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Wildland fire emissions, carbon, and climate: U.S. emissions inventories

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ABSTRACT

Emissions from wildland fire are both highly variable and highly uncertain over a wide range of temporal and spatial scales. Wildland fire emissions change considerably due to fluctuations from year to year with overall fire season severity, from season to season as different regions pass in and out of wildfire and prescribed fire periods, and from day to day as weather patterns affect large wildfire growth events and prescribed fire windows. Emissions from wildland fire are highly uncertain in that every component used to calculate wildland fire emissions is uncertain – including how much fire occurs and at what time during the year, assessments of available fuel stocks, consumption efficiency, and emissions factors used to calculate the final emissions. As shown here, these component uncertainties result in large-scale differences between estimation methods of wildland fire emissions including greenhouse gas totals, particulate matter totals, and other emissions. Four recent emissions inventories for the contiguous United States are compared to determine inter-inventory differences and to examine how methodological choices result in different annual totals and patterns of temporal and spatial variability. Inter-model variability is detailed for several current models, and current knowledge gaps and future directions for progressing fire emissions inventories are discussed.

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1. Introduction/background

Fire emissions are gases and particulates released during all phases of combustion. Wildland fire emissions include fine particulate matter (⩽2.5 microns, $PM_{2.5}$), black carbon (BC), carbon dioxide (CO_2), carbon monoxide (CO), and other trace gases (Urbanski et al., 2008). These emissions affect both air quality (e.g., Wotawa and Trainer, 2000) and global climate (e.g., Crutzen and Andreae, 1990). Large amounts of CO_2 are emitted annually around the globe during biomass burning (Andreae and Merlet, 2001). In addition to CO_2, trace gases methane, nitrous oxide, and other climate forcing compounds (Houghton et al., 1996) are emitted during both the flaming and smoldering phases of combustion (Fearnside, 2000). Their ratios relative to emitted CO_2 differ depending on fuel type, moisture, and combustion phase (Akagi et al., 2011). Wildfires are episodic events that can emit significant amounts of $PM_{2.5}$ into the atmosphere (Hodzic et al., 2007), which can then alter the natural radiative forcing through additional scattering and/or absorption (e.g., Shekar Reddy and Venkataraman, 2000). Black carbon emitted from wildfire can be deposited on snow and ice leading to albedo changes and feedbacks that can contribute significantly to radiative forcing changes, particularly in the Arctic (Hansen and Nazarenko, 2004; Quinn et al., 2008). Quantification of biomass emissions is required to understand the impact of fire on climate (Larkin et al., 2010) and to predict poor air quality during an ongoing biomass burning event (O'Neill et al., 2009; Strand et al., 2012).

Emission inventories are developed to quantify emissions from various activities and natural processes. Fire emissions inventories are used within models to predict regional air quality during ongoing biomass burning, to quantify shifts in atmospheric chemistry due to the sudden influx of particulates and gases, and to ascertain the impact of fire on climate (e.g. Wiedinmyer et al., 2006). These inventories are developed to assist with the understanding of current emission trends and are often the basis for policy decisions such as regulation and permitting. Unlike most other emissions sources, wildland fires are highly episodic across both the spatial and temporal scales (Liu, 2004). Wildland fire emissions change considerably due to yearly fluctuations of overall fire season severity, seasonally as regions pass in and out of wildfire and prescribed fire periods, and daily due to synoptic weather patterns that affect large wildfire growth events and prescribed fire windows. This variability is also reflected spatially within the United States throughout the year. On smaller spatial scales (~km), the variability in emissions is evident across ridges and valleys that face different directions as solar radiation affects fuel moisture and type of vegetation cover. The spatial and temporal variability in emissions

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makes fire emission inventory development difficult, and there is often a wide range of uncertainty associated with wildfire emission inventories.

In the following text we discuss the process of computing a fire emissions inventory and address the sources of uncertainty in such inventories, using four emissions inventories created for the contiguous United States (CONUS) as a test case example: the United States Environmental Protection Agency National Emissions Inventory (US EPA NEI), the Global Fire Emissions Database (GFED), the Fire INventory NCAR (FINN), and the US EPA Greenhouse Gas Inventory (US EPA GHG). It is important to note that each of these emissions inventories was developed to serve a different purpose: the NEI is a national accounting of emissions developed for use in modeling for national regulatory and policy purposes among other uses; GFED and FINN were designed for use in continental and global modeling of the atmosphere and modeling of chemical processes; and the EPA GHG inventory is specifically designed to meet the requirements for reporting national aggregate emissions to the United Nations Framework Convention on Climate Change, which includes specifics on what types of fires are to be included in the inventory. Nonetheless, these four inventories are modern representations of wildland fire emissions over CONUS and a comparison of their similarities and differences, and how these arise from methodological choices within each inventory, illustrates the difficulties in both developing, and in using, fire emissions inventories.

1.1. Scope and objectives

We examine here the fundamentals of how fire emissions and fire emissions inventories are calculated, and how different choices made in creating fire emissions inventories underpin their differences. Four current emissions inventories are examined including their inter-annual and seasonal variability. Inter-model variability is detailed for several current models, and current knowledge gaps and future directions for progressing fire emissions inventories are discussed.

The focus of this discussion is CONUS because this region has significant observational data, yet also shows the difficulties in creating fire emissions inventories that encompass different types of fire, ecosystems, and burning seasons. In addition, the availability of reporting systems that record fire location, size, and duration varies considerably across the many different land owners (private, federal, state, tribal, etc.) and fire types found in this region. Finally, many models of fuels, fire consumption, and fire emissions have been developed for application within CONUS, allowing for illustration of the uncertainties involved in current fire emission inventory development. The relative wealth of officially reported information and models compared to other regions highlights difficulties even in the most well monitored and studied ecosystems.

It is worth noting that much of the U.S. effort in developing emissions inventories and their component models and datasets (e.g. of fire information, available fuels, consumption models, and emissions factors) has been driven less by the need to report greenhouse gases (e.g. per international agreements), and more by the operational needs of land management (e.g. to account for activities on managed lands), as well as needs arising from laws and regulations governing air quality. The U.S. has a complex system of air quality regulations stemming from the 1972 Clean Air Act that identify required ambient air quality standards for certain pollutants, including particulate matter and ozone, and also mandate long-term planning to ensure visibility in protected airsheds such as within the U.S. National Park system. Fires, particularly large wildfires, significantly and adversely affect the values protected by these standards, and so accounting for wildland fire emissions is important in meeting and/or claiming exceptions to air quality targets that can have fiscal penalties if not met.

1.2. Calculating fire emissions

Calculation of fire emissions can be understood (Eq. (1), adapted from Seiler and Crutzen, 1980) as combining information on the size of the fire (***A***), the available biomass (***B***, per unit area) from the location of the fire, the relative consumption (***C***, as a % of the biomass) that occurred, and the emissions factor for the particular species of interest (***EF$_i$***).

$$\text{Amount of Species}_i \text{ Emitted} = A * B * C * EF_i \quad (1)$$

The size of the fire can be taken from any number of sources including ground reports, helicopter perimeters, ground or satellite measurement of burn scars, and planning documents for prescribed burns. It can also be inferred from satellite hot spot detections and intensity measurements (see also Hao and Larkin, 2014). The available biomass can be taken from local knowledge of the ecology, comparisons with photographs of known fuel loadings, detailed measurements such as LiDAR or plot measurements, and/or mapped fuel loading data that combine intensive local measurements with satellite maps to allocate fuels across the landscape (see also Weise and wright, 2014). Consumption is typically modeled using relationships derived from observations collected both pre- and post-burn to relate overall consumption to parameters such as fuel moisture, wind, and season (see also Ottmar, 2014). The emissions factor is then applied to determine the amount of the specific species of interest emitted (see also Urbanski, 2014). It is worth noting that, in general, the percentage consumed can also be related to the available biomass (***B***), and the specific emissions factor to use can be related to both the biomass type and the overall consumption efficiency; these connections make the above equation less separable than it appears.

An alternative to Eq. (1) is to use measures of fire intensity, typically as detected by satellites, to determine fire emissions. This method uses an empirical relationship that relates emissions to detected fire radiative energy, estimated from instantaneous satellite-based measurements of fire radiative power. The relationships are typically developed by region and vegetation type and bypass the need to more explicitly know the underlying biomass and calculate consumption, resulting in a simplified equation: $Emissions = C_e * R_{fre}$, where C_e is a region specific emissions coefficient and R_{fre} is the rate of release of radiative energy (Ichoku and Kaufman, 2005).

1.2.1. Fire emissions inventories

To create a fire emissions inventory, the above suite of methods must be pared down to a specific methodological choice (Table 1). The choice of which fire occurrence dataset, biomass dataset, consumption model, and emissions factors to use all affect the final emissions inventory, as shown below. Perhaps the clearest choice involves which fire occurrence dataset to use, as this directly controls the area covered (e.g., a particular state or the area observed by a particular satellite), the types of fire covered (e.g. wildfires, prescribed fires and/or agricultural fires), and other limitations (e.g., ability to detect small fires) of the final emissions inventory. However, other choices, such as the specific choice of fuel loading maps or the specific collected set of fire emissions factors used, may affect the final result as much, but be less tractable.

Fire emissions inventories, particularly those used in air quality modeling, need to specify emissions by hour; this is because the specific location(s) of air quality impacts will move as the transport winds, lofting height and rate of the emissions change throughout

Table 1
Emissions inventory methodologies summary. The methods used for each inventory are listed for the area burned, fuel loadings, consumption, and emissions factors. See Section 2 for additional discussion.

EI	Area burned	Available fuel	Consumption fraction	Emissions factors
GFED	MODISBurn scar method.Active fire detects through regression trees.	Carnegie-Ames-Stanford-Approach (CASA) biogeochemical model	Lookup table fraction of fuel type scaled by soil moisture	Based on latest updates of Andreae and Merlet
FINN	MODIS active detects scaled by land cover type and percent bare cover	MODIS land cover lookup table	Function of% tree cover	Primarily from Akagi et al., 2011
NEI+	NOAA HMS (includes MODIS, AVHRR, GOES active detects).MTBS perimeters.Incident reports.	LANDSAT derived map of FCCS fuelbeds	Calculated by consume fuelbed consumption model	Calculated by FEPS emissions model
EPA GHG	NIFC wildland fire statistics scaled by (forested area/area under fire protection)	Forest carbon density from FIA (includes aboveground biomass, dead wood, litter)	0.45 (from IPCC methodology)	Based on IPCC methodology

the day. To determine hourly emissions, first daily fire growth information is used to calculate daily fire emissions, and then diurnal profiles are used to allocate the emissions by hour. Some emissions inventories also include vertical injection height information; this requires knowledge of the atmospheric conditions such as stability and the spatial and temporal distribution of heat from the fire to calculate. Typically such calculations are more uncertain than the total fire emissions themselves. For comparison purposes here we focus on longer time scale aggregations of emissions (annual and monthly), and postpone questions associated with plume injection height.

1.3. CONUS fire emissions inventories used

We compare four current fire emissions inventories for the CONUS region: the methodology used in the national scale processing for the wildfire component of the EPA National Emissions Inventory (NEI, Raffuse et al., 2012), the Fire INventory NCAR (FINN, Wiedinmyer et al., 2011), the Global Fire Emissions Database, version 3.1 (GFED, van der Werf et al., 2010), and the EPA emissions inventory used for reporting greenhouse gas emissions to the United Nations Framework Convention on Climate Change (UNFCCC). As discussed below (see Section 2), these inventories represent a range of methods and underlying datasets, and are among the most used inventories for this area.

The NEI is a detailed estimate of emissions from all emissions sources in the US. NEI emission estimates are used for air quality modeling, tracking progress in meeting Clean Air Act requirements, setting policy, and answering questions from the public. An approximate version of the NEI using a nationally unified methodology is used here (see Section 2 for discussion). FINN and its predecessors have been used in several global and regional studies (Hodzic et al., 2007; Pfister, 2008; Fast et al., 2009). GFED is a widely used global database of fire emissions. It is the primary fire emissions source for GEOS-Chem (Bey et al., 2001) and studies often compare their results to the GFED data set (e.g., Permadi and Oanh, 2013; Shvidenko et al., 2011). The EPA GHG Report represents the United States Government's official inventory in support of the UNFCCC. Though it is also prepared by the US EPA, it is completely independent from the NEI.

All of these inventories include the major greenhouse gas species including CO_2 and CH_4. Not all of these inventories include N_2O, which is required for the calculation of CO_2 equivalent (CO2e), fine scale particulate matter (less than 2.5 microns, $PM_{2.5}$), and black carbon (BC). In order to best examine how these inventories compare, we supplement the existing inventory data using simple emissions factor ratios to produce results for N_2O, $PM_{2.5}$, and BC wherever possible. The specific methods used are listed in Section 2.

2. Methods

2.1. Emissions inventory processing

We utilize four emissions inventories for the bulk of this work. The Global Fire Emissions Database (GFED) version 3.1 (van der Werf et al., 2010) is available through http://www.globalfiredata.org/Data/index.html, the Fire INventory from NCAR (FINN, Wiedinmyer et al., 2011) is available through http://bai.acd.ucar.edu/Data/fire/, and the EPA Greenhouse Gas Inventory (EPA GHG) is available as a final report (U.S, 2012a). We have also used an inventory processed using the same methodology as that used for the National Emissions Inventory (NEI) for 2008 (Raffuse et al., 2012), but processed for the years 2007–2011 available through http://airfire.org/data/emissions. This inventory is not the official NEI, which is only produced every 3 years and which includes state submitted data and other modifications to the base national scale processed inventory used here. Therefore, while this inventory matches the national scale processing done for the 2008 NEI, to distinguish this inventory from the official NEI inventory for 2008, and to represent that it includes additional years, we here refer to this inventory as NEI+ because it spans years that the official NEI does not and does not incorporate revisions to the inventory submitted by individual U.S. states through the triennial NEI process.

All of the data sets represent wildland fire (or wildland and agricultural fires) across CONUS and are available across various spatial and temporal ranges and resolutions. GFED was acquired for the years 2002–2011 and is available on a $0.5^\circ \times 0.5^\circ$ spatial and monthly temporal resolution. FINN was acquired for the years 2002–2011 is available on a 1 km^2 spatial and daily temporal resolution. NEI+ is available for 2007–2011 on a 1 km^2 spatial and daily temporal resolution. EPA GHG emissions for 2001–2010 were acquired from the final report at annual temporal resolution and CONUS-wide spatial resolution. All data sets were converted into the same spatial and temporal dimensions and units. A summary of spatial and temporal processing is shown in Table 2.

2.2. Additional species

To create a more complete matrix for comparison, emissions estimates for species not reported by a given inventory were added using ratios of emissions factors. This was done for BC and N_2O. BC emissions for NEI+ were calculated as a ratio of BC emissions to $PM_{2.5}$ of 0.06. This ratio was developed by applying the overall average ratio of $BC/PM_{2.5}$ emission factors from the FINN model. The minimum and maximum of these ratios for all fires in the FINN inventory were 0.015 and 0.12 respectively. N_2O emissions for FINN and NEI+ were calculated using the overall average N_2O/CO_2 ratio from GFED (1.2e-4). The minimum and maximum of

these ratios for all fires in the GFED inventory were 6.9e-9 and 1.6e-4, respectively.

2.3. Calculation of 2008 emissions

In order to investigate the effects of different methodological choices on emissions estimates, comparisons from 2008 were also calculated using a variety of fuel loading, consumption, and emissions models with a standard set of fires (Section 4). Fire perimeters and total area from the Monitoring Trends in Burn Severity dataset (Eidenshink et al., 2007) for the year 2008 were used. Fuel loadings were calculated by intersecting the fire perimeters with various fuel loading maps including the Fire Characteristic Classification System (FCCS, Sandberg et al., 2001) original 1-km map (McKenzie et al., 2007, here labeled FCCS), the FCCS–LANDFIRE crosswalk map at 30-m (McKenzie et al., 2012, here labeled FCCS–LF), and the LANDFIRE fuel loading models (Lutes et al., 2009). Fuel consumption and emissions were then calculated using Consume version 3.0 (Prichard et al., 2006) and the First-Order Fire Effects Model (FOFEM, Reinhardt et al., 1997) for each fuel loading map. For comparison, the FINN fuel loading, consumption, and emissions processes were also used to calculate emissions from the 2008 MTBS fire perimeters.

3. Comparison of four current CONUS fire emissions inventories

Current emissions inventories vary in their assessment of how much emissions from fire occur. Table 3 presents values from four current emissions inventories, including long-term means, 5-year means, and annual values for the period 2007–2011. Of these four, the NEI+ shows the highest long-term mean values for area burned and for the listed emitted species, while the GFED inventory shows the lowest long-term means for all the listed species and the EPA GHG shows the lowest overall burned area. While most values are within a factor of 3, the overall inter-inventory range for each species varies from a factor of around 4 (NO_X) to over a factor of over 10 (CH_4). Some of this inter-inventory variance is due to the burned area used; however, this does not explain all the variability, as the overall range in burned area is only a factor of 4.5. The five-year means reflect similar results.

The total emissions and emissions differences exhibit considerable temporal and spatial variability. For instance, there are significant differences from year to year in total CO2e (Fig. 1). Notable here is that not only do all four emissions inventories exhibit considerable (factor 2+) interannual variability, but that their relative variability from year to year changes. This is likely due to differences in the types of fire and detection capabilities of the systems used by each to detect fire. It may also reflect regional differences in year to year fire occurrence and in the fuel loading and/or consumption models used by each inventory.

Annual totals of CO2e for each of the 48 states within CONUS for GFED, NEI+, and FINN are shown in Fig. 2. The EPA GHG report does not detail the location of the emissions and is therefore omitted. The top row shows the 5-year mean emissions, and the bottom row shows 2008 alone. In general, the overall total emissions differences are exhibited, with GFED having the lowest overall emissions across the map, FINN next, and the NEI+ the highest. Regional differences are evident in the Southeast and Northwest, and in particular in Minnesota and North Carolina, which do not show significant emissions except in the NEI+. Again, these differences are likely due to the specific fuel loadings and consumption algorithms used. Minnesota and North Carolina have significant deep organic layers that, when burned, can result in large amounts of emissions; the models used in the NEI+ include more of this type of consumption than those used in GFED and FINN.

The 5-year seasonal cycle of emissions is shown in Fig. 3 (again the EPA GHG report is omitted because it provides only annual totals). GFED emissions exhibit a summertime peak when wildfires are expected. Both the NEI+ and FINN show side lobes in the spring and fall seasons during which prescribed burns can occur. The difference in area burned is a direct result of the fire information database used by each inventory (see Table 1). The largest burned areas, which result from the NEI+ method, are due to the use of multiple satellite detection systems through the use of the SmartFire v2 fire information reconciliation system. As used in the NEI+, SmartFire v2 uses collected satellite detects from both polar and geostationary systems via the NOAA Hazard Mapping System (HMS) combined with the large fire perimeters from MTBS and fire incident reports from the Incident Command System. Each of the other systems used a subset of this data: FINN and GFED used satellite data from the MODIS polar orbiting system (which are included in the HMS system as well); FINN the MODIS hot spot detects and GFED the MODIS derived burn scar estimates (see Hao and Larkin, 2014 for further discussion). EPA GHG derives their fire area from the total wildland fire area reported through the Incident Command System to the National Interagency Fire Center, reducing this area to represent only forest fires by multiplying the reported area by the ratio of total forest land area to the total area considered to be under protection from fire. Because of these methodological differences, the various inventories contain different mixes of prescribed fires and wildfires.

The Southeast region (indicated in the upper left panel of Fig. 2) is known to have considerable prescribed burning. Fig. 4 shows the burned area from this region for each inventory. The NEI+ and to a lesser extent FINN have significant burning in this region in the spring and fall, with GFED showing only limited burning. This is likely due to differences in how fires are detected and then used to describe fire-area. Prescribed burns tend to be smaller than wildfires and can be of lower intensity and/or burn underneath obscuring canopies. Thus differences can arise simply due to detection probabilities declining as fires get smaller and/or less intense,

Table 2
Access and processing specifics for the four inventories analyzed.

	NEI+	FINN	GFED	EPA GHG
Access	Our work[a]	Requested[b]	Acquired via web[c]	Acquired via web[d]
Date range	2007–2011	2002–2011	2002–2011	2001–2010
Spatial processing	Individual fire lat/lon intersected with state area	Individual fire lat/lon intersected with state area	0.5 × 0.5 degree grid centroids intersected with state area	No spatial information
Temporal processing	Aggregated to months and years as needed	Aggregated to months and years as needed	Aggregated to years as needed	Yearly totals given
Species added	BC N_2O	N_2O	Contained all species	$PM_{2.5}$ BC

[a] http://www.airfire.org/emissions/.
[b] http://bai.acd.ucar.edu/Data/fire.
[c] http://www.falw.vu/~gwerf/GFED/GFED3/emissions/.
[d] http://www.epa.gov/climatechange/ghgemissions/usinventoryreport.html.

Table 3
Annual area and emissions totals for CONUS. Burned area (in millions of hectares) and CO2e, CO_2, CH_4, N_2O, BC, $PM_{2.5}$, and NO_X emissions from GFED, FINN, the NEI+, and the EPA GHG inventories. A long term mean (LTM) is listed as the average of 2002–2011 (GFED, FINN), 2001–2010 (EPA GHG), and 2007–2011 (NEI+). A 5-year mean of 2007–2011 (GFED, FINN, NEI+), and 2006–2010 (EPA GHG) is also listed. The individual years 2007–2011 are shown. Data that are not available are listed with a dash (–). Data that have been developed following the methodologies of the various inventories are shown in orange; data that have been added by computing emissions using ratios (see Section 2) are shown in green.

	EI	LTM	5 Yr	2007	2008	2009	2010	2011
Burned area in Mha	GFED	1.61	1.78	2.64	1.34	1.28	1.01	2.62
	FINN	3.75	3.90	4.39	4.11	3.39	3.68	3.93
	NEI+	7.13	7.13	7.76	7.47	5.51	5.44	9.49
	RX only	*4.76*	*4.76*	*4.45*	*5.43*	*4.18*	*4.34*	*5.40*
	EPA GHG	1.58	1.79	2.47	1.47	1.14	1.00	-
	RX only	*0.55*	*0.55*	*0.65*	*0.40*	*0.52*	*0.51*	-
CO2e in Tg	GFED	36	42	72	44	26	20	50
	FINN	97	103	123	111	84	90	106
	NEI+	254	254	361	222	201	171	315
	EPA GHG	158	187	262	156	104	86	-
CO2 in Tg	GFED	32	38	65	39	23	18	45
	FINN	88	93	111	100	76	82	96
	NEI+	222	222	315	192	175	150	275
	EPA GHG	140	166	233	140	93	77	-
CH4 in Tg	GFED	0.09	0.11	0.19	0.12	0.07	0.06	0.13
	FINN	0.23	0.25	0.31	0.28	0.19	0.21	0.25
	NEI+	0.95	0.95	1.34	0.89	0.76	0.59	1.18
	EPA GHG	0.42	0.5	0.7	0.42	0.28	0.23	-
N2O in Tg	GFED	0.005	0.005	0.009	0.006	0.003	0.002	0.006
	FINN	0.011	0.012	0.014	0.012	0.009	0.010	0.012
	NEI+	0.028	0.028	0.039	0.024	0.022	0.019	0.034
	EPA GHG	0.023	0.028	0.039	0.023	0.015	0.013	-
BC in Tg	GFED	0.011	0.013	0.022	0.013	0.007	0.006	0.015
	FINN	0.024	0.026	0.029	0.026	0.022	0.025	0.027
	NEI+	0.102	0.102	0.144	0.095	0.081	0.063	0.126
	EPA GHG	-	-	-	-	-	-	-
PM2.5 in Tg	GFED	0.20	0.24	0.43	0.26	0.13	0.10	0.26
	FINN	0.54	0.24	0.72	0.64	0.44	0.47	0.58
	NEI+	1.67	1.67	2.36	1.56	1.32	1.04	2.06
	EPA GHG	-	-	-	-	-	-	-
NOx in Tg	GFED	0.06	0.07	0.12	0.07	0.07	0.03	0.08
	FINN	0.22	0.23	0.28	0.26	0.19	0.20	0.24
	NEI+	0.25	0.25	0.36	0.21	0.20	0.18	0.31
	EPA GHG	-	-	-	-	-	-	-

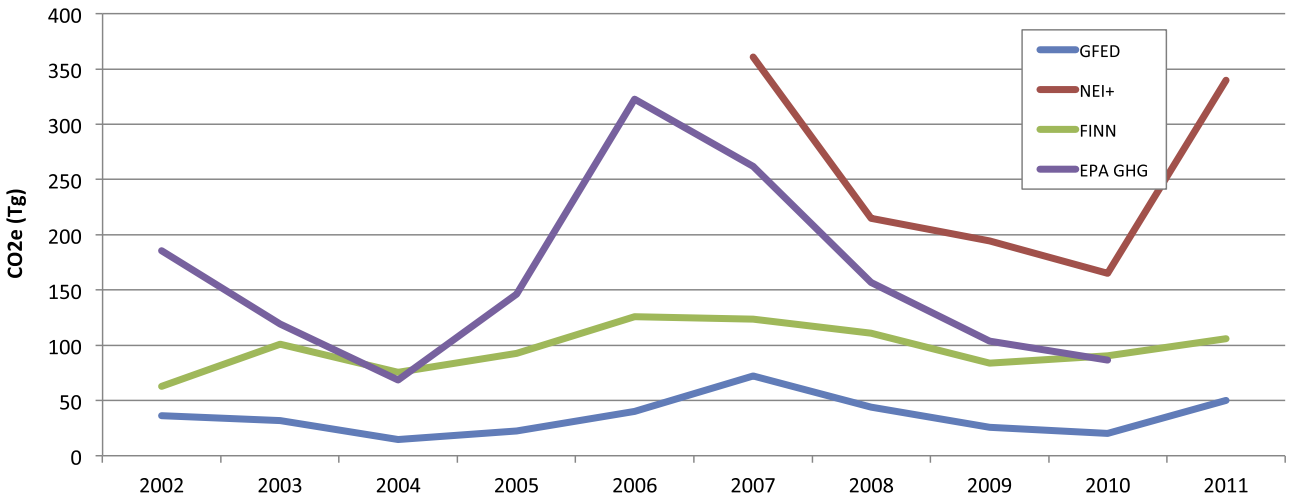

Fig. 1. Annual total CO2e emissions for CONUS from different inventories for 2002–2011. GFED (blue), the NEI+ (red), FINN (green), and the EPA GHG Report (purple) are shown. EPA GHG report data is available through 2010 and the NEI+ is only available for 2007–2011. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and the use of geostationary satellite products may help detect smaller fires. In any case, the substantial differences in fire area used contribute significantly to the overall fire emissions differences. Indeed, the NEI+ is found to show more prescribed fire acres than any other inventory, and more total area burned than the other inventories. While this level of burning is somewhat consistent with anecdotal accounts and individual state databases, the exact amount of area burned, and, in particular from prescribed burning, remains a key uncertainty in any fire emissions inventory.

Fire area is not the only predictor for the overall quantity of emissions. For example, the EPA GHG inventory resulted in the second highest emissions of CO2e, CO_2, and CH_4 despite the lower burned area estimated used in the calculations. The fuels, consumption, and even emission factors used to compute an emissions inventory all influence the result. For the EPA GHG inventory, the available fuel used in the calculations (from the Forest Inventory Analysis plot data) and the consumption fraction used (a constant 0.45 based on the IPCC methodology) produce a high consumed biomass, which results in high CO_2 emissions despite the low area burned. Additionally, fuel composition, moisture, and meteorology have also been found to affect emissions (Larkin et al., 2013), particularly as they relate to observed smoke impacts (Strand et al., 2012).

4. Examination of the effects of model choices

The above comparison shows that even recent state-of-the-science fire emissions inventories have significant differences in total emissions, interannual variability, and seasonal and regional timing. While much of the variability comes from differences in the fire occurrence databases used, significant differences also occur in the fuels, consumption, and emissions calculations employed.

To examine these effects we use a fixed set of fire locations (the large fire perimeters for 2008 from the MTBS dataset, Fig. 5) along with combinations of fuels, consumption, and emissions models to examine the effect of different model choices. Some of the models used here are directly relatable to the emissions inventories compared in the previous section, but the comparison here is to independently show how differences in models can affect calculations of emissions, rather than describe differences in the specific inventories compared above. To that end several modern models for each modeling step are utilized, but the fires used are held constant.

Results are shown in Fig. 6 for total fuel loading, total fuel consumption, and total emissions of CO_2 and $PM_{2.5}$. The MTBS perimeters used represent the larger fires, those greater than 400 ha in the west and 200 ha in the east. Primarily wildfires are represented. Because of the specific distribution of fires during this period, there is an inherent geographic bias in the results, towards the western USA (Fig. 5) but they are nonetheless illustrative of the overall effects of model choices on fire emissions.

Large differences are found in the available total fuel loading as determined by intersecting the MTBS perimeters with various fuel maps. Results for four fuel maps are shown: the 1-km Fire Characteristic and Classification System (FCCS), the 30 m LANDFIRE fuel models, the more recent 30-m FCCS–LANDFIRE crosswalk fuel map (here listed as FCCS–LF), and the MODIS land cover product used by the FINN model. Overall, the FCCS, FCCS–LF, and FINN fuels are found to be similar, with the LANDFIRE fuels being the lowest. It is worth noting that canopy fuels are included for LANDFIRE in this calculation through the use of the LANDFIRE canopy bulk density (Drury et al., 2013). However, LANDFIRE fuels, including calculated canopy fuels, are generally and in sum significantly lower (factor 2x) than the other maps. This result is in line with previous studies (Urbanski and Hao, 2012).

For consumption, the same basic pattern established for fuel loading continues, with one major exception – the FINN model. The FINN model's consumption algorithm appears to burn a lower percentage of its available fuels, bringing its consumption down significantly when compared with the results from running the

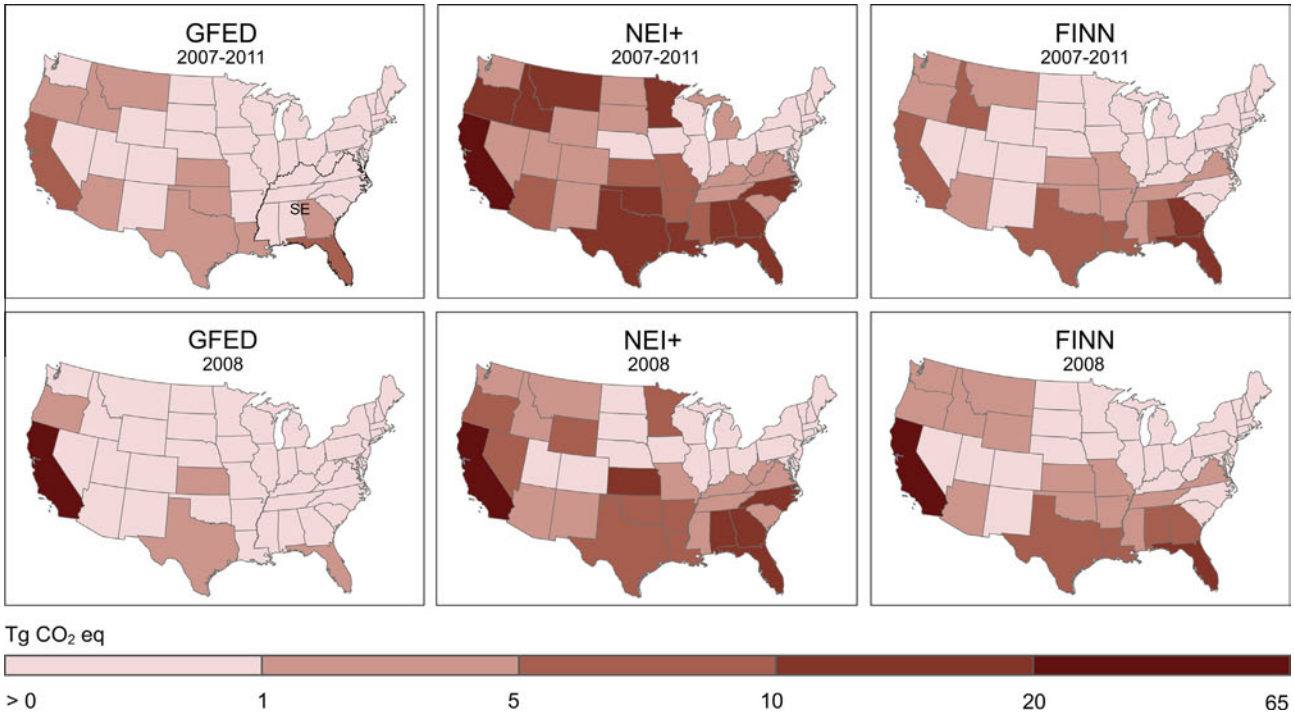

Fig. 2. Distribution of annual emissions of CO2e within CONUS. Annual emissions for each state are shown for GFED (left column), NEI+(middle column), and FINN (right column). Top row: Mean annual emissions for the 5-year period 2007–2011 are shown. Bottom row: Annual totals for 2008 are shown. The top left graphic also shows the SE region used in Fig. 4.

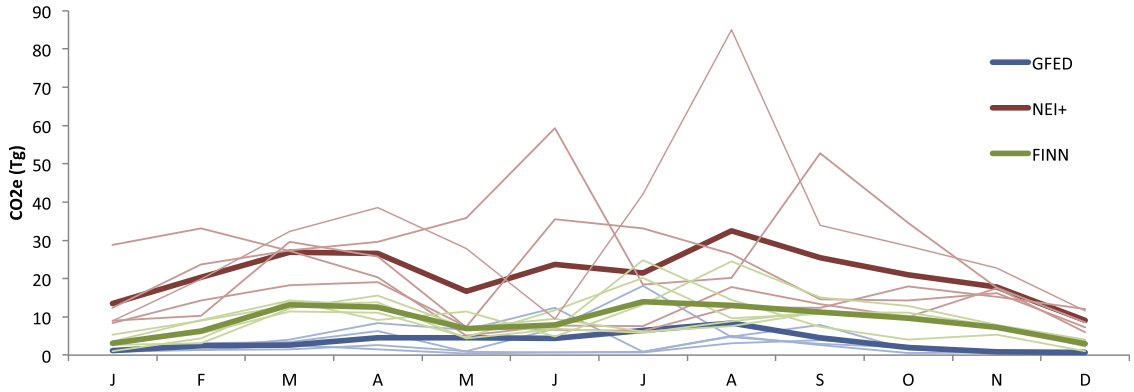

Fig. 3. Monthly variability of CONUS emissions. CO2e emissions totals for all CONUS from GFED (blue), the NEI+ (red), and FINN (green). Heavy lines indicate 5 year (2007–2011) average emissions, with individual years shown as lighter lines. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

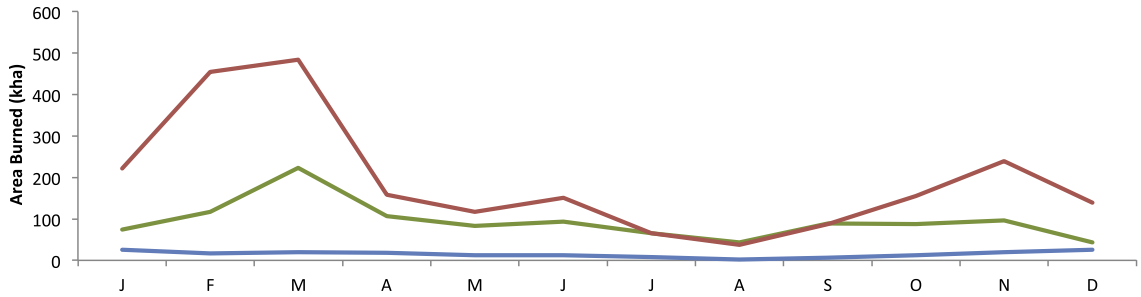

Fig. 4. Southeastern U.S. area burned. Area burned in thousands of hectares for each month in 2008 for the Southeastern (SE) region only. See Fig. 2 top left for a map of the SE region states included here.

similar overall fuel loading totals of FCCS and FCCS-LF through the CONSUME and FOFEM models. Additionally, the differences in overall consumption between CONSUME and FOFEM are small compared with the differences between the FCCS/FCCS-LF maps and LANDFIRE. However, masked by these summary numbers are significant differences that can occur in combustion of various fuel loading components, including larger downed woody fuels, organic soil layers, and canopy fuels (Drury et al., 2013); these differences are sensitive to the exact fuel structures represented. Thus, the two models (CONSUME and FOFEM) use various parts of the fuel structure differently during combustion, resulting in both different overall fuel consumption, but also different apportioning of the consumption between the flaming and smoldering phases. Here FOFEM results in overall lower fuel consumption than CONSUME, but the overall change (10–20%) is relatively small compared with the differences found between the fuel loading maps, and so the overall pattern of differences established with choice of fuel loading map remains. Only the FINN model is different, with its overall consumption lowered to being similar to the LANDFIRE fuel consumption, despite having had a factor 2x greater overall fuel loading.

The overall emission estimates trend with the same pattern established by the fuel loading map choice and consumption results, but for some minor differences. For example, FOFEM is found to have both higher CO_2 and $PM_{2.5}$ emissions than CONSUME. This is due to differences in how the models apportion combustion between flaming and smoldering, with FOFEM apportioning more smoldering during the these fires. Also, there are significant differences in emissions factors between the two models. While not all models directly yield black carbon, black carbon emissions are often computed as a percentage of $PM_{2.5}$. For example, for the four emissions inventories described in Section 3, black carbon was found to range between 4% and 6% of the $PM_{2.5}$ produced based on the long-term-mean annual totals presented in Table 3. Thus, calculated emissions of black carbon would substantially follow the emission estimates of $PM_{2.5}$ shown in Fig. 6.

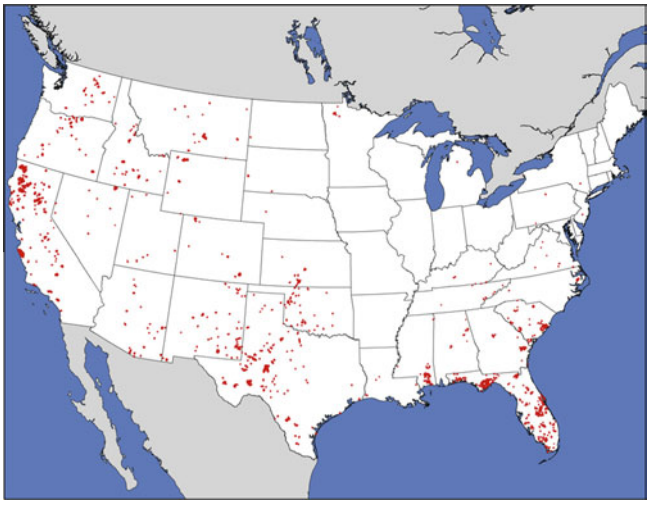

Fig. 5. Large fire locations in 2008. Based on Monitoring Trends in Burn Severity perimeters. Fires greater than 404 ha (1000 acres) are used in the western U.S.; fires greater than 202 ha (500 acres) are used in the eastern U.S. Locations shown are for the calendar year 2008.

The net result is that even relatively similar methodologies including identical input fires and the use of models with similar concept functions can produce a factor of 2 difference on the resulting overall annual total emissions. While these results cannot speak to the full collection of methods used in the studies in

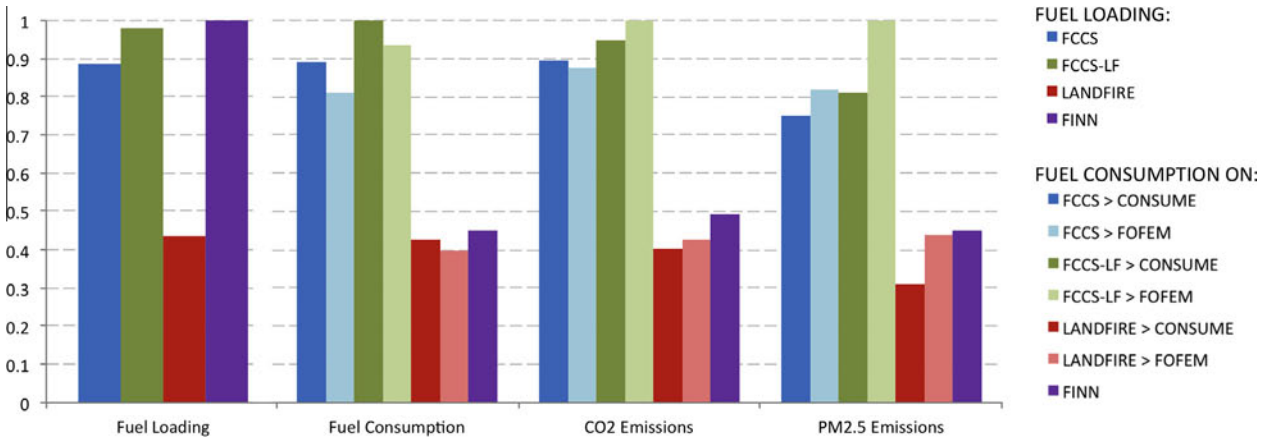

Fig. 6. Effect of different data set and model choices on CONUS fuels, consumption, and emissions totals. Normalized annual totals are shown as calculated from different fuel maps and consumption/emissions models. Each section (fuel loading, fuel consumption, CO_2, $PM_{2.5}$) has a normalized result based on the highest computed result for that section. Totals are calculated using the Monitoring Trends in Burn Severity dataset fire perimeters from 2008. For fuel loading, results from FCCS 1-km fuels map (blue, FCCS) and FCCS–LANDFIRE 30-m fuels map (green, FCCS–LF) are shown along with the LANDFIRE 30-m fuel map (red, including canopy fuels, see text), and the FINN model (purple). For fuel consumption and emissions, results for the non-FINN fuels are computed with both the CONSUME and FOFEM models, with CONSUME represented in a darker color and FOFEM represented in a lighter color. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3, these model comparison results show that model input choices (such as the choice of fuel map) and underlying model assumptions can play an important part in determining overall emissions results.

5. Knowledge gaps and future directions

Fire emissions are calculated as a function of fire area, available biomass, relative combustion, and emissions factors. Creation of a fire emissions inventory is directly affected by assumptions made by the models and datasets used. This includes differences in:

- Underlying fire area data used and what this data includes and does not include.
- Underlying fuel data used and how they are collected and used in fuel loading models.
- Methods employed to allocate these fuels across the landscape.
- Assumptions in the consumption model as to how consumption works including their effect on how combustion is allocated across flaming and smoldering phases.
- Differences in emissions factors used, including how regional and vegetation specific they are.

While the above statement holds true for all emissions inventories, the results of various studies (e.g., French et al., 2011; Drury et al., 2013; Larkin et al., 2013), including the analysis shown above, allow for specifically identifying critical knowledge gaps. These are areas where the most significant differences and/or errors in the fire emissions inventories and/or how the fire emissions inventories are/can be utilized result. They are:

- *Basic fire information*. Fire area remains the single largest factor affecting the overall fire emissions inventory. Specifically what fires are eligible for inclusion in the inventory based on the datasets used and their ability to accurately detect and reflect the area burned is a significant issue for fire emissions inventory development. For example, the ability to accurately account for prescribed burning and other relatively small or low intensity fires that are difficult to detect via satellite is important in both assessing overall regional emissions and localized effects like poor air quality. This is especially true in regions where many small low-intensity fires may burn at the same time (e.g., the Southeastern U.S.). Current work may lead to a better understanding of how to best utilize fire information from both satellites and ground reporting systems (see Hao and Larkin, 2014).
- *Fuel characterization*. Available fuel loading varies greatly among modern fuel loading databases, including the ones described herein. Recent results have demonstrated that this variable in the emissions equation is one of the largest contributors to variability within the emissions inventories (see Section 4; Larkin et al., 2013). Additionally, current fuel loading maps used in fire emissions inventories are static – reflecting neither seasonal changes nor previous disturbances (such as fires or land management activities) that occurred since the map was made. Fuel loading descriptions that describe the seasonal changes in available fuel and changes due to disturbance are an important area for emission inventory improvement.
- *Deep organic consumption*. Regions with deep organic layers, (i.e., Southeastern US, Alaska, and others) have the potential to emit large quantities of particulates and greenhouse gases. Very few studies have been conducted to characterize and quantify the suite emissions produced from deep organic fires, and current models do a poor job of characterizing their emissions. Deep organic consumption was found to be a significant issue in calculating the National Emissions Inventory (Raffuse et al., 2012), and differences between models in this area can substantially alter the overall emissions totals.

6. Summary

Wildland fire emissions and emissions inventories are important for a number of reasons, including their emissions of greenhouse gases and the ability of fires to affect air quality, human health, and climate feedback mechanisms such as black carbon deposition on snow. Recent official estimates place overall U.S. wildland fire emissions at approximately 2–3% of total U.S. CO2e emissions (based on NEI and IPCC numbers), and up to 33% of total U.S. Black Carbon emissions (U.S, 2012b).

Fire emissions estimates are still highly variable and depend on the intricacies of the methodology employed. Even using models that are conceptually and methodologically similar in their behavior can result in differences as large as a factor of 2 in aggregate national annual totals. Temporalized and localized information can be more uncertain. The exact location and time of the source emissions is important when modeling air quality or pollutant

transport (e.g. black carbon); fine scale spatio-temporal information is required for these applications.

Four recent emissions inventories for the contiguous U.S. (CONUS) were examined, with each inventory relying on specific datasets, models, and assumptions. Major differences and uncertainties are found with respect to the amount of prescribed fire represented, the overall fuel loadings used, and the ability to model deep organic combustion. These differences result in the large overall changes in the temporal and spatial patterns represented, as well as in the resulting national annual wildland fire emissions totals.

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