EPA Public Access

Author manuscript

Atmos Environ (1994). Author manuscript; available in PMC 2019 April 22.

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Published in final edited form as:

Atmos Environ (1994). 2018 ; 191: 328–339. doi:10.1016/j.atmosenv.2018.08.020.

Influence of uncertainties in burned area estimates on modeled wildland fire PM_{2.5} and ozone pollution in the contiguous U.S.

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Abstract

Wildland fires are a major source of fine particulate matter (PM_{2.5}), one of the most harmful ambient pollutants for human health globally. To represent the influence of wildland fire emissions on atmospheric composition, regional and global chemical transport models rely on emission inventories developed from estimates of burned area (i.e. fire size and location). While different methods of estimating annual burned area agree reasonably well in the western U.S. (within 20–30% for most years during 2002–2014), estimates for the southern U.S. can vary by more than a factor of 5. These differences in burned area lead to significant variability in the spatial and temporal allocation of emissions across fire emission inventory platforms. In this work, we implement wildland fire emission estimates for 2011 from three different products - the USEPA National Emission Inventory (NEI), the Fire Inventory of NCAR (FINN), and the Global Fire Emission Database (GFED4s) - into the Community Multiscale Air Quality (CMAQ) model to quantify and characterize differences in simulated PM and ozone concentrations across the contiguous U.S. (CONUS) due to the fire emission inventory used. The NEI is developed specifically for the U.S., while both FINN and GFED4s are available globally. We find that NEI emissions lead to the largest increases in modeled annual average PM_{2.5} (0.85 $\mu\text{g m}^{-3}$) and April–September maximum daily 8-h ozone (0.28 ppb) nationally compared to a “no fire” baseline, followed by FINN (0.33 $\mu\text{g m}^{-3}$ and 0.22 ppb) and GFED4s (0.12 $\mu\text{g m}^{-3}$ and 0.17 ppb). Annual mean enhancements in wildland fire pollution are highest in the southern U.S. across all three inventories (over 4 $\mu\text{g m}^{-3}$ and 2 ppb in some areas), but show considerable spatial variability within these regions. We also examine the representation of five individual fire events during 2011 and find that of the two global inventories, FINN reproduces more of the acute changes in pollutant concentrations modeled with NEI and shown in surface observations during each of the episodes investigated compared to GFED4s. Understanding the sensitivity of modeling fire-related PM_{2.5} and ozone in the U.S. to burned area estimation approaches will inform future efforts to

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assess the implications of present and future fire activity for air quality and human health at national and global scales.

1. Introduction

Wildland fires, defined as wildfires and prescribed burns, are a major source of fine particulate matter (PM_{2.5}), one of the most harmful ambient pollutants for human health globally (Lelieveld et al., 2015). Within the U.S., wildland fire activity can account for more than 20% of total PM_{2.5} emissions annually (USEPA, 2016), and up to 70% of the daily National Ambient Air Quality Standards (NAAQS; www.epa.gov/criteria-air-pollutants/naaqs-table) exceedances for PM_{2.5} in some areas during peak fire months (Kaulfus et al., 2017). Wildland fires also release nitrogen oxides (NO_x) and volatile organic compounds (VOCs) that can lead to the formation of ozone, another pollutant that is harmful to humans (Turner et al., 2016) and ecosystems (Ainsworth et al., 2012).

To represent the influence of fire emissions on atmospheric composition, regional and global chemical transport models (CTMs) rely on wildland fire emission inventories typically developed from estimates of burned area (i.e. fire size and location) combined with assumptions about fuel loading, combustion characteristics, and emission factors (French et al., 2011; Larkin et al., 2014). While these components all influence the magnitude and composition of emissions estimated for individual fires, it is the burned area estimates that control the spatial and temporal distribution of emissions within an inventory. Burned area can be estimated using a range of top-down and bottom-up approaches (Hao and Larkin, 2014), including satellite-based remote sensing (Mouillot et al., 2014) and on-the-ground incident reports (Short, 2014). Differences in burned area estimation methods lead to significant variability in the spatial and temporal allocation of emissions across fire emission inventory platforms, as well as large differences in overall magnitude of emissions estimated (French et al., 2011). For example, estimated annual total PM_{2.5} emissions for the contiguous U.S span almost an order of magnitude across different inventories during 2007–2011 (Larkin et al., 2014).

There is a rapidly growing body of literature documenting drivers of wildland fire activity within the U.S. (Morton et al., 2013; Barbero et al., 2015a; Higuera et al., 2015; Littell et al., 2016; Westerling, 2016; Balch et al., 2017) and the associated implications for regional air quality (Jaffe et al., 2013; Val Martin et al., 2015; Liu et al., 2016) and human health (Reid et al., 2016; Fann et al., 2017; Liu et al., 2017). In this work, we implement wildland fire emission estimates for 2011 from three different products – the Global Fire Emission Database (GFED4s), the Fire Inventory of NCAR (FINN), and the U.S. Environmental Protection Agency (EPA) National Emission Inventory (NEI) – into the Community Multiscale Air Quality modeling system (CMAQ; www.epa.gov/cmaq). The NEI is produced specifically for the U.S., while both FINN and GFED4s are available globally. GFED and FINN were also originally developed for different purposes -- GFED as a tool for understanding the monthly contribution of biomass burning to global carbon cycling (Van der Werf et al., 2004), and FINN as a high-resolution inventory available for near real-time assessments (Wiedinmyer et al., 2011). All three fire inventories are used frequently for a

range of earth system science applications (Bray et al., 2018; Brey et al., 2018; Cusworth et al., 2018; Harrison et al., 2018; Kumar et al., 2018). As mentioned previously, although estimating emissions from wildland fires is a complex process that requires many assumptions and inputs in addition to fire activity and burned area data, differences in emission estimates across fire inventory platforms are driven largely by the burned area estimation methods used. Our goal is to explore how variability in the representation of wildland fire activity across the contiguous U.S. (CONUS) connects to modeled PM_{2.5} and ozone concentrations across a range of spatial and temporal domains. These comparisons provide context for interpreting assessments of the air quality and human health impacts of present and future wildland fire activity at regional and global scales.

2. Methods

2.1 Burned area datasets

In order to evaluate consistency in burned area products across the U.S., we first compare several datasets that employ a range of techniques to estimate burned area: 1) the National Interagency Fire Center (NIFC; www.nifc.gov), 2) the Monitoring Trends in Burn Severity project (MTBS; www.mtbs.gov), 3) GFED4s, 4) FINN, and 5) the EPA. Burned area estimates from GFED4s, FINN, and the EPA are described below in Section 2.2.

The NIFC data are generated from on-the-ground reports of individual fire type (wild vs. prescribed), size, and cause (e.g. lightning vs. arson) (Short, 2014). Data are reported by multiple federal agencies, as well as by state, county, and local jurisdictions when available. The number and type of groups contributing reports varies by state and by year.

MTBS is a Landsat derived burned area dataset developed to track the frequency and size of severe fires across the U.S. (Eidenshink et al., 2007). Although it was designed primarily as a fire management tool, MTBS has been used extensively to study trends in fire activity (Dennison et al., 2014; Kolden et al., 2015; Yang et al., 2015; Donovan et al., 2017). The image-based analysis of fire sizes in MTBS produces detailed fire perimeter outlines. Because the purpose of MTBS is to track changes in fire severity (rather than overall fire activity), small fires (< 4 km² in the west, < 2 km² in the east) are deliberately excluded from the MTBS estimates.

2.2 Fire emission inventories

2.2.1 GFED4s—The GFED4s inventory (www.globalfiredata.org; Van der Werf et al., 2017) contains gridded monthly total dry matter (DM) emissions at 0.25° horizontal resolution derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) direct broadcast 500 m burned area product (MCD64A1; Giglio et al., 2013) and separated into six land cover types: savannah/grassland/shrubland, temperate forest, boreal forest, deforested and degraded land, peatland, and agricultural waste burning (Van der Werf et al., 2010). Accompanying emission factors specific to each land cover type can be applied to the monthly DM totals to produce monthly emission estimates of trace gases and aerosols. Daily emission fractions derived for each grid cell from MODIS active fire detections can also be applied to apportion the monthly emissions into daily emission estimates (Mu et al., 2011).

Although the base GFED4 product has been shown to underestimate burned area compared to government reports in the U.S. (Mangeon et al., 2016), additional emissions are included in GFED4s to account for fires too small to detect using the standard GFED4 burned area algorithm (Randerson et al., 2012; Van der Werf et al., 2017). In some areas of our study domain, particularly the southeastern U.S., this “small fire correction” contributes most of the GFED4s emissions throughout the year.

2.2.2 FINN—While similar to GFED4s in that both inventories are derived from MODIS fire products, the FINN inventory (v1.5, www2.acom.ucar.edu/modeling/finn-fire-inventory-ncar) was developed for the purpose of near-real time applications (Wiedinmyer et al., 2011). Rather than relying on the MODIS burn scar product, which requires multiple days of observations and post-processing time to produce quality assured burned area estimates, FINN instead uses daily MODIS active fire detections and can therefore be processed for next-day use. The use of individual fire detections also allows the FINN estimates to be produced at a higher spatial resolution, ~1 km compared to the ~25 km resolution of GFED4s. In order to estimate emissions in the absence of observed burned area, FINN assumes a theoretical burned area per active fire detection based on land cover classifications from the MODIS Land Cover Type and MODIS Vegetation Continuous Fields products. Because of its higher spatial and temporal resolution, FINN captures more small fire activity compared to the GFED approach (Reddington et al., 2016). Conversely, FINN underestimates the intensity of large fires in some environments, due at least in part to the sensitivity of the FINN approach to day-to-day variability in cloud cover (Paton-Walsh et al., 2012).

2.2.3 EPA—Burned area estimates from the EPA are generated from a combination of satellite and on-the-ground sources. Fire detections from NOAA’s Hazard Mapping System (HMS) and fire perimeter information from either MTBS (discussed above) or Geospatial Multi-Agency Coordination (GeoMAC; <https://www.geomac.gov/index.shtml>) are hierarchically combined with ground-based incident reports using the SmartFire data processing tool (Raffuse et al., 2012). Synthesized burned area estimates for individual fires from SmartFire are then fed to the BlueSky model to estimate fuel consumption and apply emission factors for individual fires based on land cover, fire type (i.e., wildfire or prescribed burn), and combustion characteristics (e.g., fuel moisture content) (Raffuse et al., 2012). Every three years (i.e., 2005, 2008, 2011, 2014), the EPA undergoes iterative collaboration with states to constrain fire activity data for inclusion in the National Emission Inventory (NEI) (USEPA, 2014). EPA fire emissions used in this work are from version 2 of the 2011 NEI inventory (USEPA, 2015a). Burned area from the EPA for non-inventory years was also produced with the SmartFire framework described above, but did not undergo the same NEI review process or include iteration with states. The EPA burned area dataset including inventory and non-inventory years is referred to in this work as “EPA-SmartFire”.

2.2.4 Exclusion of agricultural burning emissions—In this work we focus on wildland fire emissions, which includes wildfires and prescribed burns in forested areas, but not agricultural crop fires. We therefore include NEI cropland fire emissions in all simulations including the “no fire” base case in order to remove the influence of differing

estimates for agricultural crop fire emissions from our calculation of the impacts attributable to wildland fires. To avoid double counting, we also remove the contribution of agricultural fires in GFED4s (DM_AGR1) and FINN (GEN_VEG type 9, corresponding to cropland). Figure S1 in the Supporting Information (SI) shows the respective contribution of these categories within GFED4s and FINN. While agricultural burning can also include rangeland fires (Pouliot et al., 2017), in this work we do not deliberately omit the influence of rangeland fire emissions (although rangeland fires may have been unintentionally removed through the omission of the agricultural categories listed above). Despite our efforts to remove the contribution from agricultural crop burning emissions from our results, classification of agricultural fires is difficult due to the tendency of these fires to be small and on privately-owned land.

2.3 Community Multiscale Air Quality Modeling System

To simulate the formation of PM_{2.5} and ozone pollution due to wildland fire emissions, we used CMAQv5.1 (USEPA, 2015b; Appel et al., 2017) with the Carbon Bond version 2005 (CB05) chemical mechanism (Sarwar et al., 2011) at 36km horizontal resolution over a CONUS domain with 35 vertical layers, driven by meteorology from the Weather Research and Forecasting model (WRFv3.4; Skamarock and Klemp, 2008). Meteorological outputs from WRF were preprocessed for use in CMAQ with the Meteorology-Chemistry Interface Processor (MCIPv4.3; Otte and Pleim, 2010). CMAQ simulations of PM_{2.5} and ozone have been evaluated extensively over the U.S. (Zhang et al., 2014; Canty et al., 2015; Foley et al., 2015a; Foley et al., 2015b; Nolte et al., 2015; Astitha et al., 2017), particularly for the purposes of developing control strategies to attain the NAAQS established by the EPA to protect human health and the environment.

To attribute changes in pollution to each fire emission inventory, we conducted four one-year (1 Jan – 31 Dec 2011) simulations with CMAQ, one for each wildland fire inventory (NEI, FINN, and GFED4s) and one with wildland fire emissions set to zero (i.e. the “no fire” base case). To isolate the changes in PM_{2.5} and ozone concentrations due to wildland fire emissions in the U.S., we subtract the “no fire” case from each fire inventory simulation. All simulations were initialized on 22 Dec 2010 and used CMAQ default clean profile chemical boundary conditions. The default profile boundary conditions do not capture wildland fire smoke or other pollution transported into the U.S., but doing so is not the purpose of this study and would not significantly affect the results of our analysis.

For each simulation with wildland fire emissions, daily estimates of PM_{2.5}, NO_x, VOCs, SO₂, CO, NH₃, and burned area were included from each fire inventory following the methods outlined in Section 2.2 and implemented in CMAQ. Although GFED4s and FINN include emission estimates for both total and speciated PM_{2.5}, CMAQv5.1 includes detailed treatment of PM components not explicitly included in these inventories, for example crustal species. For consistency, we applied the same speciation profile to total PM_{2.5} emissions from GFED4s and FINN that is used in the NEI preprocessing for CMAQ (Baker et al., 2016). Consistent speciation profiles were also applied to partition NO_x and VOCs into individual compounds. Wildland fire emissions were pre-processed with the Sparse Matrix Operator Kernel Emissions (SMOKE; Houyoux et al., 2000) model version 4.0.

Anthropogenic emissions from non-wildland fire sectors (including agricultural fires, see Section 2.2.4) from the 2011 NEI (www.epa.gov/air-emissions-inventories/2011-national-emissions-inventory-nei-data) and biogenic emissions computed online from the simulated meteorology were the same in all simulations.

We perform an additional simulation to assess the sensitivity of our results to the heat flux parameterization used in the preprocessing for FINN and GFED4s. Treatment of plume rise and the resulting impact on downwind smoke dispersal has been identified as a major source of uncertainty for representing wildland fire pollution transport in chemical transport models (Freitas et al., 2006; Val Martin et al., 2012; Paugam et al., 2016). In CMAQ, the vertical distribution of smoke plumes from wildland fires is parameterized based on the estimated heat flux released from each individual fire. In the standard preprocessing of NEI emissions with SMOKE, including the NEI 2011 emissions used in this work, heat flux per fire is estimated based on the area burned and fuel loading information about each fire acquired from the SmartFire-BlueSky framework (Section 2.2.3). However, consistent fuel loading information is not readily available for the FINN or GFED4s emissions. For FINN and GFED4s, we instead follow the approach currently applied by the CMAQ near real-time (NRT) modeling group (www.epa.gov/cmaq/continuous-near-real-time-evaluation-cmaq) and estimate heat flux based on $\text{PM}_{2.5}$ emissions, an average fuel load (139.76 tons fuel ton $\text{PM}_{2.5}^{-1}$) from values in Wiedinmyer et al. (2011), and a constant fuel heat content (8,000 BTU lb^{-1}). To test the sensitivity of our results to the CMAQ-NRT heat flux parameterization, we performed an additional simulation with FINN-CMAQ where we instead use the median heat flux per ton $\text{PM}_{2.5}$ derived from the 2011 NEI emissions, an effective heat flux scaling of $8.1\text{e}7$ BTUs ton $\text{PM}_{2.5}^{-1}$. This alternative median heat flux is much lower than the default CMAQ-NRT scaling described above ($2.2\text{e}9$ BTUs ton $\text{PM}_{2.5}^{-1}$), and may be more representative of the smaller fires that occur frequently in the southern U.S. Results from this sensitivity assessment are discussed in Section 3.5.

2.4 Observations

We compare simulated $\text{PM}_{2.5}$ concentrations from CMAQ to ground monitoring data to assess the relative skill of each fire inventory in capturing the pollution enhancements observed during several different fire events during 2011 (Section 3.4). $\text{PM}_{2.5}$ data are from the Interagency Monitoring of Protected Visual Environments (IMPROVE) network (www3.epa.gov/ttnamti1/visdata.html).

3. Results

3.1 Burned area comparisons

We first examine estimated burned area from five different products (EPA-SmartFire, NIFC, GFED4s, MTBS, and FINN) over an extended period (2002–2014) in order to compare across years of varying fire intensity. In the national totals shown in Figure S2, the EPA-SmartFire estimates are higher than the other four datasets by at least 20% for every year after 2006 (there was a change in the EPA-SmartFire approach for estimating fire emissions in 2007 that resulted in systematically higher estimates than the previous algorithm). In 2011 the gap is particularly wide, with EPA-SmartFire estimating $\sim 90,000$ km^2 of burned area for

the CONUS, more than double the $\sim 40,000 \text{ km}^2$ estimated by the other four datasets. This large difference between EPA-SmartFire burned area and other inventory estimates is consistent with previous comparisons (Larkin et al., 2014).

As shown in Figure 1, the apparent clustering between FINN, GFED4s, MTBS, and NIFC compared to the EPA-SmartFire estimates in the national totals masks large regional variability. All five datasets agree well in the Northwest and North Plains during the 2002–2014 time period; EPA-SmartFire is again consistently higher than the other estimates, but all datasets agree within ~ 20 – 30% in most years. In the Southwest discrepancies between the datasets are more evident, with the highest and lowest estimates often differing by more than a factor of 2. FINN is consistently lower than the other inventories in this region, underestimating the next lowest inventory by almost 50% in high fire years. However, as in the Northwest, the five datasets still show some consistency in relative interannual variability (i.e. identifying low vs. high fire years).

In contrast to the western U.S., the Southeast and South Plains datasets show little coherence in either the magnitude of burned area estimated or the interannual variability of fire activity. These discrepancies are likely due in part to the higher prevalence of small fires, which are difficult to observe with remote methods due to size and/or low temperature detection limits, in the southern U.S. compared to the rest of the country. Additionally, a greater percentage of land in the western U.S. is owned and monitored by federal agencies (Gorte et al., 2012), possibly allowing for more precise tracking of wildland fire information in these areas compared to the rest of the country.

3.2 Wildland fire emissions

Figure 2 shows 2011 annual total burned area and emissions of organic carbon (OC) aerosol from each wildland fire emission inventory after applying CMAQ $\text{PM}_{2.5}$ speciation profiles (Section 2.3). In general, the spatial distribution of OC emissions maps closely to the underlying burned area values, although there are many areas where the magnitude of estimated emissions does not directly correspond to the co-located burned area severity (e.g. western Texas in GFED4s). These discrepancies indicate areas where other factors such as fuel availability and/or emission factors are also significantly modulating the emission estimates. Estimates of 2011 CONUS emission totals for select species are shown in Table S1. Total OC emitted by fires nationally for 2011 was highest in the NEI with 0.92 Tg, followed by FINN with 0.32 Tg. GFED4s was the lowest with 0.15 Tg OC, six times lower than the NEI total.

3.3 $\text{PM}_{2.5}$ and ozone from wildland fires

Figure 3 compares modeled increases in annual average $\text{PM}_{2.5}$ and April–September averages of maximum daily 8-h (MDA8) ozone attributed to each of the wildland fire emission inventories (NEI, FINN, and GFED4s). CONUS average enhancements above a “no fire” baseline in modeled annual average $\text{PM}_{2.5}$ vary by a factor of seven, with NEI leading to the largest increase ($0.85 \mu\text{g m}^{-3}$) nationally, followed by FINN ($0.33 \mu\text{g m}^{-3}$) and GFED4s ($0.12 \mu\text{g m}^{-3}$). Increases in modeled April–September MDA8 ozone are more

consistent in magnitude (0.28, 0.22, and 0.17 ppb respectively), but vary in their spatial distributions.

Regional mean pollutant enhancements are most variable over the southern U.S., ranging from 0.2–1.6 $\mu\text{g m}^{-3}$ $\text{PM}_{2.5}$ and 0.1–0.6 ppb ozone in the Southeast and 0.1–1.2 $\mu\text{g m}^{-3}$ $\text{PM}_{2.5}$ and 0.2–0.5 ppb ozone in the South Plains. While NEI fires lead to the largest enhancements in most areas, FINN produces significant increases in both $\text{PM}_{2.5}$ and ozone over southeastern Georgia (up to $\sim 4 \mu\text{g m}^{-3}$ $\text{PM}_{2.5}$ and ~ 5 ppb ozone), the only region where modeled surface pollutant concentrations are higher with FINN than with NEI (Figure S4). We discuss this area in more detail in Section 3.4.

To highlight both the far-reaching effects of wildland fire smoke across the U.S. and the regional variability in these impacts, we also compare the number of modeled exceedances of the Air Quality Index (AQI) levels considered unhealthy for sensitive groups (35 $\mu\text{g m}^{-3}$ for $\text{PM}_{2.5}$ and 70 ppb for ozone; <https://airnow.gov/index.cfm?action=aqibasics.aqi>) due to wildfires during 2011 (Figure 4; totals summed across all grid cells by region are shown in Figure S5). In our simulations, NEI fires lead to the largest increase in modeled AQI exceedances nationally, with 2,700 more $\text{PM}_{2.5}$ exceedances and 3,400 more ozone exceedances compared to the “no fire” case, followed by FINN with 600 and 3,000 respectively. GFED4s results in the fewest additional exceedances with only 50 additional $\text{PM}_{2.5}$ exceedances and 1,300 additional ozone exceedances.

Aggregated regionally, the Southeast sees the most additional exceedances across the three inventories, ranging from 30 to 950 for $\text{PM}_{2.5}$ and 230 to 1,500 for ozone, followed by the South Plains (5–640 for PM, 590–1,700 for ozone), consistent with the significant emissions in these regions shown in Figure 2. Despite experiencing very low local wildland fire activity (Figure 1), the Midwest and Northeast regions nonetheless experience a moderate impact on modeled AQI exceedances, likely due to the combination of 1) high concentrations of PM and ozone precursor emissions already present from other sources, and 2) prevailing westerly winds transporting wildland fire pollution to those regions from upwind areas (Figures 2–3).

Figure 5 shows time series of monthly mean wildland fire $\text{PM}_{2.5}$ modeled with each emission inventory averaged by region (corresponding time series of wildland fire OC emissions by region are shown in Figure S6). Distinct regional differences in wildland fire seasonality are evident in all three inventories, particularly the fall (August–November) burning in the Northwest/North Plains compared to the spring (February–April) prescribed burning peaks in the Southeast and South Plains.

3.4 Fire event case studies

Figure 6 shows time series of organic mass (OM) observations from the IMPROVE network compared with modeled OM from CMAQ during five major wildland fire events in 2011. Although other sources also emit organic aerosol, we assume that large, short-term increases above background concentrations are likely due to wildland fire smoke episodes. Opportunities to directly compare modeled OM concentrations during individual fire episodes to observations from the IMPROVE monitors are scarce given the limited temporal

coverage of the IMPROVE data, which are available only every three days and are sometimes missing data during smoke episodes (Baker et al., 2016). For this reason, it is difficult to conduct a quantitatively rigorous evaluation of model performance during these episodes using the IMPROVE data. The comparisons shown in Figure 6 are instead intended to 1) illustrate the relative behavior of each CMAQ-emission inventory combination across a range of wildland fire environments, and 2) show an approximation of what was captured in the IMPROVE observations during each event when available.

3.4.1 Pagami Creek, MN – BOWA1—The Pagami Creek fire was ignited by a lightning strike on 18 August 2011 and burned a total of 370 km² in northeastern Minnesota during August–November 2011 (USFS, 2012). Smoke generated by the Pagami Creek fire was observed as far away as Germany (Dahlkötter et al., 2014). As shown in Figure 6a, daily average OM concentrations at a nearby IMPROVE site (BOWA1) were elevated during this period, spiking from a baseline of less than 10 µg m⁻³ before August up to over 120 µg m⁻³ in early September. NEI-CMAQ simulates a sharp enhancement in OM up to 150 µg m⁻³ coinciding with the mid-September peak in the IMPROVE OM of ~100 µg m⁻³. FINN also produces a modest enhancement on this day of ~45 µg m⁻³. GFED4s leads to a slight increase above baseline during this time, but much smaller in magnitude at only ~5 µg m⁻³. None of the inventories produce significant OM concentration increases on the day of the IMPROVE peak, which occurred a week earlier.

3.4.2 Honey Prairie, GA – OKEF1—Started by lightning on 18 April 2011, the Honey Prairie fire consumed over 1,200 km² in the Okefenokee Swamp in Georgia (NASA, 2011a). The Honey Prairie fire was not fully extinguished until April 2012; land cover in the Okefenokee Swamp area is dominated by wetlands, leading to prolonged smoldering burns that can last for months at a time (Watts and Kobziar, 2013). During May–June 2011, FINN-CMAQ leads to OM concentrations of 40–50 µg m⁻³ at the nearby OKEF1 IMPROVE monitor (Figure 6b), while neither NEI-CMAQ nor GFED4s-CMAQ result in significant enhancements above background concentrations at this location. The FINN-CMAQ peak in early May is also far lower than the observed IMPROVE concentrations of over 100 µg m⁻³. We further discuss the effects of estimated burned area distributions and resulting vertical plume allocations on modeled surface smoke concentrations at OKEF1 below in Section 3.5.

3.4.3 Pains Bay, NC – SWAN1—During May–July 2011, over 180 km² of the Alligator River National Wildlife Refuge burned due to the lightning-caused Pains Bay fire (Geron and Hays, 2013). IMPROVE OM concentrations spike several times during this period at the SWAN1 site, peaking around 60 µg m⁻³ in late June (Figure 6c). While none of the CMAQ simulations show high concentrations coinciding with the largest IMPROVE enhancement in late June, NEI-CMAQ leads to moderate increases above background OM on several occasions during the May–July time frame, peaking around 50 µg m⁻³ in early June. The IMPROVE data are also elevated at this time and closely match the NEI-CMAQ enhancement around 5 June, but are missing data during the NEI-CMAQ peak the day before. Similarly, NEI-CMAQ produces elevated concentrations of up to ~40 µg m⁻³ in early May that agree well with the IMPROVE data initially, but no IMPROVE data are available during peak NEI-CMAQ concentrations on the subsequent days. The SWAN1 site was also

the only site investigated here in which the MTBS perimeter and IMPROVE monitor location were not contained within the same CMAQ grid cell, and there were other fires upwind in South Carolina and Georgia during this time that may have transported smoke to the SWAN1 monitor (NASA, 2011b).

3.4.4 Flint Hills, KS – TALL1—The Flint Hills region of central Kansas experiences frequent prescribed burn activity. A significant amount of burning occurred during April 2011 (Baker et al., 2016). During this time, modeled OM concentrations with NEI emissions near the TALL1 IMPROVE site show several enhancements, the first of which occurs on 3 April and reaches $\sim 40 \mu\text{g m}^{-3}$, more than double the concentrations simulated using either GFED4s or FINN (Figure 6d). Observations from IMPROVE just before this first peak on 2 April show OM concentrations of $\sim 10 \mu\text{g m}^{-3}$, which is consistent with concentrations modeled by NEI-CMAQ. However, IMPROVE data are missing during the peak NEI-CMAQ values between 3–14 April. During the last of the NEI-CMAQ peaks on 16 April the IMPROVE site also measured elevated OM concentrations of $\sim 20 \mu\text{g m}^{-3}$, consistent with the peak modeled using NEI emissions. Baker et al. (2016) compared daily OC from NEI-CMAQ simulated at 12 km resolution against observed concentrations from six nearby IMPROVE sites during the Flint Hills fires in 2011 and found consistently high model bias across several sites during concurrently sampled days, including TALL1 where the average model bias was $\sim 10 \mu\text{g m}^{-3}$. However, consistent with our findings in Figure 6d, Baker et al. (2016) noted the lack of concurrent monitoring data throughout much of the fire episode, making a direct comparison between observed and modeled smoke concentrations difficult.

3.4.5 Wallow, AZ – BALD1—The Wallow fire, one of the largest U.S. wildfires in recent years, burned over 2,000 km² in Arizona during June 2011 (USFS, 2011). Both NEI-CMAQ and FINN-CMAQ simulate sharp enhancements in OM between 1 June and 15 June at the BALD1 IMPROVE site, up to $\sim 140 \mu\text{g m}^{-3}$ and $\sim 60 \mu\text{g m}^{-3}$ respectively (Figure 6e). GFED4s-CMAQ also produces a modest enhancement in modeled OM at the BALD1 site during this time of $\sim 10 \mu\text{g m}^{-3}$. The IMPROVE OM registers an enhancement of $\sim 75 \mu\text{g m}^{-3}$ on 15 June, but there are no IMPROVE OM data during the largest increase in modeled PM_{2.5} between 2 June and 15 June. As with the Flint Hills event, Baker et al. (2016) found a high bias of several $\mu\text{g m}^{-3}$ in modeled OC at the monitor locations closest to the Wallow fire, although comparisons further downwind showed a mix of high and low biases depending on location.

3.5 Vertical smoke profiles

Figure 7 shows monthly mean vertical PM_{2.5} profiles simulated by each CMAQ-emission inventory configuration corresponding to the fire event case studies discussed in Section 3.4. Differences in the vertical smoke profiles are particularly pronounced during June 2011 at OKEF1, likely related to the spatial distribution of burned area estimated in NEI compared to FINN for the Okefenokee Swamp region during this time. Total burned area in 2011 estimated by the NEI for the three Georgia counties that contain the Okefenokee Swamp (Charlton, Ware, and Clinch counties; 1,335 km²) was nearly double the estimate from FINN (773 km²). However, almost all burned area within the NEI was attributed to Charlton county, while in FINN the burned area was more evenly distributed across the three counties.

This concentration of fire activity in Charlton county in the NEI leads to a higher calculated heat flux, so that most of the modeled smoke pollution is lofted away from the surface and out of the boundary layer over the OKEF1 grid cell in CMAQ as shown in Figure 7. Similarly, vertical profiles during June 2011 from the BALD1 location suggest that a greater fraction of the Wallow Fire PM_{2.5} in GFED4s-CMAQ was lofted away from the surface compared to simulations with FINN and NEI. GFED4s burned area estimates during June for the BALD1 grid cell were 40% higher than FINN and 15% higher than the NEI. While some of the simulated PM_{2.5} aloft at OKEF1 and BALD1 may be from other fires in the domain, non-local sources are likely not a significant contributor for either case given the obviously elevated surface concentrations in these grid cells and the decreased concentrations aloft with decreased heat flux in the FINN sensitivity simulations.

Figure 7 also shows FINN-CMAQ profiles modeled with an alternative (lower) heat flux parameterization (Section 2.3). Surface PM_{2.5} enhancements are more than a factor of two higher at the BOWA1, OKEF1, and BALD1 sites with the alternative heat flux parameterization compared to the original FINN-CMAQ simulation. While small decreases ($< 0.1 \mu\text{g m}^{-3}$) in far-field surface PM_{2.5} enhancements are evident in parts of the Northeast and Midwest, most areas near wildland fire activity in 2011 experience an approximate doubling in surface PM_{2.5} enhancements with the alternative heat flux scaling (Figures S8). The sensitivity of modeled surface concentrations to vertical smoke plume allocation in CMAQ and the demonstrated dependence on both 1) the spatial distribution of burned area and 2) the assumed heat flux characteristics of individual fires highlights the need for accurate plume rise parameterizations in chemical transport models.

4. Discussion and Conclusions

In this work, we used the CMAQ chemical transport model to simulate wildland fire PM_{2.5} and ozone over the contiguous U.S. during 2011. We implemented three commonly used emission inventories derived from different burned area estimation methods, and found that modeled pollution increments varied by more than a factor of 3 across inventories implemented ($0.1\text{--}0.9 \mu\text{g m}^{-3}$ for annual average PM_{2.5} and $0.1\text{--}0.3$ ppb for April–September MDA8 ozone). While other factors relevant for estimating fire emissions (e.g. assumptions about fuel type and combustion characteristics) also differ across these inventories, burned area inputs heavily influence the spatio-temporal distribution of the emissions estimated. Simulated wildland fire PM_{2.5} concentrations varied by an order of magnitude over the Southeast ($0.2\text{--}1.6 \mu\text{g m}^{-3}$) and South Plains ($0.1\text{--}1.2 \mu\text{g m}^{-3}$), consistent with the large variability in burned area datasets for these regions. We also found that both the Midwest and Northeast experienced moderate wildland fire pollutant enhancements across all three CMAQ-fire inventory configurations, emphasizing the far-reaching impacts of wildland fire pollution even in areas where local fire activity is low.

The results in this work illustrate differences in potential suitability among burned area approaches used by wildland fire inventories for specific applications, supporting conclusions from previous assessments (Reddington et al., 2016). While comparisons between FINN and GFED4s vary significantly by region (Shi and Matsunaga, 2017), the findings of this work illustrate several fundamental differences between these global

inventories that should be considered for future studies. Burned area estimates from GFED4s were higher than FINN across much of the southwestern U.S. (e.g. west Texas), where drier climates tend to facilitate the rapid spread of wildfires. Many of these fires did not lead to particularly high emission estimates in 2011, likely due to relatively sparse vegetation coverage in the southwestern U.S. compared to other regions. In contrast, FINN estimates were significantly higher than GFED4s across much of the Southeast where small fires are common, suggesting that FINN may capture more emissions in places with a high density of small fires. Additionally, the daily frequency and higher spatial resolution of FINN compared to GFED4s may allow for more realistic representation of pollution from individual fire events such as those discussed in Section 3.4. Capturing these higher frequency, shorter duration episodes could be increasingly important for assessing health impacts from wildfire events as the evidence for short-term health effects from smoke exposure builds (Liu et al., 2017).

Since the NEI is specifically developed for the U.S. and incorporates ground-based information from states and incident reports not included in global inventories, it is likely that the NEI captures a higher percentage of wildland fire activity in the U.S. compared to either FINN or GFED4s. However, the EPA-SmartFire approach is still reliant on satellite-derived data, and in some cases fires included in EPA-SmartFire are detected by satellites in the HMS system without corresponding fire size information from other sources (i.e. GeoMAC or ground reports). In these instances, an assumed fire size derived from historical MTBS data is applied based on land cover type. In addition to deliberately excluding small fires, MTBS fire perimeters can also include unburned areas within the observed fire extent, potentially leading to overestimates in area burned of 20–30% for some ecoregions (Kolden et al., 2012; Sparks et al., 2015; Meddens et al., 2016). For these reasons, the default fire sizes currently assumed in the NEI may be overestimated for some parts of the U.S., particularly areas where small fires dominate the fire size distribution. As discussed in Section 3.4, previous work has shown that NEI-CMAQ may overestimate $PM_{2.5}$ concentrations compared to observations during wildland fire episodes (Baker et al., 2016). Conversely, X. Liu et al. (2017) suggest that wildland fire emissions in the NEI may be significantly underestimated. Overestimated burned area in CMAQ also leads to overestimated heat flux, lofting smoke pollution higher into the atmosphere and reducing simulated concentrations locally. Identifying sources of uncertainty and improving the representation of wildland fire pollution within chemical transport models is an active area of investigation.

In addition to the many challenges associated with accurately representing wildland fire emissions in inventories, our assessment has several other limitations. First, for computational efficiency we chose to conduct relatively coarse 36-km CMAQ simulations rather than employing higher spatial resolution. While annual average $PM_{2.5}$ concentrations attributable to wildland fires in our 36 km NEI-CMAQ simulations are similar to 12 km NEI-CMAQ simulations for 2011 in other work (Fann et al., 2017), corresponding 12 km simulations with the GFED4s and FINN emissions are currently unavailable for comparison and may differ from the results shown here. Higher resolution models may also resolve aspects of individual smoke plume dynamics not captured in our simulations, which could affect the comparisons shown in sections 3.4 and 3.5. Next, we applied CMAQ speciation

profiles to total estimated PM_{2.5}, NO_x, and VOCs from GFED4s and FINN, which may have led to differences in modeled PM_{2.5} and ozone concentrations compared to what would have been simulated using speciated emissions directly from these inventories. Finally, we investigated only one year of wildland fire pollution, but both wildland fire activity and smoke transport patterns vary significantly from year to year. A similar analysis conducted for other years may therefore yield different results (although both the influence of burned area patterns on modeled fire pollution and the differences between inventories would remain evident).

Although projections of future wildland fire activity are highly uncertain (McKenzie and Littell, 2017), it is likely that some regions of the U.S. will experience significant changes in wildland fire potential due to changes in climate (Yue et al., 2013; Barbero et al., 2015b; Gergel et al., 2017) and other drivers (Prestemon et al., 2016). Continuing to develop and compare approaches for representing wildland fire pollution in the present day will 1) help identify aspects most in need of further development across inventories and modeling platforms (e.g. accurate representation of small fires), and 2) provide context for evaluating the projected impacts of wildland fires on future air quality in the U.S. and globally.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors would like to thank Ana Rappold and Tom Pierce (US EPA) for their time and helpful comments on this manuscript. We also thank Kirk Baker, Tesh Rao, and Sergey Napelenok (US EPA) for useful discussions related to fire emissions and the presentation of results.

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Figure 1.

Total annual burned area estimates by region during 2002–2014. EPA-SmartFire burned area is shown in yellow circles; estimates from the National Interagency Fire Center (NIFC) are shown in black triangles; the Global Fire Emission Database (GFED4s) is shown in blue diamonds; the Monitoring Trends in Burn Severity (MTBS) database is shown in grey squares; and the Fire INventory of NCAR (FINN) is shown in pink diamonds. Maps showing the geographical extent of each region are inset. Burned area estimates for the entire CONUS domain are shown in Figure S2.

Figure 2.

Total burned area in km² (left column) and emissions of organic carbon in Mg (right column) from wildland fires in 2011 in the National Emissions Inventory (NEI; top row), Fire INventory from NCAR (FINN; middle row), and the Global Fire Emissions Database (GFED4s; bottom row). Burned area and emissions shown for GFED4s include the small fire correction described in Section 2.2.1. The contributions of small fires to GFED4s emissions in 2011 are shown in Figure S3. (Values in some areas exceed colorbar maxima, up to 1380 km² for burned area and 3e5 Mg for organic carbon emissions).

Figure 3. Enhancements in annual average surface $\text{PM}_{2.5}$ (left column) and April-September MDA8 ozone (right column) due to wildland fire emissions during 2011 modeled with the Community Multiscale Air Quality modeling system (CMAQv5.1). Concentrations are attributed to wildland fire emissions by subtracting out a “no fire” simulation where wildland fire emissions have been removed but emissions from all other sectors are the same. (Negative changes in ozone are not shown, but do not exceed -0.04 ppb. Enhancements in some areas exceed the maximum colorbar value, up to $6.5 \mu\text{g m}^{-3}$ $\text{PM}_{2.5}$ and 5.6 ppb ozone.)

Figure 4.

Same as Figure 3 but for number of days each grid cell exceeded the Air Quality Index levels considered unhealthy for sensitive groups ($35 \mu\text{g m}^{-3}$ for PM_{2.5} and 70 ppb for MDA8 ozone) due to wildland fire pollution. (Values in some areas exceed the maximum number of days indicated by the colorbar, up to 27 additional days for PM_{2.5} and 18 additional days for ozone.)

Figure 5.

Monthly average wildland fire PM_{2.5} concentrations by region, calculated by subtracting results from the “no fire” simulation. Bars indicate standard deviations of monthly means across all grid cells in each region. Geographic areas corresponding to each region are shown in Figure 1. Figure S7 shows monthly average PM_{2.5} concentrations from all sources by region.

Figure 6.

Time series of organic aerosol concentrations at sites near five significant wildland fire episodes during 2011. Observations of organic mass (OM) from the IMPROVE site closest to each fire are shown by black circles, compared to modeled CMAQ OM concentrations using emissions from NEI (orange line), FINN (pink line), and GFED4s (blue line) for each location. IMPROVE site locations are shown by light blue circles in the lower right-hand panel. MTBS perimeters for each fire event are also shown by red polygons, along with the co-located CMAQ grid cells shown by grey rectangles. OM is calculated by multiplying modeled and observed organic carbon (OC) concentrations by 1.8, following the scaling used in the IMPROVE data. IMPROVE observations are daily averages and occur every three days. CMAQ values also represent daily averages of hourly outputs.

Figure 7.

Monthly mean vertical profiles of wildland fire $\text{PM}_{2.5}$ concentration modeled by CMAQ during each fire event discussed in Section 3.4. Profiles represent average concentrations sampled for the individual CMAQ grid cells shown inset in Figure 6. The corresponding IMPROVE site name and month of interest for each profile are shown inset. $\text{PM}_{2.5}$ concentrations were attributed to wildland fire emissions by removing $\text{PM}_{2.5}$ concentrations present in the “no fire” simulation. Results using an alternative heat flux parameterization with FINN emissions (described in Section 2.3) are shown by the dashed lines. Black lines indicate the monthly mean boundary layer height simulated by WRF for each grid cell.