splitted into two regions of western (WTNA) and eastern (ETNA) to considering more prevalent prescribed burning in the eastern United State (Zeng et al., 2008). Effects of different vegetation within a region on wildfires were considered through PFT data, which were derived from MODIS Landcover dataset MCD12Q1 (e.g., Channan et al., 2014). To be consistent with wildfire modeling (Zou et al., 2019), we used the same six PFT categories as the Common Land Model (Lawrence & Chase, 2007) (CLM, Lawrence and Chase, 2007), that is, needle leaf forest, broad leaf forest, shrub, grass, crop, and unvegetated, which are simplified from the 16 MODIS landcover dataset categories. The spatial PFT distribution is shown in Figure S2 in the Supplement.

2.1.2 Fire size and total fire energy flux

We used the MODIS MCD14ML global monthly fire location products (Giglio, 2013) to compute the size of an observed fire. Following the approach by (val Martin et al., 2012), the fire size per grid cell (A_{gc} in km^2) was calculated,

$$A_{gc} = \Delta r * \frac{FRP_{gc}}{MFRP} \quad (1)$$

where Δr is the resolution of the detected fire (1 km^2 for MODIS MCD14ML data), and FRP_{gc} is the FRP of the fire grid cell. *MFRP* is define as the 99th percentile value of all detected FRP_{gc} values for a given wildfire region, PFT type, and calendar month from 2001 to 2014. The values of MFRP are listed in Table S3. Adjacent non-zero *FRPgc* grid cells are aggregated to be one fire (Kahn et al., 2007; val Martin et al., 2009), i.e. the sums of *Agc* and the products of *FRPgc* and *Agc* of these fire grid cells are the size and FRP of this fire, respectively.

Another fire parameter for the 1-D model is the total fire energy flux. Previous studies showed that the satellite detected fire radiative energy is about 10% of the total fire energy (Freeborn et al., 2008; Wooster et al., 2005). We followed the work by val Martin et al. (2012) to compute the total fire energy flux of a fire (*E*),

$$E = 10 * FRP_{fire} \tag{2}$$

where FRP_{fire} (in MW) is the FRP value of an identifiws fire.

2.1.3 1-D fire plume rise model modifications

The meteorology and fire data described above were fed into the 1-D plume-rise model developed by Freitas et al. (2007, 2010) to compute an offline global smoke plume height dataset (Fig. 1). This physical fire plume-rise model scheme is governed by the conservations of energy, vertical momentum, and mass. It was previously implemented in regional air quality and climate models (e.g., Grell et al., 2011; Pfister et al., 2011; Stein et al., 2009). The prognostic equation of vertical momentum (Freitas et al., 2007) is,

$$\frac{\partial w}{\partial t} + w\frac{\partial w}{\partial z} = \frac{1}{1+\gamma} gB - \frac{2\alpha}{R} w^2 + \frac{\partial}{\partial z}\left(K_{zz}\frac{\partial w}{\partial z}\right) \tag{3}$$

where w is the vertical velocity, *t* is the time, z is the vertical distance, *g* is the acceleration due to gravity, and γ is the parameter for non-hydrostatic pressure perturbations and was set to be 0.5 in this study (Simpson & Wiggert, 1969). The parameter, *B,* is the buoyance term related to the difference of temperature between fire plume air parcel and the ambient environment. The initial velocity and temperature difference between fire plume and ambient air (δT in Fig. 2) are functions of fire size, MFRP, surface air temperature, and surface pressure (Freitas et al., 2007). The parameter, α, is the entrainment coefficient with a default value of 0.1. R is the radius of the plume air parcel. The eddy diffusion coefficient, K_{zz}, was assumed to be constant in the original model. Following the work by Myrup and Ranzieri (1976), we set the K_{zz} vertical profile as a parabolic function, increasing from the surface, reaching the peak in the middle of the boundary layer and decreasing to a small value at the top of boundary layer. The default K_{zz} value of 500 $m^2 s^{-1}$ was used in the tropics and subtropics (30°N-30°S). A lower value of 300 $m^2 s^{-1}$ was used for higher latitudes reflecting less solar heating than the tropics. Further details on the 1-D model is described in the Supplement.

2.1.4 The diurnal variation of fire plume height

The meteorological effects on the diurnal variation, such as the variation of the atmospheric stability and boundary layer height (Sofiev et al., 2012; val Martin et al., 2012) were simulated using hourly CFSR data. Another important factor is the diurnal variation of fire burning (e.g, Mu et al., 2011). We followed the work by Ellicott et al. (2009) and Vermote et al. (2009) and parameterized the FRP diurnal variation using a modified Gaussian Function on the basis of the measurements by the Spinning Enhanced Visible and InfraRed Imager (SEVIRI):

$$FRP(t) = FRP_{peak} * [b + e^{\frac{-(t-h)^2}{2\sigma^2}}] \quad (5)$$

where the *FRP* is a function of time (hour), FRP_{peak} is the peak *FRP* value during a day at time *h*, *b* is a constant *FRP* value at night, and σ is the standard deviation value for the Gaussian function. The values of *h, b* and δ were parameterized as functions of the observed Terra-to-Aqua FRP ratio (*r*):

$$h = -1.23r + 14.57 \quad (6)$$

$$\delta = 3.89r + 1.03 \quad (7)$$

$$b = 0.86r^2 - 0.52r + 0.08 \quad (8)$$

$$r = FRP_{terra}/FRP_{aqua} \quad (9)$$

Since the parameterizations of equations (5)-(9) for regional fires were based on hourly SEVIRI measurements, we computed the averaged regional *r* values using the MODIS MCD14ML products by selecting the measurements at local time 10:30 and 13:30 for Terra and Aqua satellites, respectively, from 2001 to 2014.

After calculating the *r, b,* δ and *h* values for a given region, the FRP_{peak} value of a detected fire spot was determined by equation (10),

$$FRP_{peak} = FRP_T/(b + e^{\frac{-(t_T-h)^2}{2\sigma^2}}) \quad (10)$$

where FRP_T is the FRP value of a fire hotspot by Terra MODIS and t_T is the Terra overpass time during daytime, which is given by MODIS MCD14ML products. Using equation (5), we computed the hourly FRP values. The regional parameter values of *b,* δ and *h* are listed in table S4 in the Supplement and the regional diurnal FRP variation was calculated. For illustration purposes, we computed the typical regional MFRP diurnal profiles using equation (10) (Figure S3 in the Supplement).

Using equations (1) and (2) and calculated FRP data, we computed hourly fire size *A(t)* and total fire energy *E*(t). These data and CSFR meteorology fields were applied to the 1-D fire plume rise model (section 2.1.3) to calculate plume heights (Figure 1).

2.1.5 MISR fire plume heights

The plume height dataset from the MISR plume height project was used to evaluate offline 1-D fire plume model results (Kahn et al., 2008; val Martin et al., 2009). This dataset includes fire plumes from 2002 to 2009 over eight regions, Africa, Alaska, Canada, Indonesia, North America, Siberia, South America, and Southeast Asia (http://misr.jpl.nasa.gov/getData/accessData/MisrMinxPlumes/). The data availability was summarized in Table S4. In this study, we only used the data with a "good" quality tag. The maximum MISR plume height of each hotspot was compared with the 1-D estimated fire plume height of the corresponding hotspot. A total of 7843 MISR plumes were included (Figure 3b). In general, the fire plume heights are higher in high latitudes and lower in low latitudes. While the MISR plume height project 2 data have been available since 2015, the "good" quality data are limited and the results are similar (Figure S3).

As both MISR and MODIS are onboard the Terra satellite, we found MODIS fire hotspots corresponding to MISR data. By obtaining the fire information, including location, time, FRP, from MCD14ML product, we calculated the fire plume heights using the 1-D model and compared the results to corresponding MISR data (Figure 3).

2.1.6 The AOD data

The Cloud-Aerosol Lidar and Infrared Pathfinder Satellite observations (CALIPSO) provide a multiyear global dataset of lidar aerosol and cloud profiles with six identified aerosol types: clean marine, dust, polluted continental, clean continental, polluted dust, and smoke, measured by the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) instrument (Winker et al., 2010). Schuster et al. (2012) compared CALIPSO with AERONET AOD measurements at 147 AERONET sites and suggested a low bias of 13% in CALIPSO data due to a bias in the assumed lidar ratio. However, for biomass burning aerosols, the measurement bias is relatively low and the measurement sensitivity of the CALIOP instrument is higher than MODIS (Ma et al., 2013). In this study, we used the CALIPSO level 3 all-sky daytime monthly mean fire AOD data associated with a 2° x 5° resolution.

2.2 Model experiments on the sensitivity of fire AOD distribution to plume rise

In this study, we used the Community Earth System Model (CESM) version 1.2 in a configuration of the community atmosphere model version 5 (CAM5) (Neale et al., 2012) coupled with community land model version 4.5 (CLM4.5) (Oleson et al., 2010). The 3-mode Modal Aerosol Model (MAM3) is included in CAM5 to simulate the aerosol lifecycle (X. Liu et al., 2012). In MAM3, the aerosol mass and number mixing ratio were simulated in three lognormal modes: Aitken, accumulation, and coarse mode. BC and primary organic matter (POM) from wildfires and anthropogenic sources were emitted into the accumulation mode.

Three model experiments were carried out to examine the effects of plume rise on fire AOD distribution: the control run without fire emissions (NO-Smk), the surface run with fire emissions released from the surface (Srf-Smk), and the fire plume run with fire emissions released at altitudes up to computed fire plume heights (Plm-Smk). The experiments are summarized in Table 1. The wildfire emissions used in the study were from GFED4s (Randerson et al., 2012), which has a 0.5°x 0.5° resolution and a 3-hour temporal resolution. The emission data are available from 1997 to present.

The three model experiments were constrained by NASA GEOS-5 reanalysis data. The fire emissions were the observation-based GFED inventory. As a result, we used offline 1-D model computed fire plume height dataset in the Plm-Smk run. The fire emissions were distributed towards the top of a fire plume with a half-Gaussian shape (Fig. S5), which gives 0 emission at the surface and the maximum at the top (e.g. Simpson and Wiggert, 1969; Yanai et al., 1973; Fraitas et al., 2010; Romp, 2010).

The model simulations were carried out for the period of 2006-2010 since the CALIPSO fire AOD data became available in 2006. By comparing Plm-Smk to NO-smk results, we examined the effects of fires on the global AOD distribution, which was compared to CALIPSO data. By comparing Plm-Smk to Srf-Smk results, we analyzed the effects of plume rise to fire AOD distribution.

Table 1. Three model experiments to investigate fire aerosol effects

Experiment	Fire Emission	Plume Height
NO-Smk	Off	Off
Srf-Smk	On	Surface
Plm-Smk	On	Defined

2.3 Online parameterization of fire plume height in CESM

The offline observation-based fire plume height database described above cannot be used in a climate model directly since the climate model is not meant to reproduce the observed day-to-day weather, which strongly affects fire occurrences. Embedding the 1-D fire plume model in the climate model is computationally expensive and the results may have large systematic errors occasionally because of the biases of climate simulations. We therefore developed an online parameterization to compute fire plume height for CESM. The online REgion-Specific ecosystem feedback Fire (RESFire) model that simulates fire occurrence and burned area in CAM5 and CLM4.5 was described by (Zou et al., 2019). The fire, ecosystem, and meteorological parameters for computing fire plume height were computed by RESFire, CLM4.5, and CAM5, respectively. The online region- and PFT-specific parameterizations were based on the offline fire plume height dataset and meteorological reanalysis data (Fig. 2). It cannot be used in online climate model simulations directly because of systematic biases in simulated meteorological variables that are important for fire plume rise; we correct the model biases using a cumulative distribution function (CDF) mapping method in the same manner as Zou et al. (2019). An alternative is to use climate model meteorological data directly with the offline fire plume height dataset. We chose not to do it for two reasons: (1) the weather data simulated by the climate model do not correspond to the observed fires in the offline dataset; (2) any change of the climate model will require the construction of new online parameterizations.

2.3.1 Online fire plume height parameterization

The online region-specific fire plume-rise height parameterization is based on the statistical relationship between meteorological variables and the fire plume height dataset (Fig. 2) for the same 15 wildfire regions used to compute the dataset (Figs. S1). We used only MODIS detected hotspots with a confidence level of >95% from 2002 to 2010. The important parameters for fire plume height include the initial fire plume velocity and the temperature difference between fire and ambient air (Latham, 1994; Turner, 1979; Freitas et al., 2007, 2010). As in 1-D modeling, we calculated the initial velocity and temperature difference between fire and ambient air as functions of fire size, MFRP, surface air temperature, and surface pressure following Freitas et al. (2007). We found that fire plume initial velocity is better correlated with MISR observed fire plume height than FRP (Fig. S6), which was used previous studies (e.g., Doherty et al., 2013; Sofiev et al., 2012; val Martin et al., 2012). In the parameterization, we also considered other 25 meteorological parameters: the boundary layer height (1 parameter), the vertically potential temperature difference at an interval of 500 m from the surface to 6 km in altitude (12 parameters), the horizontal wind speed at an interval of 500 m from surface to 3 km (6 parameters), and the specific humidity for the same layers as wind speed (6 parameters).

Including the constant term, a total of 28 terms were used in the linear regression process for a given fire region and PFT. By using the interactive stepwise multilinear regression function in MATLAB with a 0.01 threshold, the number of effective parameters was reduced from 28 to < 12. As plume heights has diurnal, seasonal, and regional variations, the parameterizations were developed to capture the hourly, monthly, and regional variations. The selected parameters and regression coefficients are listed in supplementary materials (selected_terms.txt and coefficients.txt), respectively. More details are in supplementary materials (ST2).

2.3.2 CDF mapping

Zou et al. (2019) discussed the large biases in estimated fires due to the systematic biases of the climate model simulations when the fire model was developed using the observations. The fire plume height parameterization developed here is based on MODIS fire hotspot observations and CSFR reanalysis meteorology data. We expected that direct application of this parameterization with CAM5 and CLM4.5 simulation results could lead to large biases in fire plume height estimates due in part to the biases in the fire parameters simulated by the climate model. As in Zou et al. (2019), we applied the CDF mapping method to correct the simulation biases (Piani et al., 2010; Teutschbein and Seibert, 2012). The CDFs of model simulated data were linearly mapped to those of the observation-reanalysis data such that the statistical distributions of mapped model data are the same as the observation-reanalysis data. In this manner, we reduced the mean biases of model data while maintaining the simulated dynamic variability. See Zou et al. (2019) for more details about the application of mapping to reduce biases.

Figure 2 illustrates the application of the CDF mapping in the online fire plume height parameterization. Since large diurnal variation of fire height was expected, hourly CDF mapping of meteorology data was applied. An example is shown for Boreal North America (BONA) in Fig. S7 in the supplement. In addition to meteorological variables, we also needed to compute the initial velocity and temperature difference between fire and ambient air functions of fire size, MFRP, surface air temperature, and surface pressure (Freitas et al., 2007). MFRP data were obtained from Terra MODIS observations with prescribed diurnal variations based on Terra and Aqua MODIS data described in sections 2.1.3 and 2.1.4. Therefore, no CDF mapping is necessary. Hourly fire FRP data were estimated using the RESFire model (Zou et al., 2019) and we applied the CDF mapping of RESFire model FRP data to MODIS FRP data described in section 2.1.1. Then we computed fire size by scaling CDF mapped FRP to MFRP of the grid cell (section 2.1.2). The resulted fire size and MFRP were used to calculate the initial fire plume velocity and temperature difference, as described in section 2.1.2 and 2.1.3. Since FRP was based on model data, we applied the CDF mapping of fire size to the observation based fire size dataset described in section 2.1.2. An example of the FRP CDF of BONA is shown in Fig. S8 in the supplement. The resulting online plume height data were evaluated with the MISR observations with the results provided in the following section.

3 Results and discussion

3.1 Evaluation of observation-constrained fire plume height simulations

The MISR fire plume heights are shown in Figure 3a. The MISR plume height dataset has a higher sampling density over North America and Siberia, and a lower sampling density over tropical region. In general, the average fire plumes are > 1800 m over Alaska and Canada and > 1300 m over Siberia, while the fire plume heights are largely < 1200 m over South America and Africa. This pattern can be summarized as low in low latitudes and high in high latitudes. The offline 1-D model simulated fire plume heights (Fig.3b) largely agree with this latitudinal pattern, which is a major improvement compared to previous studies (e.g., Sofiev et al., 2012, 2013; val Martin et al., 2012). Since the tropical regions including South America, Africa and Southeast Asia are most frequently burned regions over the world, the agreement with the MISR observations over these regions is important for accurately simulating the impacts of wildfire emissions on climate and pollution. Previous studies tend to greatly overestimate the fire plume heights in the tropics but underestimate in high latitudes (e.g., Sofiev et al., 2012, 2013). The overestimation in the tropics could lead to a high bias on the effects of black carbon on the Hadley circulation (Tosca et al., 2013b, 2015). The underestimation of fire plume heights in high latitudes could affect transport of black carbon from the mid latitudes to the Arctic and the consequent snow and ice melting in the region (Keegan et al., 2014).

The points-to-point comparison between MISR and 1-D fire plume heights are shown in Figure 3c. The uncertainty level of the MISR data is 500 m (refs); we therefore consider model simulations within 500 m of MISR data “good” quality. About two-thirds of model data fall in this range, much better than the previous study by Sofiev et al. (2012). While the systematic low bias from the previous study was corrected, our results still have a low bias when MISR fire plume heights are > 3 km, probably due to the insufficient latent heat release in the 1-D plume-rise model. The low bias for high-altitude fire plumes is also shown in the histogram comparison (Figure 3d). The simulated distribution shows that globally fire plume height occurrence frequency peaks at 1 km and decreases rapidly with increasing altitude, which is in good agreement with MISR observations. Overall, the 1-D model results captured the observed spatial and histogram distributions of fire plume height.

The diurnal variations of fire plume height are shown in Figure 4. As shown in Figure 3, the simulated average CSFR plume height is in good agreement with the MISR data. The simulated diurnal variation of plume rise, constrained by Terra and Aqua FRP observations, is similar to that of the PBL height. The average plume height value at 14:00, around the Aqua satellite overpass time, is 2041 m, almost double the mean MISR derived plume height of 1300 m.

Figure 4 also shows the average fraction of fire plumes above the PBL observed by MISR at around 19%, same as val Martin et al. (2012). The model simulated a somewhat higher above-PBL fraction of 25%. This fraction keeps on increasing till reaching a maximum of 53% at 15:00-16:00 in late afternoon. This also can be seen in the increasing overlap between the ranges of plume rise and PBL heights from 11:00 to 16:00 (Fig. 4a). Accounting for the large increase of fire plume rise above the PBL in the afternoon, when most of the wildfire burning occurs based on satellite FRP observations (Ellicott et al., 2009; Vermote et al., 2009), implies that a higher fraction of wildfire plume reached the free troposphere than the fraction of ~20% estimated using MISR observations by val Martin et al. (2012) and the resulting fire emissions of aerosols and gases underwent faster free tropospheric transport than the boundary layer affecting larger geographical regions.

The observation-based 1-D model simulated plume rise height distributions are shown in Figure 5. At the overpass time of Terra (11:00 am LT), the results fill the gaps in MISR observations (Figure 3) and show a general pattern of higher fire plume rise at high latitudes than the tropics. Fire plume rise heights at Alaska, Canada, western United States, and Siberia reach 1500 to 3000 m in comparison to 500 to 1200 m in the tropical regions.

At 14:00 in January, fire plume heights are much higher in the Southern Hemisphere (SH), where most fires occur, than the Northern Hemisphere (NH). The SH fire plumes can reach 3000 m in most regions whereas the NH plumes are largely < 1000 m due to a more unstable atmosphere and strong burning intensity in the SH. At 14:00 in July, wildfires over Alaska, Canada, and western United States have highest fire plumes in the NH. The fire plume heights in Siberia are moderate. In the SH, tropical burning over the central South America and Africa has high fire plumes but not reaching the maxima of January burning in the regions. The observation-based distributions are in better agreement with limited MISR observations than (Sofiev et al., 2012). More global observations of fire plume heights, preferably in the afternoon, are necessary to improve model simulations.

The zonal mean cumulative vertical distribution of fire emission at 14:00 LT, when is the peak emission time in the GFED hourly emission data (Mu et al., 2011), is shown in Figures 6 and 7 for January and July, respectively. In January, as shown in Fig. 5, most burning takes place in the tropical grass-savanna (PFT4) and forest (PFT2) (Giglio et al., 2013). Most fire emissions are released between 0~20º N, where the median fire plume heights for PFT2 and PFT4 are at 1500 ~ 2000 m and the 75th percentile values reach 3000 m (Fig. 6), which are much higher in altitude than the 0 ~1000 m distribution setting in AeroCom protocol (Dentener et al., 2006). Due in part to solar heating, fire plume heights in the southern tropics are higher than the northern tropics.

July is the month of most burning globally over 8 fire regions: Boreal North America, Boreal Asia, West Temperate North America, Europe, Middle East, Central Asia, South Hemisphere South America and South Hemisphere Africa (Giglio et al., 2013). Over the tropical SH (SHSA and SHAF) with frequent burning, the median fire plume heights of PFT2 and PFT4 are at 1500 to 2500 m and the 75th percentile heights reach the range of 2500 to 3000 m (Fig. 7), much higher than the range of 0 ~ 1000 m in AeroCom protocol (Dentener et al., 2006). In the NH temperate regions, the median fire plume heights of forests (PFT1 and PFT2) are at 2000 to

2500 m and the 75^{th} percentile heights reach 3500 to 4000 m, while the median heights of grass-savanna (PFT4) burning are at 2500 to 3000 m and the 75 percentile height is up to 4000 m. In comparison, the fire emission is released at 0 to 2000 m in these regions in the AeroCom protocol (Dentener et al., 2006).

3.2 Effects of plume rise on fire AOD simulations

Zhang et al., (2019) evaluated model simulated fire AOD with MODIS observations, using the observation-constrained fire plume height data described here, over fire burning regions. There was a general agreement but the GFED fire aerosol emissions appeared to have a low bias. In this study, we compare model simulated fire AOD with CALIPSO smoke AOD data (Omar et al., 2009), which are more specific for fire aerosols but also have relatively large uncertainties (Tackett et al., 2018). We calculated the fire AOD distributions by subtracting the control run results (without fire emissions) from the simulation results with GFED4s fire emissions and the observation-based fire plume rise dataset.

Observed and the corresponding model results for January and July during the period of 2006 to 2010 are shown in Figure 8. While observed and simulated data have similar spatial patterns, differences in details can be identified. The satellite smoke aerosol observation data tend to show high concentrations over industrialized regions, such as India and China in January, and China, western Europe, and eastern United States in July, where the model results show insignificant wildfire emissions. Over North America, the model shows high amounts of fire emissions over Alaska and Canada in July in contrast to higher smoke AOD data over eastern than western United States and Canada. It appears that satellite smoke retrievals over industrialized regions may have a high bias.

Over the tropical burning region, model simulated fire AOD data tend to be higher than the satellite observations. In January, simulated African fire AOD data are higher than CALIPSO retrievals but lower in the northern South America. In July, simulated fire AOD data are higher over South America, but lower over Africa. Decreasing fire emissions may help improve the comparison with CALIPSO retrievals in the model. However, the model evaluations by Zhang et al. (2019) suggested that the model fire aerosol emissions have a low bias in general.

Some of the model and satellite retrieval differences may be related to uncertainties in fire plume rise simulated in the model. We examine the effects of plume rise on fire AOD distribution by examining the AOD difference between the model simulation results with plume rise to those in which fire emissions were released in the surface layer. Figure 4 shows that fire plume rise above the top of the boundary usually occur in daytime. Therefore, the differences of AOD distribution between the two model simulations are due to daytime mixing. Fire aerosols released in the surface layer can be easily mixed into the boundary layer. Therefore, we selected three typical summer months in Figure 9 to show that the largest changes of fire AOD occurred in the region with large wind shear between the boundary layer and free troposphere. Fire AOD tends to increase in the downwind regions of free-tropospheric transport and decrease in the downwind regions of boundary-layer transport. Although the relative changes can be as large as 20-50% in some regions where background AOD is low and fire impact is large. However, the fire-induced absolute AOD changes are small relative to the differences between observed and simulated AOD data (Zhang et al., 2019).

3.3 On-line fire plume-rise implementation

The comparison between MISR observations and the online parameterization results are shown in Figure 10. The input data used for online parameterizations are the same as the 1-D fire plume-rise dataset. The general distribution features are similar. For example, tropical fire plume-rise heights are lower than at northern mid and high latitudes, in agreement with MISR observations (Figure 3), improving upon the previous studies (e.g., Sofiev et al., 2012, 2013). However, the low biases over Canada, western U.S., and Siberia, where fire plumes are often higher than 2-3 km, are worse than the 1-D fire plume-rise dataset (Figure 3), similar to the results by Sofiev et al. (2012, 2013). The larger biases of the online parameterizations, in which linear regression of fire plume-rise height with fire and meteorological parameters are considered, than the 1-D dynamic model results reflect the importance of nonlinear meteorological processes [e.g., Eq. (3)). Incorporating nonlinear dynamic processes will likely be a useful pathway to improve the online parameterizations of fire plume rise.

The on-line parameterizations must deal with various biases of the climate model simulations. We made use of the CDF mapping method (Section 2 (Zou et al., 2019)). To evaluate the performance of the online plume-rise parameterizations, we ran the coupled CAM-CLM for one full year. As a fully coupled simulation, it is not possible to reproduce the meteorology conditions exactly like the conditions of MISR measurements. Therefore, we used the monthly mean plume-rise heights in the evaluation. The results are shown in Figure 11. Since fire burned areas are simulated using the RESFire model by Zou et al. (2019), the locations of simulated fires do not necessary overlap with the time periods of MISR-derived fire plume-rise height data. As a result, the pattern of fire distribution in Figure 11 differs from Figure 10. The general pattern of coupled plumes is similar to MISR data (Figure 3): higher fire plumes in mid and high latitudes and lower fire plumes in the tropics. The quality of fire plume-rise simulation is similar to using off-line data (Figure 10). The averaged diurnal cycle of fire plume-rise height in July is shown in Figure 12. The diurnal cycle resembles that of the observation-constrained 1-

D model computed dataset (Figure 4), peaking at 14:00 local time with a maximum height at around 2 km.

4 Conclusions

We developed an observation-based global fire plume-rise dataset for 2002-2012, using a modified 1-D plume-rise model on the basis of observed fire size and MFRP data as a function of plant functional type (PFT) for different regions. This study developed long-term plume height dataset through using modified 1-D plume-rise model and region- and PFT-specific MFRP and fire size data as inputs, as well as CFSR meteorology variables. Compared to corresponding MISR data in the morning, the observed general geographical distribution feature is well captured: lower in the tropics and higher at northern mid and high latitudes, improving over the previous results of higher fire plume-rise heights in the tropics than mid and high latitudes (Sofiev et al., 2012, 2013).

The diurnal variations of fire plume rise due to the changes of fire size and FRP and boundary-layer mixing were assessed. The key parameter for the impacts of fire emissions is the fraction of fire plumes penetrating above the boundary layer, which tends to increase during the day as the boundary-layer is destabilized and fires intensify. While at the time of MISR observation (10:30 am LT) it is relatively low at 20%, the fraction increases to an average of ~55% in the late afternoon. The resulting fire emission vertical distributions show much more fire emissions at higher altitudes in the tropical and temperate regions than the zonal-mean emission distributions specified by the AeroCom Protocol (Dentener et al., 2006), which is widely used in the climate model simulations. Comparing model simulations using observation-based global fire plume-rise dataset to those assuming surface emissions only, we found 20 to

50% fire caused monthly AOD increases globally, suggesting larger effects of fire emitted aerosols in downwind regions on air quality and radiative and cloud forcing.

Using the 2002-2012 observation-based dataset, we developed online fire plume-rise height parameterizations for 15 global wildfire regions using up to 28 parameters for use in climate model simulations. While the general geographical distribution of the computed fire plume-rise height is reasonable, the parameterization has a considerably larger low bias than the 1-D model computed data when compared to MISR observations. The low biases are similar in magnitude to the previous results by Sofiev et al. (2012, 2013). The low biases are likely due to the use of linear regression in our study; the nonlinear dynamics of fire plumes could be represented better using the 1-D modeling approach (Frietas et al., 2007; 2010). We recommend investigating computationally efficient nonlinear regression-based parameterizations in future studies to improve the representation of fire plume rise in climate models. Furthermore, MISR-like global observations of fire plume heights, particularly in the afternoon, are necessary to improve our understanding of fire plume rise processes, model simulations, and climate model parameterizations.

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CFSR meteorology hourly data:

https://rda.ucar.edu/datasets/ds094.2/

MODIS MCD14DL (fire hotspot) data:

https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms

MISR plume heights data:

https://misr.jpl.nasa.gov/getData/accessData/MISRPlumeHeight/

CESM-CAM5:

http://www.cesm.ucar.edu/models/

CALIPSO data:

http://www.cesm.ucar.edu/models/

The data and source code produced by this study:

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