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Emissions

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Chapter 5

Emissions



Shawn P. Urbanski, Susan M. O'Neill, Amara L. Holder, Sarah A. Green, and Rick L. Graw

Abstract This chapter assesses the current state of the science regarding the composition, intensity, and drivers of wildland fire emissions in the USA and Canada. Globally and in the USA wildland fires are a major source of gases and aerosols which have significant air quality impacts and climate interactions. Wildland fire smoke can trigger severe pollution episodes with substantial effects on public health. Fire emissions can degrade air quality at considerable distances downwind, hampering efforts by air regulators to meet air standards. Fires are a major global source of aerosols which affect the climate system by absorbing and scattering radiation and by altering optical properties, coverage, and lifetime of clouds. A thorough understanding of fire emissions is essential for effectively addressing societal and climate consequences of wildland fire smoke.

Keywords Emission factors · Emissions · Emission inventories · Smoke

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5.1 Introduction

Wildland fire smoke contains hundreds of gases (Urbanski 2014; Hatch et al. 2015) and aerosols diverse in size, composition, and morphology (Reid et al. 2005a, b) (Box 5.1).¹ Globally and in the USA wildland fires are a major source of gases and aerosols (Bond et al. 2013; Werf et al. 2017), and the production, dispersion, and transformation of fire emissions have significant air quality impacts and climate interactions. Wildfire smoke can trigger severe, multi-week pollution episodes over large areas with substantial impacts on public health (Chap. 7). Wildland fires are a major source of fine particulate matter PM_{2.5} (particulates with an aerodynamic diameter <2.5 μm) (Lu et al. 2016; Brey et al. 2018) and can contribute to ozone (O₃) production (McClure and Jaffe 2018), both of which are criteria pollutants regulated under the U.S. Clean Air Act. Aerosols from fires affect the climate system by absorbing and scattering radiation (Bond et al. 2013); altering optical properties, coverage, and lifetime of clouds (Lohmann and Feichter 2005; Koch and Genio 2010); and lowering snow and ice albedo in the Arctic (Hansen and Nazarenko 2004).

Box 5.1 Biomass Burning Aerosol

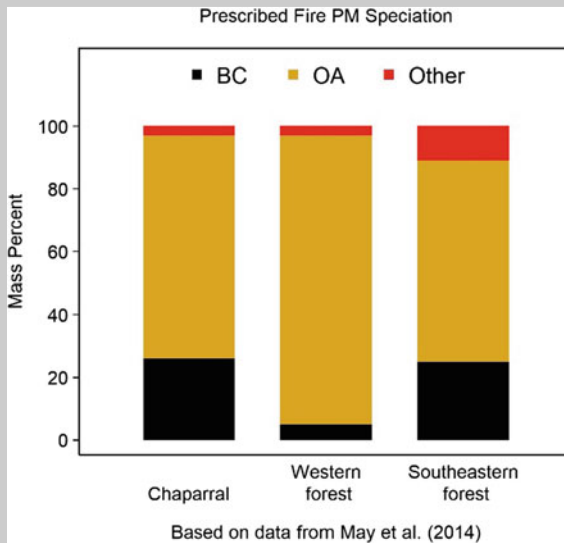
The terms aerosol, particle, and particulate matter (PM) are used interchangeably in atmospheric sciences and in this chapter. Atmospheric aerosols are liquid and/or solid particles dispersed in air. Aerosols are often described according to aerodynamic size thresholds:

Aerodynamic diameter (<i>D</i>) (μm)	Nomenclature	Term
<0.1	PM _{0.1}	Ultrafine
<1	PM ₁	Submicron
<2.5	PM _{2.5}	Fine
2.5–10	PM _{2.5} –PM ₁₀	Coarse
<10	PM ₁₀	

The particle count and mass in fresh smoke from wildland fires is predominantly PM₁ (Reid et al. 2005b, Sect. 5.2.2.1). For context, a typical cloud droplet has a diameter of ~20 μm, the width of human hair is ~50 μm (see Fig. 7.1), and the diameter of a typical raindrop is ~2000 μm. PM_{2.5} and PM₁₀ are among the six criteria pollutants for which the USEPA has set National Ambient Air Quality Standards under the federal Clean Air Act. The relationship between particle size and health impacts is discussed in Chap. 7.

¹ The terms aerosol, particle, and particulate matter (PM) are used interchangeably in atmospheric sciences and in this chapter.

In addition to size, aerosols are also classified according to composition: organic (OA), non-refractory (non-light absorbing and non-volatilizing), inorganic (sulfate, SO_4^{2-} ; nitrate, NO_3^- ; ammonium, NH_4^+ ; and chloride, Cl^-), black carbon (BC), and many other trace elements (e.g., K, Ca, Mg). The terms BC, rBC (refractory BC), elemental carbon, and soot are often used interchangeably to refer to light-absorbing carbonaceous particles with a graphitic-like structure (Buseck et al. 2014; Lack et al. 2014). OA is a mixture of thousands of chemical species (Gilardoni 2017), many of which absorb light preferentially in the UV wavelength range and are labeled as “brown carbon.” The carbon fraction of OA is referred to as organic carbon (OC). OA dominates the composition of particles in fresh smoke, comprising >60% of PM_{10} mass as seen below:



Understanding emissions—the composition and intensity of smoke—is vital for addressing the wide spectrum of decision support needs initiated by wildland fire smoke. Accurately characterizing the dependence of emissions on fuels, fire behavior, and environmental conditions is a key to improving basic smoke management practices and facilitating use of prescribed fire. Emissions are essential input to smoke forecasting systems relied upon by public health officials, air quality forecasters, and fire management teams to mitigate the impacts of wildland fire smoke on public health and safety. Air regulators need better fire emission estimates to quantify the contribution of wildland fires to air pollution and thereby inform decision making about control and regulation of anthropogenic air pollution sources. Robust emission estimates are also needed to quantify the contribution of fires to urban air pollution, assess human smoke exposure, and elucidate the role of smoke in climate forcing.

This chapter assesses the current state of the science on emissions from wild-land fires in the USA and Canada. The chapter opens with a summary of current knowledge regarding the composition, intensity, and drivers of emissions. Next, we review emission datasets and tools available for smoke forecasting, regulatory activities, smoke management, and research. The chapter concludes with a discussion of critical gaps in our understanding of emissions.

5.2 Current State of the Science

5.2.1 Fuel Properties, Combustion Processes, and Emissions

The relative abundance of pollutants in fresh smoke (smoke which has not experienced significant photochemical processing, generally less than ~30 min old; see Akagi et al. 2011) is quantified with emission factors (EFs). EFs are determined by measuring the concentration of gases and aerosols in fresh smoke and in the ambient air outside the smoke plume. For a chemical species X , the concentration difference between the fresh smoke plume and background air defines the excess mixing ratio, $\Delta X = X_{\text{plume}} - X_{\text{background}}$. The EF for species X (EF $_X$), the mass of X emitted per mass of dry biomass consumed, can be calculated from ΔX using the carbon mass balance method, a common implementation of which is shown in Eqs. 5.1 and 5.2 (Box 5.2). The carbon mass balance method assumes all biomass carbon is volatilized as gases and aerosol is measured as excess mixing ratios and included in the sum of Eq. 5.2. In practice, many of the carbonaceous gases produced in combustion are not measured. However, because >90% of the carbon emitted is contained in carbon dioxide (CO₂), carbon monoxide (CO), and methane (CH₄), inclusion of only these gases in Eq. 5.2 results in only a slight overestimate of EFs (Yokelson et al. 1999). Additional assumptions of the carbon mass balance method are uniform mixing of all smoke components and constant background composition.

Box 5.2 Emission Factor by the Carbon Mass Balance Method

$$EF_X = F_c \times 1000 \text{ (g kg}^{-1}\text{)} \times \frac{MM_X}{12} \times \frac{ER_X}{C_T} \quad (5.1)$$

In Eq. 5.1, F_c is the mass fraction of carbon in the dry biomass, MM_X is the molar mass of X (g mole⁻¹), 12 is the molar mass of carbon (g mole⁻¹), ER_X is the emission ratio of X to CO₂, and C_T is given by Eq. 5.2.

$$C_T = \sum_{j=1}^n N_j \times \frac{\Delta C_j}{\Delta CO_2} \quad (5.2)$$

In Eq. 5.2, n is the number of carbon-containing species measured, N_j is the number of carbon atoms in species j , and ΔC_j is the excess mixing ratio of species j .

Principal factors that affect combustion, and hence the composition, of fresh wildland fire emissions are the structure and arrangement of fuels—size, shape and packing of fuel particles, and fuel condition—moisture content, growth stage, and soundness of woody material (Chap. 2). Fuel chemistry is also important. Emissions of gases and particles containing trace elements such as nitrogen (N), sulfur (S), and chlorine (Cl) are limited by the amounts of these elements in the fuel. Further, compounds often present in biomass (e.g., terpenoid compounds) can be released through distillation prior to the onset of pyrolysis. Ambient conditions, such as wind and terrain, influence both fire behavior and emissions.

The general relationship among fuel bed properties, combustion processes, and emissions is depicted in Fig. 5.1. Small fuel particles with high surface-to-volume ratio, loosely packed fuels, and low moisture content favor flaming combustion (Chap. 2). Grass, foliage, loosely packed litter, and fine woody debris tend to burn predominantly by flaming combustion, given moderate to low moisture content. Smoldering is an important process in the combustion of large-diameter woody fuels, dominating the burning of duff, organic soil, and peat. The relative amount of smoldering combustion increases with fuel moisture content.

In wildland fires, the combustion processes—preignition/distillation, flaming, smoldering, and glowing/char oxidation—occur simultaneously and often in proximity (Yokelson et al. 1996; Ottmar 2001; Chaps. 2 and 3). The chemical composition of smoke is related to the relative amounts of flaming and smoldering combustion (Chap. 6). Some species are emitted almost exclusively by flaming or smoldering

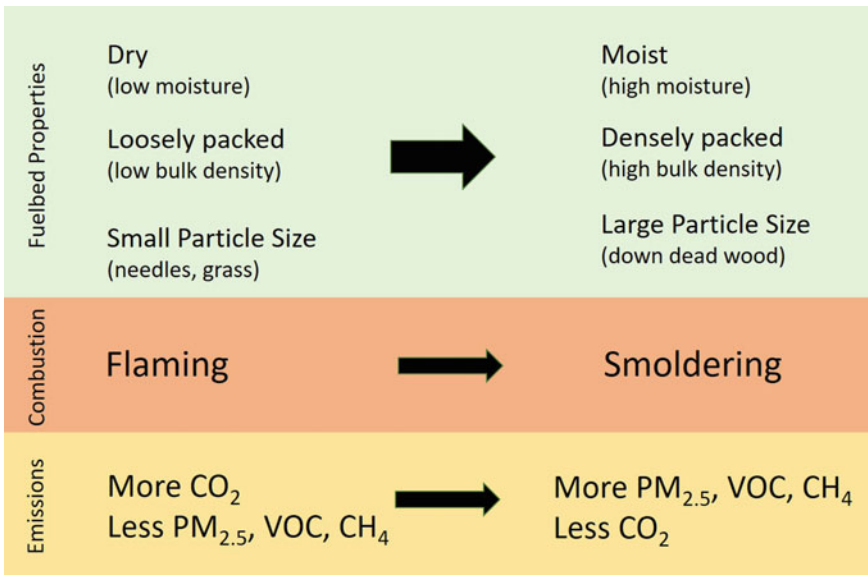


Fig. 5.1 General relationships among fuel bed properties, combustion processes, and emissions. VOC is volatile organic compound

combustion. Flaming combustion produces CO_2 , nitrogen oxides (NO_x), hydrogen chloride (HCl), sulfur dioxide (SO_2), nitrous acid (HONO) (Burling et al. 2010), and black carbon (BC) (McMeeking et al. 2009). CO , CH_4 , ammonia (NH_3), many non-methane organic gases (NMOG), and organic aerosol (OA) are associated with smoldering combustion (McMeeking et al. 2009; Burling et al. 2010). Several NMOGs are produced during both flaming and smoldering combustion (Burling et al. 2010).

The fraction of combusted fuel carbon emitted as products other than CO_2 increases with the proportion of smoldering combustion. A widely used metric for characterizing burning conditions is modified combustion efficiency, MCE ($\text{MCE} = \Delta\text{CO}_2 / (\Delta\text{CO}_2 + \Delta\text{CO})$), an index of the relative amount of flaming and smoldering combustion (Yokelson et al. 1999). Carbonaceous emissions of greatest consequence for air quality (NMOGs and OA) are products of incomplete combustion, and their EFs increase with the proportion of smoldering combustion (Fig. 5.1). The EFs of many NMOGs are negatively correlated with MCE. EFs measured in the laboratory for four NMOGs are plotted versus MCE in Fig. 5.2. The strength of the EF–MCE relationship tends to differ with fuel, being greatest for fine understory forest fuels (litter, woody debris, grass) and weakest for fuels prone to long-term smoldering and glowing combustion such as logs and organic soil.

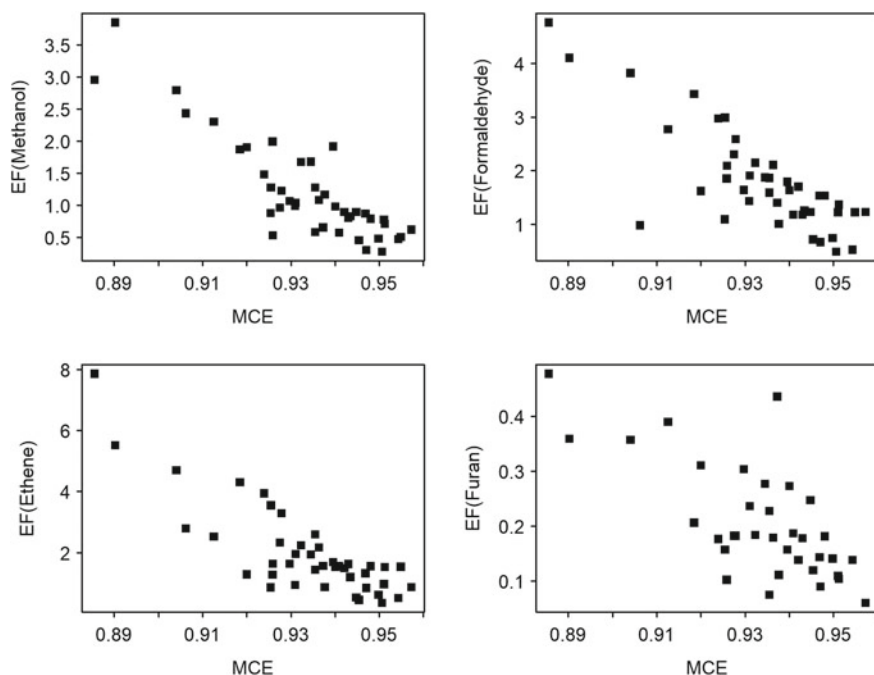


Fig. 5.2 Emission factors for methanol, formaldehyde, ethene, and furan plotted versus modified combustion efficiency (MCE). Data from burning of western US coniferous ecosystem fuels during the FIREX laboratory intensive study (excludes duff and logs) (Selimovic et al. 2018)

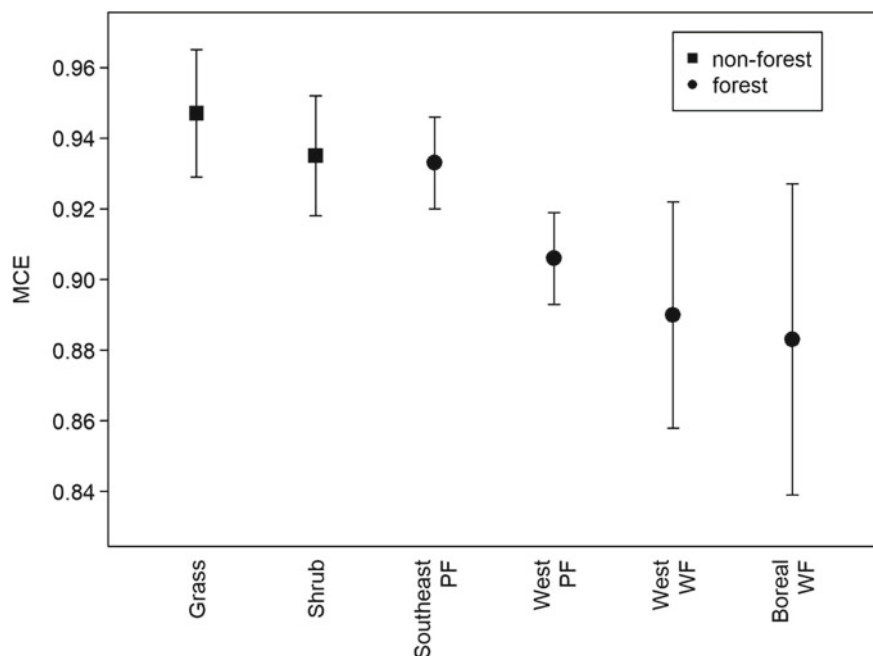


Fig. 5.3 Modified combustion efficiency (MCE) for different fire types. PF = prescribed fire, WF = wildfire. Grass, shrub, and prescribed forest fire based on Urbanski (2014). Wildfire MCE based on Liu et al. (2017), O’Shea et al. (2013), Urbanski (2013), Hornbrook et al. (2011), and Simpson et al. (2011)

The tendency for NMOG and OA EFs to be correlated with MCE provides insight into how emissions of these species differ across fuel types. MCE is highest for fires in herbaceous and shrub fuels and lowest for forest fuels (Fig. 5.3). Forest wildfire MCEs are lower than those for prescribed forest fires. These observed MCEs indicate total NMOG and OA emissions, per unit mass of fuel burned, trend as: herb/shrub < forest prescribed fire < forest wildfire.

5.2.2 Smoke Composition and Emission Factors

The primary emission products of wildland fire are CO_2 and H_2O . However, the minor components of smoke—aerosols, NMOGs, and inorganic gases—are of primary concern to atmospheric scientists, public health officials, air regulators, and land managers. A synthesis by Andreae and Merlet (2001) reported EFs for 92 species. Between 2006 and 2016, a series of laboratory studies at the U.S. Forest Service Missoula Fire Sciences Laboratory brought together over 100 researchers from more than 20 institutions to characterize gaseous and particulate emissions from simulated

wildland fires (McMeeking et al. 2009; Burling et al. 2010; Koss et al. 2018). During the same period, several field studies validated laboratory results and developed a framework for extrapolating laboratory-measured EFs to “real fires” in the natural environment. As a result, more than 500 gases have been identified in fresh smoke, and our knowledge regarding the physical characteristics (size and morphology), chemical composition, and optical properties of aerosols has expanded greatly. This section reviews the current state of the science regarding the composition of wildland fire emissions based on recent advances from these laboratory and field studies.

5.2.2.1 Aerosol Emissions

Aerosols are classified by their physical characteristics (size and morphology), chemical composition (inorganic, black carbon, organic species, degree of oxidation, etc.), and/or optical properties (Box 5.1). Of most interest for measuring and modeling impacts of aerosol from smoke are the primary emissions of particles—primarily OA and lesser amounts of BC and inorganic species. In addition, it is important to identify the numerous volatile and semi-volatile organic compounds (SVOCs) that can exist in both the gas phase and particle phase. These SVOC compounds can contribute to secondary organic aerosol (SOA) that is formed by reactions in the atmosphere. SVOC species can also coat BC, which modifies its optical, physical, and chemical properties.

Particulate matter (PM) is the pollutant principally responsible for the detrimental public health impacts and visibility degradation caused by wildland fire smoke (Chap. 7). Although PM air quality has improved across much of the USA over the past 30 years due to reduced anthropogenic emissions, it has deteriorated in regions prone to smoke impacts from wildfires (McClure and Jaffe 2018). Therefore, characterizing the range of EFs for particulate matter (EFPM) for wildfires is critical.

PM produced by wildland fires is dominated by OA with a range of volatilities. In the natural environment, as a fresh smoke plume dilutes and cools, competing condensation/evaporation processes can alter $PM_{2.5}$ mass and hence the measured $EFPM_{2.5}$ (Grieshop et al. 2009). For this reason, extrapolating $EFPM_{2.5}$ measured in laboratory studies, where smoke concentrations are typically very high, to real fires is generally unreliable (May et al., 2014, 2015), so wildfire $EFPM_{2.5}$ are based on limited field observations.

Measurements of EFPM for US wildfires are limited; Liu et al. (2017) reported $EFPM_1$ (aerosol with an aerodynamic diameter $<1.0 \mu\text{m}$) for only three wildfires. However, Garofalo et al. (2019) reported OA:CO emission ratios ($\Delta\text{OA}/\Delta\text{CO}$) for 16 western US wildfires. Since wildland fire-produced PM_1 is mostly OA (Box 5.1), this extensive dataset can provide an improved estimate of the average magnitude and range of wildfire $EFPM_1$.

Using methods described below (Sect. 5.4.2), Garofalo et al. (2019) showed that $\Delta\text{OA}/\Delta\text{CO}$ can be combined with EFCO measured for western wildfires in previous studies to estimate EFOA for a wider range of fires than reported in Liu et al.

(2017). Based on study average EFCO from Liu et al. (2017) (89 g kg^{-1} , $n = 3$) and Urbanski (2013) (135 g kg^{-1} , $n = 9$), the Garofalo et al. (2019) $\Delta\text{OA}/\Delta\text{CO}$ ($0.26 \mu\text{g sm}^{-3} \text{ ppbv}^{-1}$, $n = 16$) indicates an EFOA range of 26–40 g kg^{-1} .

This exercise suggests EFP_1 for some wildfires may be up to 50% higher than that reported by Liu et al. (2017). The choice of which EF to use in a model can have significant implications for current air quality forecasting and projections of emissions and air quality impacts associated with an anticipated increase in wildfire activity in the western USA (Yue et al. 2013; Liu et al. 2016; Ford et al. 2018; Chap. 1).

Concern has arisen about the health impacts of ultrafine particles (UFPs) or nanoparticles (aerosol with a diameter $<100 \text{ nm}$) (Leonard et al. 2007), which may react differently in the body than larger particles (Chap. 7). However, it has been difficult to draw firm conclusions on exposure and health effects of UFPs because of limited field measurements and problems resolving the effects of $\text{PM}_{2.5}$ and UFPs in epidemiologic and experimental studies (Baldauf et al. 2016). Nevertheless, it is clear wildland fires release large numbers of UFPs, and their concentration differs with combustion conditions and smoke age. As for other size ranges, UFPs differ with combustion conditions and smoke age. For example, a laboratory study of burning chaparral vegetation found the most numerous particles emitted were in the range of 30–50-nm diameter; the total concentration of particles decreased approximately 100-fold from the flaming to smoldering phase of combustion, while the relative fraction of very fine particles increased (Hosseini et al. 2010).

BC, commonly known as soot, is non-reactive, insoluble, and strongly light absorbing. Globally, biomass burning is the largest single source of BC to the atmosphere (Bond et al. 2013). Terminology for BC is not consistent and generally depends on measurement techniques: thermal–optical methods measure elemental carbon (EC) on filter samples; optical measurements derive BC mass from in situ absorbance and/or scattering data or light attenuation through filter deposit using a mass conversion factor; and laser-induced incandescence (LII) measures refractory BC (rBC) from single-particle incandescence (Petzold et al. 2013). Inconsistencies among measurement techniques and terminology have resulted in uncertainties in EFs, although newer methods (e.g., LII) are beginning to identify relationships between the different methods (May et al. 2014; Li et al. 2019a, b).

Aerosol from biomass burning consists mainly of OA, which typically makes up over 90% of the mass. Almost all BC is produced from flaming phases of combustion, whereas smoldering phases shift emissions toward a greater mass of OA and more particles overall (Bond et al. 2013; May et al. 2014). Jen et al. (2019) found that EFs for EC increase with MCE (flaming), and OC decreases with MCE, with both fitting well to logarithmic functions. Some material is emitted as primary organic aerosol (POA), especially during smoldering phases; other organic compounds are initially emitted as gases, which may condense upon cooling as they move away from the combustion zone. The reverse process also occurs, in which compounds evaporate as the primary particles are diluted in an expanding smoke plume, as much as 80% of POA mass may be lost during this phase (May et al. 2013, 2015). These competing processes will be governed by the temperature and concentration in the plume as

it is transported away from the fire. Finally, particles can increase in size through collisions (accumulation mode), growing from a peak count median diameter of ~ 110 nm at the point of emission to ~ 250 nm downwind (Janhall et al. 2010). Thus, the size class distribution of particles in an evolving smoke plume is dynamic over seconds to hours after combustion.

Organic gases can be oxidized photochemically or by O_3 as it ages. Oxidation of NMOGs generates SOA. Enhancements of SOA production by up to a factor of two have been observed from burning source materials with different NMOG emissions. A detailed study of the chemistry of particles emitted from laboratory burns of forest and shrubland fuels from the western USA found that 20–65% of the particle emissions (by mass) could be categorized into 12 chemical classes, with the majority of identifiable species being sugars, organic N compounds, and aliphatic or oxy-aliphatic species (Jen et al. 2019). The fraction of emissions that could be classified differed considerably among fuels; decayed logs emitted fewer identifiable substances ($\sim 10\%$ classified) than fresher fuels. EFs were approximately log-linear with MCE for both total mass and some of the chemical classes, with $\log(\text{EF}) = -a * \text{MCE} + b$.

5.2.2.2 Gas Emissions

EFs for the 20 most abundant gases (excluding CO_2 , CO , and CH_4) measured in laboratory studies burning common US fuels are shown in Fig. 5.4. The largest EFs for all fuel types are low molecular weight and/or oxygenated species. The NMOGs with the largest EFs common to all fuel types are formaldehyde (HCHO), ethene (C_2H_4), acetic acid (CH_3COOH), and methanol (CH_3OH). The majority of gases emitted are NMOGs with EFs that span >4 orders of magnitude (Yokelson et al. 2013; Koss et al. 2018). The relative magnitude of the NMOGs emitted differs across fuels. Based on laboratory data, southwestern shrubs (e.g., chaparral and mesquite [*Prosopis* spp.]) have the lowest total NMOG emissions (~ 9 g kg^{-1}), western forest fuels have the highest (~ 29 g kg^{-1}), and southeastern pine understory fuels have an intermediate value (19 g kg^{-1}) (Yokelson et al. 2013; Koss et al. 2018).

The observed NMOGs can be sorted into structural categories: aromatics (benzene-type compounds), oxygenated aromatics, terpenes, furans, aliphatic hydrocarbons, oxygenated aliphatic hydrocarbons, and compounds containing nitrogen or sulfur. Non-aromatic oxygenated compounds and furans comprise the largest portions of NMOGs (by EF) for western forests, chaparral, and wire grass (*Aristida stricta*) (Fig. 5.5). Terpenoids, a highly reactive class of compounds thought to be important SOA precursors (Chap. 6), are produced and stored in plant resins and can be released when resinous vegetation is heated (Greenberg et al. 2006; Hatch et al. 2019). Because terpenoid emissions result from distillation rather than combustion, they depend strongly on vegetation type (Greenberg et al. 2006; Hatch et al. 2019) and comprise a much larger fraction of western forest fuel emissions compared with non-forest fuels (Fig. 5.5). Total EFNMOG of forest fuels far exceeds that of the non-forest fuels. This stems from a combination of burning conditions and fuel properties.

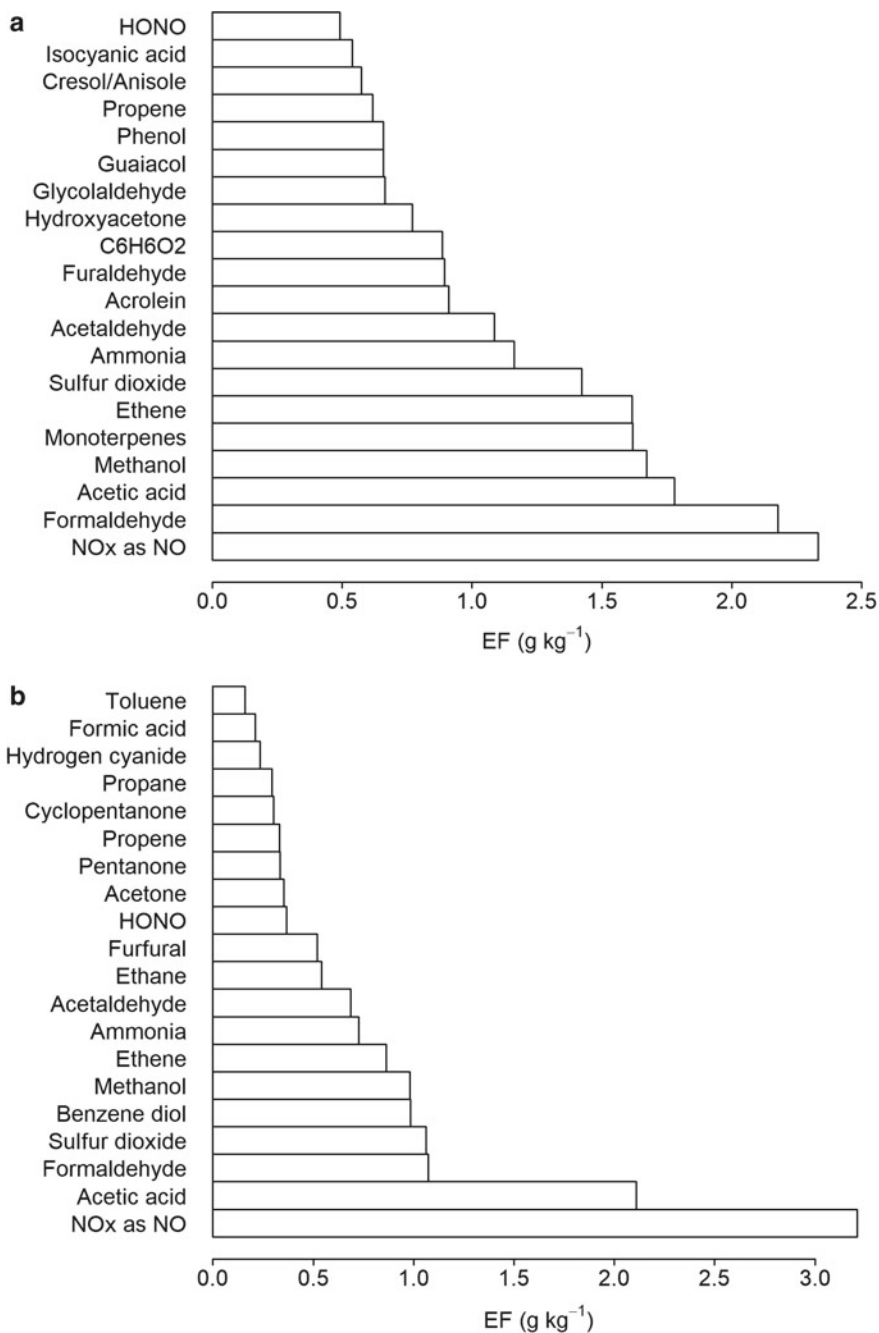


Fig. 5.4 Emission factors (EFs) for the 20 most abundant gas emissions (excluding CO₂, CO, and CH₄) from common US fuel types as reported in laboratory studies (Burling et al. 2010; Gilman et al. 2015; Koss et al. 2018; Selimovic et al. 2018). Panel: **a** western conifer forest, **b** southeastern forest, **c** chaparral

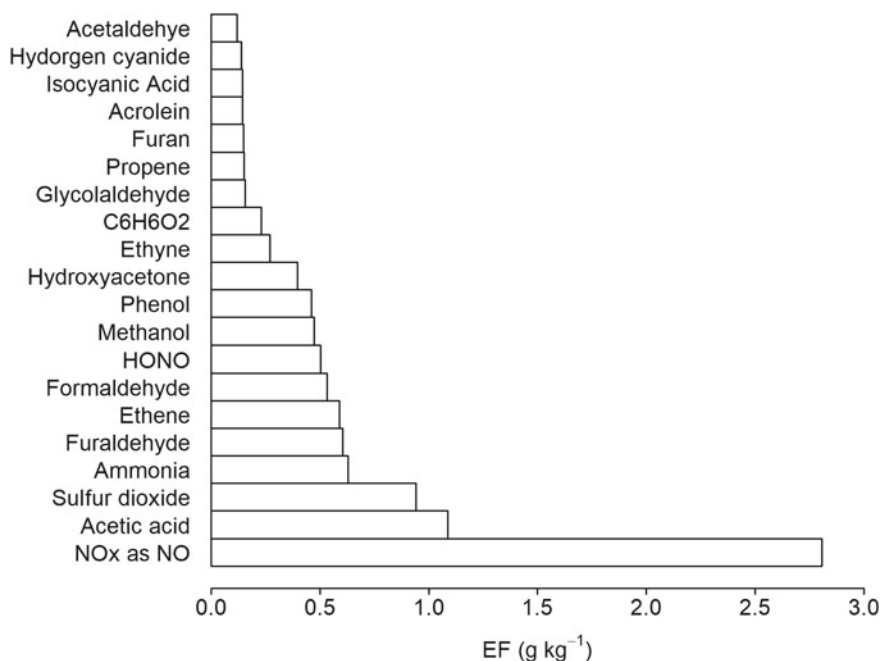


Fig. 5.4 (continued)

The rank in total EFNMOG (western forest > chaparral > wire grass) (Fig. 5.5) is partly a function of burning condition as represented by the MCE of 0.921, 0.955, and 0.971 for western forest, chaparral, and wire grass, respectively.

Photochemical processing of NMOG emissions in the atmosphere can lead to O₃ and SOA formation (see Chap. 6). Quantifying NMOG reactivity with OH identifies which emissions may have the greatest potential to form these secondary pollutants. The variability in OH reactivity of emissions from different fuel types can be considerable due to large differences in the magnitude and relative composition of NMOG emissions. The OH reactivity of NMOG emissions from western forest fuels ($\sim 90 \text{ s}^{-1} [\text{ppb CO}]^{-1}$) is nearly three times that of chaparral fuels ($\sim 30 \text{ s}^{-1} (\text{ppb CO})^{-1}$), with the reactivity of southeastern understory forest fuels having an intermediate value (Gilman et al. 2015; Koss et al. 2018).

In experiments employing airborne sampling platforms, over 90 gases have been measured in fresh smoke from montane and boreal wildfires and US prescribed fires (Box 5.3). However, emissions have been measured using advanced chemical analysis techniques for relatively few wildfires. There are only three such EF datasets based on in situ airborne measurements in US and Canadian fires (Simpson et al. 2011; Akagi et al. 2013; Liu et al. 2017). Prescribed fire emissions have been more thoroughly studied, in part due to relative ease of logistics and the concerns of land management agencies regarding prescribed burn impacts on air quality.

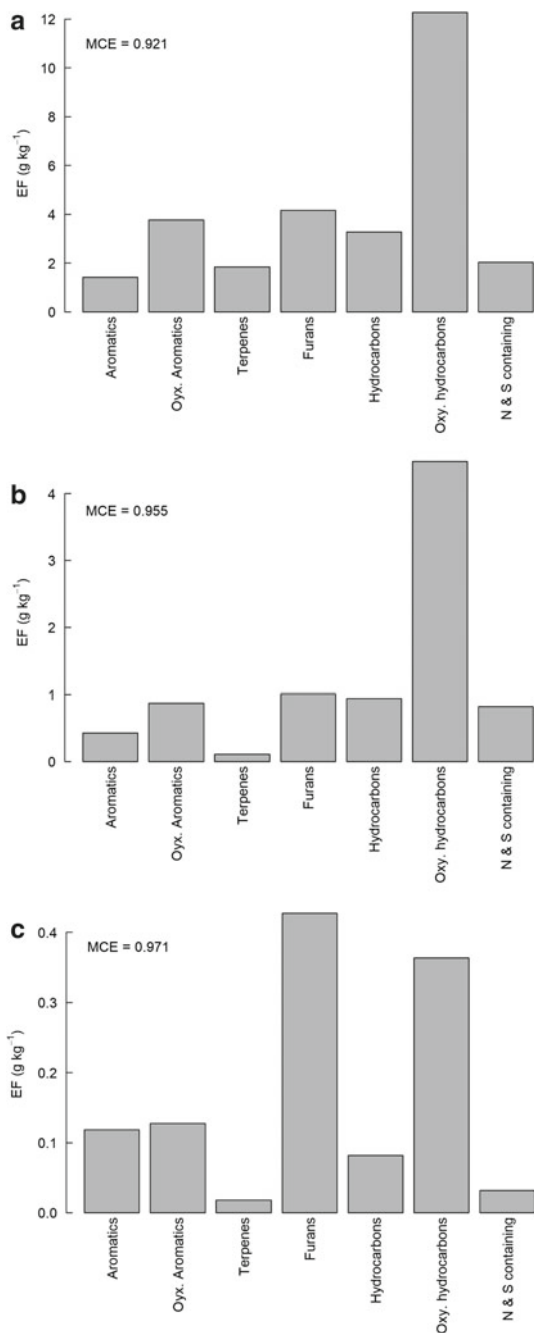
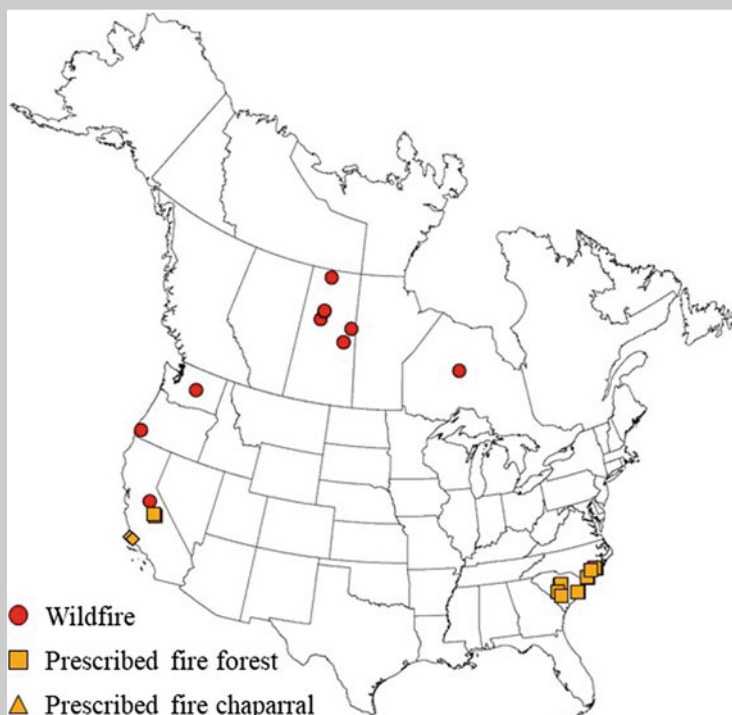


Fig. 5.5 Laboratory-measured non-methane organic gas emission factors (EFs) aggregated by structural class for **a** western forest fuels, **b** chaparral, and **c** wire grass. Based on data from Hatch et al. (2015) and Koss et al. (2018)

Box 5.3 Locations of Airborne Smoke Plume Sampling

Four contemporary peer-review studies have reported detailed NMOG analysis of smoke plumes sampled from airborne platforms: Burling et al. (2011), Simpson et al. (2011), Akagi et al. (2013), and Liu et al. (2017). The most frequently sampled fire types are understory prescribed fires in southeastern forests ($n = 13$).



NMOGs for which EFs have been measured in the field comprise 36–58% (by mass) of total NMOG emissions quantified in laboratory studies (Simpson et al. 2011; Yokelson et al. 2013; Liu et al. 2017; Koss et al. 2018). EFs for select compounds measured for prescribed fires in three different fuel types (chaparral, southeastern forest, and western conifer forest) and western wildfires are plotted versus MCE in Fig. 5.6. There is high variability within and across fire types for these chemical species, which are among the most abundant emitted by fires. Large fuel-type differences in NMOG EFs observed in laboratory studies are less pronounced in field data, presumably due to the small sample size and large natural variability in fuels and fire behavior which tend to homogenize the emissions at the point and time of

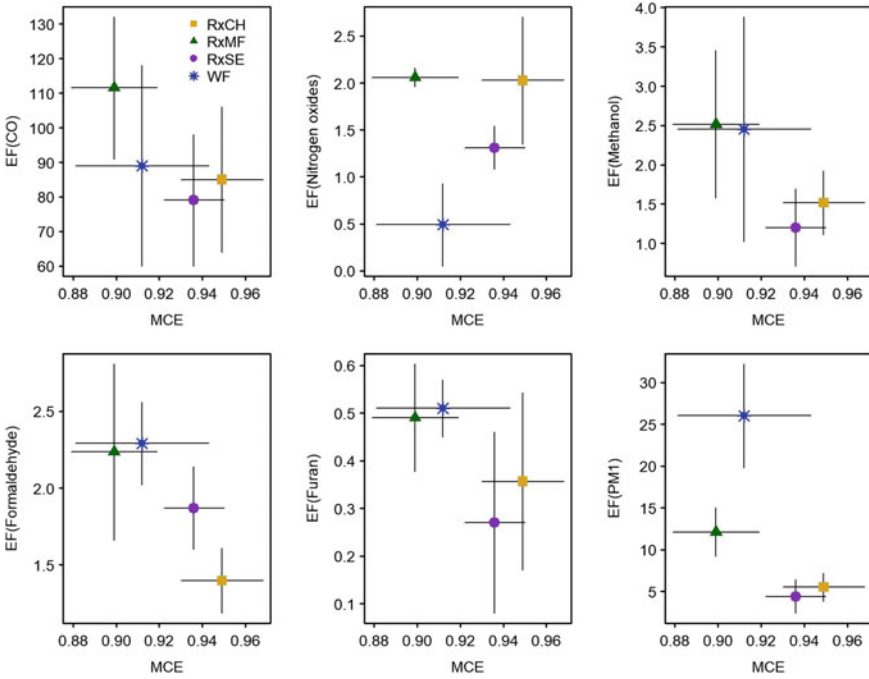


Fig. 5.6 Emission factors (EFs) for select compounds versus modified combustion efficiency (MCE). Data are from airborne measurements of prescribed fires in chaparral [RxCH; Burling et al. (2011)], southeastern conifer forest [RxSE; Akagi et al. (2013)], western conifer forest [RxMF; Burling et al. (2011)], and western wildfires [WF; Liu et al. (2017)]. EF for particulate matter data for prescribed fires is from May et al. (2014). Horizontal and vertical bars are one standard deviation

measurement (Fig. 5.6). The EFs in Fig. 5.6 tend to group according to MCE which is consistent with laboratory findings (see Figs. 5.2 and 5.3).

5.2.2.3 Emissions from Residual Smoldering Combustion

Long-term smoldering combustion that is not influenced by fire-related convection sufficient to loft the smoke above the surface layer is referred to as residual smoldering combustion (RSC; Wade and Lunsford 1989). RSC includes glowing combustion, which is strong smoldering that produces high local temperatures (Santoso et al. 2019) and often does not produce visible smoke. RSC emissions are generated from logs, stumps, duff, and organic soils which are prone to sustained smoldering combustion. Following ignition during flame-front passage, these fuel components can smolder for hours to days (Ottmar 2018). Replicating RSC in the laboratory is challenging for these fuel components, and limited data are available.

Two field studies of prescribed fires in North Carolina and South Carolina pine understories augmented airborne measurements with ground-based sampling of RSC

emissions. These studies found EFs of gases associated with smoldering combustion; CO, CH₄, and many NMOGs were much higher for RSC than those measured from airborne platforms (Burling et al. 2011; Akagi et al. 2013). Akagi et al. (2013) measured over 90 NMOGs from airborne and ground-based platforms for three prescribed fires in South Carolina pine understory. They found EF_{NMOG} for RSC ($34.18 \pm 20.40 \text{ g kg}^{-1}$) was more than twice that measured in the lofted plume ($14.56 \pm 0.72 \text{ g kg}^{-1}$), with differences between RSC and lofted plume EFs for individual NMOGs being highly variable. Emissions of NO_x, which result from flaming combustion, were negligible from RSC (Burling et al. 2011; Akagi et al. 2013).

Organic soils (peat) and duff burn predominantly by smoldering combustion (Chap. 2), which can persist for days. When wildfires occur in landscapes with deep organic soil layers, such as in the southeast USA and northern boreal ecosystems, smoke production can continue for weeks after fire spread is contained and produce vast quantities of pollutants (Ottmar 2018). Limited field measurements of PM emissions from smoldering organic soil (North Carolina coastal plain) found EF_{PM_{2.5}} $\geq 40 \text{ g kg}^{-1}$ (Geron and Hays 2013). This is more than twice the EF_{PM_{2.5}} observed for the burning of southeastern understory forest fuels with ground-based measurements (Geron and Hays 2013; Urbanski 2014) and considerably larger than EF_{PM₁} measured from aircraft (May et al. 2014) (Fig. 5.6). In situ measurements of gaseous emissions from RSC show EF_{CO} = 200–300 g kg⁻¹ and EF_{VOC} ~40 g kg⁻¹ (VOC = NMOG + CH₄) (Hao and Babbit 2007; Geron and Hays 2013).

Interpretation and application of RSC EFs are challenging due to the uncertain representativeness and potential sampling biases associated with RSC measurements. A limited comparison of EFs measured for smoldering fuel components and for drift smoke along burn-unit perimeters indicates smoldering, and possibly scattered flaming combustion of other fuel types (e.g., litter and shrubs), may contribute to unlofted emissions (Akagi et al. 2014). Thus, using only EFs based on RSC-prone fuel components may not give an accurate depiction of unit-level emissions, firefighter exposure, or local smoke impacts. Given the scarcity of RSC measurements, extrapolation of data from Geron and Hays (2013) to other ecosystems is needed. In addition, because comprehensive field measurements of EFs for smoldering organic soil and peat are even more limited, laboratory-measured EFs must currently be relied upon to estimate emissions for fires involving these fuel types and associated combustion characteristics.

5.2.3 Emission Calculations

Quantifying EFs of wildland fires is only the starting point for characterizing emissions. Decision support activities (e.g., forecasting smoke impacts) and research (e.g., climate forcing of aerosols) require mass flux estimates ($\text{kg m}^{-2} \text{ s}^{-1}$) of pollutants released into the atmosphere by wildland fires. Here, we refer to the mass flux of pollutant *X* as “emissions of *X*” (E_X) which can be calculated bottom-up or top-down. Bottom-up calculations are based on surface data (fuel loading and

burned area), whereas top-down methods calculate emissions using observations of fire energetics, independent of fuel loading and burned area.

5.2.3.1 Emission Calculations: Bottom-Up Methods

In simplified form, bottom-up emission calculations may be described with Eq. 5.3:

$$E_X = A \times F \times C \times EF_X \quad (5.3)$$

where the mass flux of species X , E_X ($\text{kg-X m}^{-2} \text{s}^{-1}$) is the product of area burned (A , m^2), fuel loading (F , kg-fuel m^{-2}), combustion completeness (C), and EF_X (kg-X kg-fuel^{-1}). In practice, this calculation involves several components (Ottmar 2018): (1) fire activity, (2) fuel characteristics, (3) fuel consumption, (4) emission factors, (5) temporal allocation of emissions, (6) vertical allocation of emissions, and (7) the atmosphere (Fig. 5.7).

First, fire activity information is necessary—when and where a fire occurred, and size of the area burned. Availability of fire activity data is constrained by the intended use of the emissions. Smoke forecasting requires rapid data accessibility for recent fire activity (e.g., previous 24 h) as well as predictions of fire activity and resultant emissions for the forecast period (typically 24–48 h). In contrast, research activities can usually use emissions calculated a long period time after the actual fire activity, allowing access to post-fire data products.

Fire activity data collected as part of fire management activities are often available with a timeliness suitable for smoke forecasting. These data include incident management reports for wildfires and burn permit records and agency reporting for prescribed fires. This reporting provides fire location and size, and may include size increase since last report. Prescribed fire data differ widely depending on the agency, jurisdictional reporting requirements, and land ownership. During large wildfire operations, fire perimeter data are commonly obtained from airborne mapping, usually via infrared-based instruments. For both prescribed fire and wildfire, fire size is not necessarily equivalent to the actual area burned. Meddens et al. (2016) determined that approximately 20 percent of the area within a wildfire perimeter was unburned.

Satellite detection of active fires (“hotspots”) can provide a large-scale (regional to continental) view of fire activity (Chuvienco et al. 2019a). Satellite fire detection data in the USA and Canada have variable spatial and temporal resolution. The MODIS and VIIRS instruments on polar-orbiting satellites provide data with a nadir (surface point centered directly below the satellite) pixel size of 375 m to 1 km, and a return time of 12 h per satellite. The latest generation National Oceanic and Atmospheric Administration’s Geostationary Operational Environmental Satellites (GOES-16 and GOES-17) provide fire detection data with a frequency of 5–15 min and nadir pixel resolution of 2 km. Although widely used, these data have limitations. Clouds, forest canopy cover, and low fire intensity can inhibit satellite fire detection. The data do not provide actual fire size, since detectability depends on many factors including fire intensity (Schroeder et al. 2014; Szpakowski and Jensen 2019).

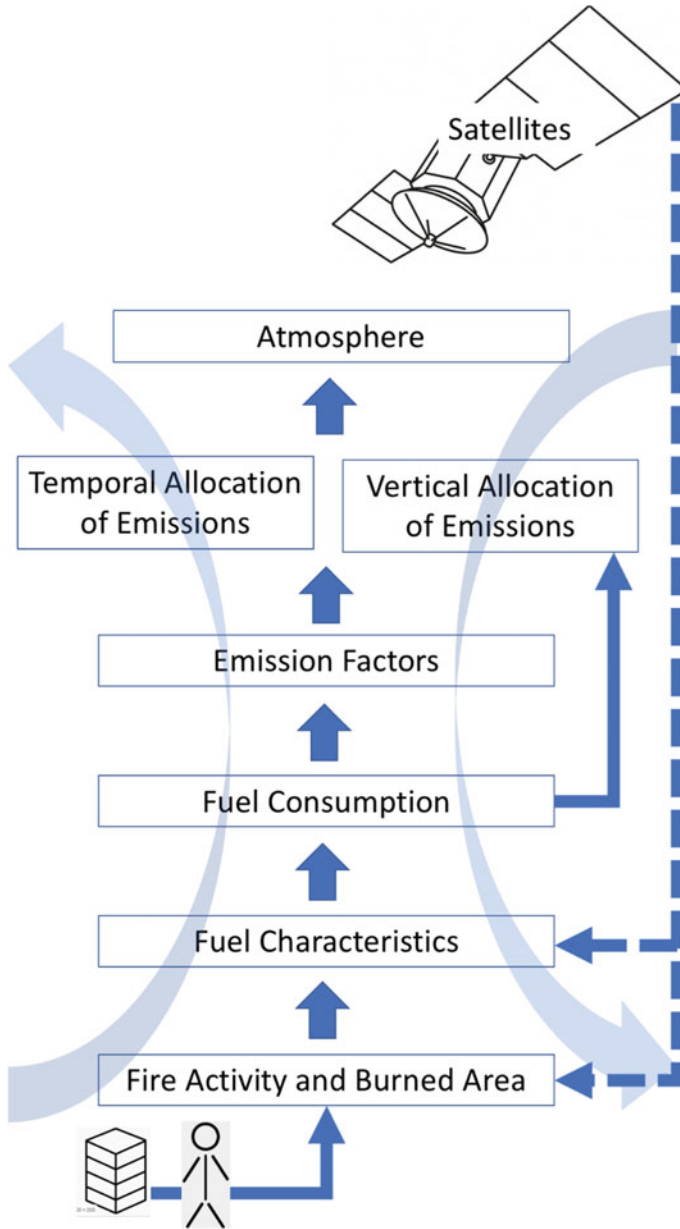


Fig. 5.7 Components in calculating emissions from wildland fire

Emission calculations used in retrospective analyses can leverage fire activity data not available for real-time smoke forecasting. For example, burned area products derived from satellite time series of MODIS and LANDSAT observations (Chuvieco et al. 2019a, b) provide robust burned area mapping. The relaxed time requirements of retrospective analyses also enable use of detailed, vetted databases constructed from multi-agency fire reports such as the Fire Occurrence Database (Short et al. 2020). Combining disparate data sources on fire activity in a consistent dataset optimized for emission calculations is challenging. Tools and efforts described in the Comprehensive Fire Information Reconciled Emissions (CFIRE) Inventory (Larkin et al. 2020) addressed these issues in an attempt to develop a cohesive dataset of fire activity information for a region and time period.

Once a fire is located and its size is estimated, vegetation information is required to infer fuel loading data. Vegetation types, such as Douglas fir (*Pseudotsuga menziesii*) forest or sagebrush (*Artemisia* spp.) shrubland, can be obtained from national-scale mapped datasets such as the Fuel Characteristic Classification System (FCCS; Prichard et al. 2013) or on a site-specific basis (Wright et al. 2010b). Fuel classification systems associate vegetation types with an estimate of fuel loading by stratum (duff, litter, woody fuels, etc.). These datasets typically represent the mean for vegetation types whose fuel loading may in reality vary greatly. The high variability of fuel loading is one of the largest contributors of uncertainty in wildland fire emission estimates (Larkin et al. 2014; Chap. 2).

Once burned area and fuel loading are obtained, information on the fraction of fuel consumed across the different fuel strata (combustion completeness) is needed. Fuel consumption (Chaps. 2 and 3) is determined by the combustion process, consisting of four phases: (1) preignition involving distillation and pyrolysis, leading to (2) flaming, (3) smoldering, and (4) glowing (char oxidation) combustion. Fuel properties (type, moisture content, and arrangement), environmental conditions (e.g., wind speed and terrain), and ignition method in the case of prescribed fires can affect the amount of biomass consumed during various combustion stages. CONSUME (Prichard et al. 2014), FOFEM (Lutes 2019), and Pile Calculator (Wright et al. 2010a) are three widely used fuel consumption models.

The composition and relative abundance of emission species produced during fuel consumption are a function of fuel type, combustion process, and atmospheric interactions. The role of these complex processes in determining EFs is discussed in Sect. 5.2.2.

Finally, emissions must be allocated temporally and vertically in the atmosphere. For prescribed fires, temporal allocation of emissions is often conducted using the Fire Emissions Production Simulator (FEPS; Anderson et al. 2004), where soon after ignition, a large spike in flaming emission occurs which then decays exponentially until 6 pm local time, at which time all flaming emissions end and smoldering emissions continue through the evening (Ferguson and Hardy 1994). For wildfires, time profiles based on diurnal cycles derived from a fusion of fire activity observations from geostationary and polar-orbiting satellites (Mu et al. 2011, Li et al. 2019a, b) or from the work of the Western Region Air Partnership (WRAP) are typically applied.

Future work with fire detection data from the GOES-16 and GOES-17 satellites is anticipated to improve temporal profiles for large wildfires.

The vertical distribution of emissions in the atmosphere depends on smoke plume dynamics (Chap. 4). Heat released from the fire is estimated from the consumption model and is often used to estimate the maximum height in the atmosphere under which emissions are distributed, known as plume rise. A Briggs (1976) approach has been historically used in systems such as BlueSky (Larkin et al. 2009). Other plume modeling methods have been used for emissions and smoke modeling (e.g., DAYSMOKE; Achtemeier et al. 2011; Chap. 4).

Concurrent with plume rise is how emissions are distributed underneath the plume top. Typically, smoldering emissions are allocated to the lowest level of the atmospheric model (near the surface). Flaming emissions are usually distributed evenly (vertically) through the atmosphere beneath the nominal plume-rise height. How plume-rise height interacts with mixing height, as well as quantity of flaming versus smoldering emissions, has implications for the quantity of emissions retained near the surface versus lofted and transported long distances.

5.2.3.2 Emission Calculations: Top-Down Methods

Bottom-up emission approaches combine fuel loading maps with estimates of area burned and fuel consumption to derive biomass burned, to which EFs are applied to calculate pollutant emissions (Fig. 5.7; Eq. 5.3). Fuel consumption, the product of fuel loading and combustion completeness, is the largest source of uncertainty in bottom-up emission calculations (French et al. 2011; Urbanski et al. 2011; Leeuwen et al. 2014). Top-down emission methods use satellite observations of fire radiative power (FRP), a measure of the radiant energy release rate from burning vegetation, to estimate fuel consumption, circumventing the need to explicitly consider fuel loading and combustion completeness.

FRP is one of the parameters provided in the active fire products derived from observations of the MODIS and VIIRS sensors (and other satellite-based sensors) (Wooster et al. 2003; Zhang et al. 2017). FRP is based on the fire pixel temperature observed in mid-wavelength infrared, typically around $4\ \mu\text{m}$ ($3.96\ \mu\text{m}$ for MODIS) (Wooster et al. 2003). Laboratory and field experiments have shown that (1) FRP is linearly related to the vegetation combustion rate, and (2) fire radiative energy (FRE) (time-integrated FRP) is linearly related to the mass of vegetation combusted (Wooster et al. 2005; Freeborn et al. 2008; Hudak et al. 2016). Most top-down approaches estimate emissions by combining fuel consumption inferred from FRE with biome/land cover-specific EFs (Kaiser et al. 2012; Zhang et al. 2012). A variation of this approach used estimates of atmospheric column PM loading (derived from MODIS aerosol optical depth) to develop land cover-specific PM emission coefficients (kg-PM MJ^{-1}) for predicting PM emissions directly from FRE (kg MJ^{-1}) (Ichoku and Ellison 2014).

Top-down emission inventories typically use FRP retrievals from the MODIS and VIIRS sensors which are on polar-orbiting satellites. In addition to providing

Table 5.1 Databases, syntheses, and reviews for emission factors (in order of last update)

Emission factor dataset	References	Availability	Last update
Smoke Emissions Repository Application	Prichard et al. (2020)	https://depts.washington.edu/nwfire/sera	2019
Andreae biomass burning emission factors	Andreae (2019)	https://doi.org/10.17617/3.26	2019
Urbanski	Urbanski (2014)	https://www.fs.usda.gov/tree-search/pubs/45727	2014
Wildland fire emissions factors database	Lincoln et al. (2014)	https://www.fs.usda.gov/rds/archive/catalog/RDS-2014-0012	2014
Akagi et al.	Akagi et al. (2011)	http://bai.acom.ucar.edu/Data/fire/	2011
USEPA AP-42	USEPA (1996)	https://www3.epa.gov/ttn/chief/ap42/ch13/index.html	1996

global coverage, these sensors offer a higher spatial resolution (nominal resolution at nadir of 1 km for MODIS and 750 m/375 m for VIIRS) than sensors on geostationary orbiting satellites (e.g., GOES-11/13/15) (nominal 4 km at nadir). However, polar-orbiting satellites offer limited temporal coverage (two observations a day per satellite) compared with geostationary satellites. For example, the GOES imagers provide observations every 5–15 min across the contiguous USA.

Since FRP is an instantaneous indicator of heat flux and does not provide information on fire evolution, the sparse temporal coverage of polar-orbiting satellites is a major limitation of the top-down emission approach. Recent efforts to combine FRP data from polar-orbiting satellites (MODIS/VIIRS) and higher temporal resolution GOES fire products are promising for providing improved spatiotemporal FRP coverage (Li et al. 2019a, b). Application of this approach to the new generation of GOES imagers (GOES-16/17), which have improved spatial resolution (nominal 2 km at nadir for fire products), may be an effective emission inventory method.

5.3 Existing Data, Tools, Models, and Other Technology

5.3.1 Emission Factors

Publicly available EF syntheses and databases are listed in Table 5.1. Andreae (2019) and Akagi (2011) support global emission modeling and provide EFs for broad fire types such as “temperate forest” and “peat fires,” as well as other biomass sources (e.g., biofuel use and trash burning). Urbanski (2014) uses more specific fire classifications, designed for US and Canadian fires, such as “prescribed fire southeast conifer forest” and residual smoldering of “stumps and logs.”

The Smoke Emission Reference Application (SERA) is an online database that allows users to explore and summarize an extensive repository of EFs for smoke management and emission inventory activities (Prichard et al. 2020). The Lincoln et al. (2014) database compiles EFs from a large body of field and laboratory studies. The SERA and Lincoln et al. databases do not synthesize data to derive “best estimate” EFs. Chapter 13 of “Compilation of Air Pollutant Emissions Factors” (AP-42) (USEPA 1996) provides recommended EFs for a limited number of pollutants for US fire types and was published prior to the advances achieved in the past 15 years in characterizing emissions of wildland fires.

5.3.2 Emission Inventories

An emission inventory is a compilation of data that lists, by source, the amount of air pollutants released into the atmosphere in a defined geographic area during a specific time period. Table 5.2 provides nine wildland fire emission inventories that cover the contiguous USA (CONUS). The domain and temporal coverage differ among the inventories. A number of inventories (GFED, FiNN, QFED, GFAS, FEER, and GBBPx) are global in coverage, and others focus on the USA (WFEIS, MFLEI, and NEI) (Table 5.2). Although the spatial resolution of the inventories uses different metrics (500 m to 0.25°), all provide emissions with a 1-day temporal resolution. Many atmospheric model applications, whether operational forecasts or retrospective analyses, require hourly emissions. High temporal frequency observations of fire activity from geostationary satellites have proven useful for deriving hourly emission profiles from daily estimates (Mu et al. 2011; Li et al. 2018).

Several inventories (FiNN, QFED, GFAS, FEER, and GBBPx) calculate emissions in near-real time for use in atmospheric chemistry forecasting. FiNN and QFED are used in the Whole Atmosphere Community Climate Model (<https://www.acom.ucar.edu/waccm/forecast>). GFAS is used in Copernicus Atmosphere Monitoring Service (<https://atmosphere.copernicus.eu/global-forecast-plots>), and GBBPx is an operational product currently being used by the NGAC v2 aerosol model at the National Center for Environmental Prediction. GFED, WFEIS, MFLEI, and NEI are all retrospective inventories that estimate emissions with a time lag of one to three years. Retrospective inventories have the potential to provide more accurate emission estimates than their real-time counterparts as they can leverage burned area and burn severity geospatial data products that are not available in real time (Urbanski et al. 2018).

Different inventories include different pollutant species. For example, FiNN emissions are speciated for three different atmospheric chemistry model mechanisms; MFLEI provides fuel consumption and emissions of CO₂, CO, CH₄, and PM_{2.5}; GFED offers fuel consumption according to fire type, with recommended EFs for over 20 species. Most of the inventories include fuel consumption which can be used to calculate emissions for any species for which EFs are available; this requires information or assumptions regarding fire type and vegetation burned.

Table 5.2 Emission inventories

Inventory	Domain	ΔX	Δt	Active	Access
<i>Bottom-up emission calculations</i>					
Global Fire Emissions Database (GFED)	Global	0.25°	1 day to 1 month	Yes	https://www.globalfiredata.org/
Wildland Fire Emissions Information System (WFEIS)	USA	1 km	1 day	No	https://wfeis.mtri.org/
Fire Inventory from NCAR (FiNN)	Global	1 km	1 day	Yes	https://www2.acom.ucar.edu/modeling/finn-fire-inventory-ncar
Missoula Fire Lab Emission Inventory (MFLEI)	CONUS	500 m	1 day	Yes	https://www.fs.usda.gov/rds/archive/catalog/RDS-2017-0039
National Emission Inventory (NEI)	USA	Variable	1 day	Yes	https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei
<i>Top-down emission calculations</i>					
Global Fire Assimilation System (GFAS)	Global	0.1°	1 day	Yes	https://atmosphere.copernicus.eu/global-fire-emissions
Quick Fire Emission Dataset v2.4 (QFED)	Global	0.1°	1 day	Yes	https://www.acom.ucar.edu/waccm/register.shtml
Fire Energetics and Emissions Research v1 (FEER)	Global	0.1°	1 day	Yes	https://feer.gsfc.nasa.gov/projects/emissions/
Blended Global Biomass Burning Emissions Product (GBBEPx V3)	Global	0.1°	1 h	Yes	https://www.ospo.noaa.gov/Products/land/gbbepx/

5.3.2.1 Emission Estimates for CONUS, Canada, and Alaska

A map of annual average $PM_{2.5}$ emissions from 2003 to 2018 estimated by GFED (Werf et al. 2017) is shown in Fig. 5.8. Emission hotspots are concentrated in the boreal regions and, to a lesser extent, in the western USA and southern British Columbia. An emission hotspot is also present on the Georgia–Florida border owing to a series of intense fires in the Okefenokee Swamp region. GFED annual sums of $PM_{2.5}$ emissions for CONUS and Alaska/Canada for 2003–2018 are shown in Fig. 5.9. The GFED-estimated annual $PM_{2.5}$ emissions for Alaska and Canada exceed

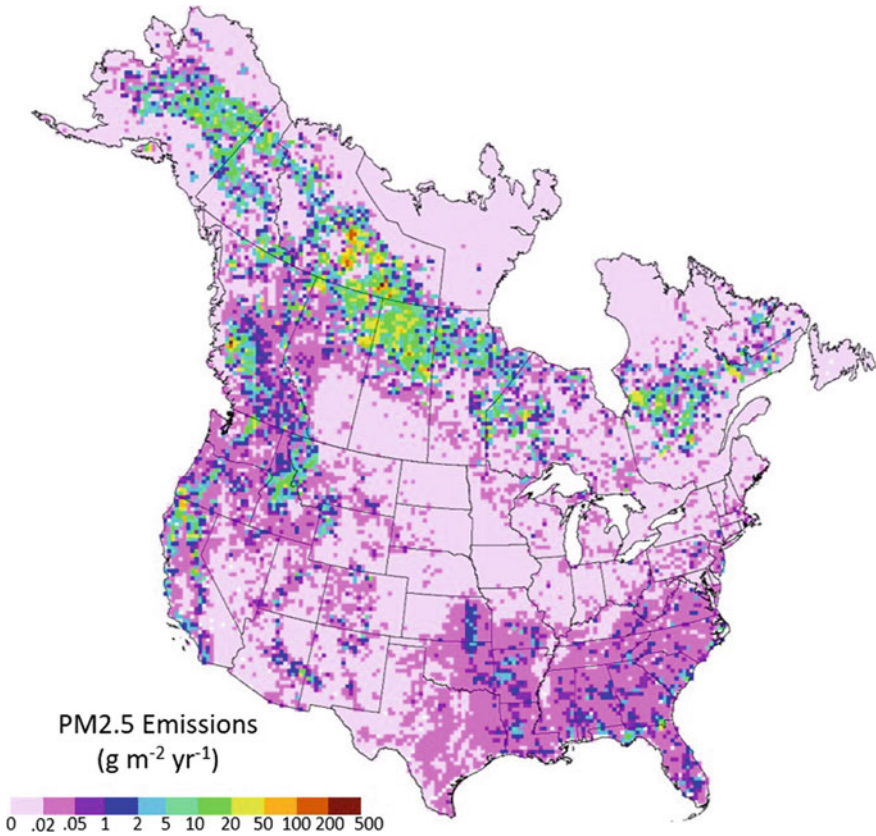


Fig. 5.8 Annual average PM_{2.5} emissions for 2003–2018. Based on data from the global fire emissions database (Werf et al. 2017)

those of CONUS by a factor of 2–20, depending on the year. Interannual variability in emissions is similar for the two regions, with coefficients of variation near 0.5.

Monthly average GFED PM_{2.5} emissions are shown in Fig. 5.10. Across the northern tier, emissions are concentrated in the summer months (90% between June and August). CONUS emissions are spread more broadly across the year, with the peak three months (July–September) accounting for 60% of the annual total. Putting the magnitude of emissions into context, Fig. 5.11 plots summer emissions (July–September) for the western 11 CONUS states with PM_{2.5} emissions from non-fire sources as estimated from the EPA 2014 NEI v2. During the heart of the western USA wildfire season, GFED-estimated PM_{2.5} emissions regularly exceeded anthropogenic sources by a factor of 2–4 during severe fire years (2007, 2012, 2017, 2018).

Annual magnitude, seasonality, and spatial distribution of fire emission across the USA and Canada are summarized in Figs. 5.8, 5.9, 5.10 and 5.11. There is uncertainty in emission inventories, especially at spatiotemporal scales relevant for

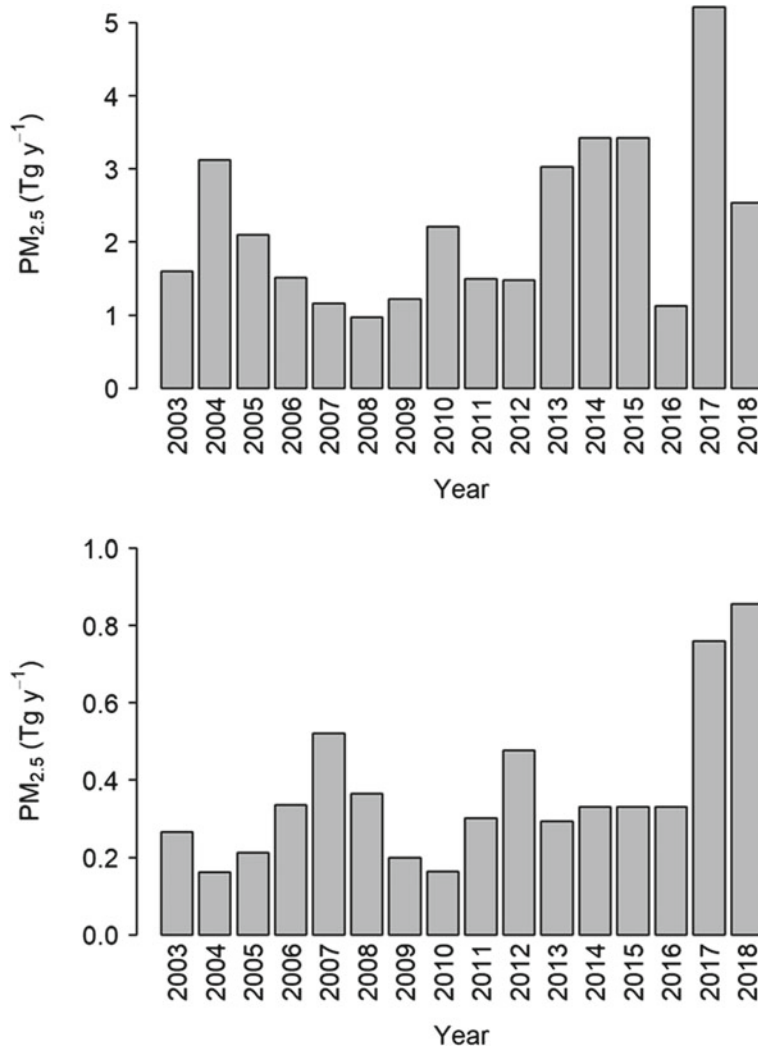


Fig. 5.9 Annual sums of PM_{2.5} emissions for 2003–2018 for Alaska/Canada (top panel) and the CONUS (bottom panel). From the global fire emissions database

understanding and predicting smoke impacts. PM_{2.5} emissions based on four inventories are shown in Fig. 5.12: PM_{2.5} emissions range from 80 to 230% of the ensemble mean. Different data and methods—burned area, fuel-type classification maps, fuel loading and consumption, and EFs—all contribute to this variability.

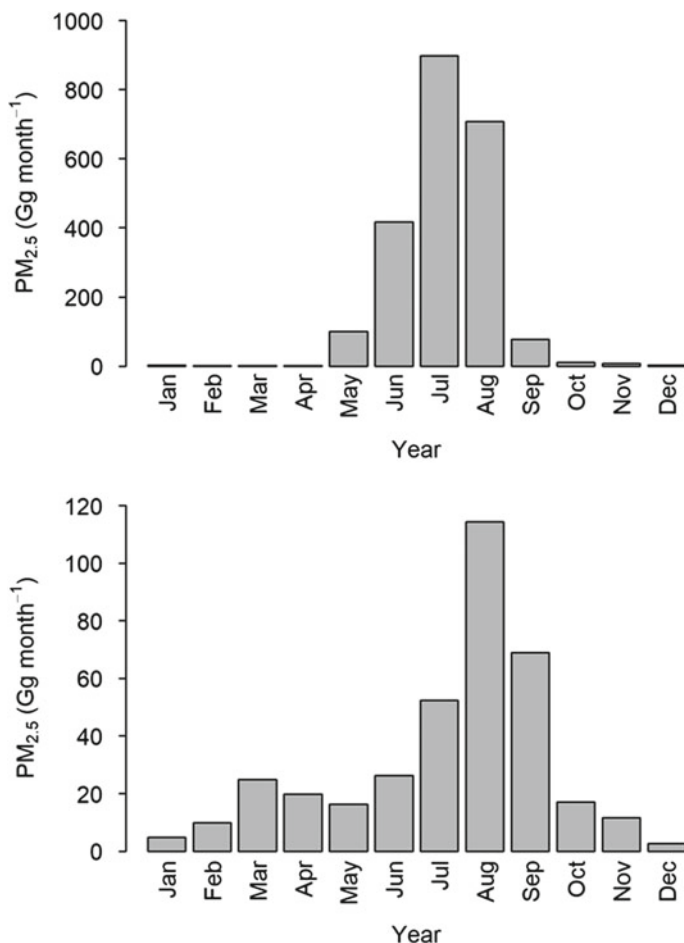


Fig. 5.10 Monthly average PM_{2.5} emissions for 2003–2018 for Alaska/Canada (top panel) and CONUS (bottom panel). From the global fire emissions database

5.3.3 Emission Models for Land Management

Prescribed fire is used to maintain and restore ecosystem function and health and mitigate wildfire risk through reduction of hazardous fuel. Smoke impacts are an important consideration for prescribed burning, and effective smoke management strategies are generally required for successful use of prescribed fire. Emission reduction techniques (ERTs) are central to the basic smoke management practices recommended by the National Wildfire Coordination Group (Peterson et al. 2018). ERTs take into consideration area burned, fuel load, fuel produced, amount of fuel consumed, and combustion efficiency. Smoke emission models designed for land managers and

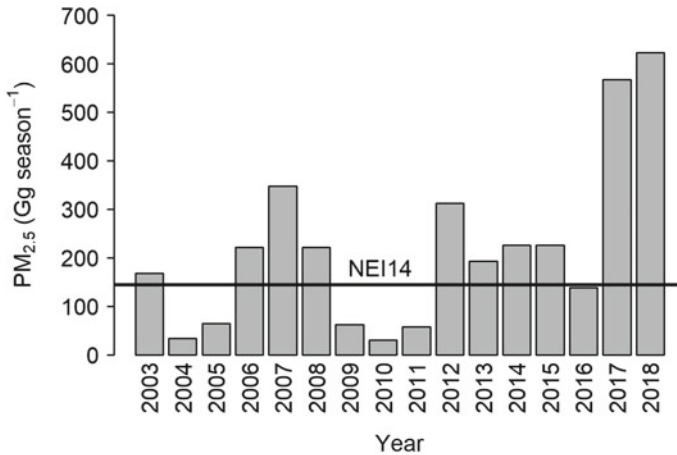


Fig. 5.11 Summer (July–September) PM_{2.5} emissions for the western 11 CONUS states (bars) and PM_{2.5} emissions from non-fire sources as estimated from the USEPA 2014 NEI v2 [solid horizontal line; USEPA (2014)]

prescribed fire practitioners are important tools for implementing ERTs. Smoke emission models commonly used for planning of prescribed fires in the USA (Table 5.3) predict emissions based on fuel loading, fuel moisture, and environmental factors.

A number of models are available for managers to use in prescribed fire planning. The First Order Fire Effects Model (FOFEM) predicts the immediate consequences of wildland fire, including fuel consumption, smoke production, soil heating, and tree mortality. CONSUME is a module within BlueSky, WFEIS, and the Fuel and Fire Tools (FFT) suite that predicts total fuel consumption, emissions, and heat release. FEPS predicts hourly emissions, heat release, and plume-rise values for wildland fires; can import consumption and emission data from CONSUME and FOFEM; and is included in FFT. The software application FFT integrates CONSUME and FEPS with fuel data from the FCCS and Digital Photo Series (Chap. 2) into a single user interface (Ottmar 2014). BlueSky Playground (Larkin 2018) provides interactive access to several models enabled by the BlueSky Framework and allows users to enter basic fire information to simulate fuel consumption and pollutant emissions, as well as model plume rise and smoke dispersion.

5.4 Gaps in Data, Understanding, and Tools/Technology

5.4.1 Emission Factors for Wildfires

The paucity of EF measurements for wildfires is a significant gap in our understanding of emissions. With the exception of prescribed fires in southeastern US forests, most fire types have received limited field investigation. The small number of wildfires

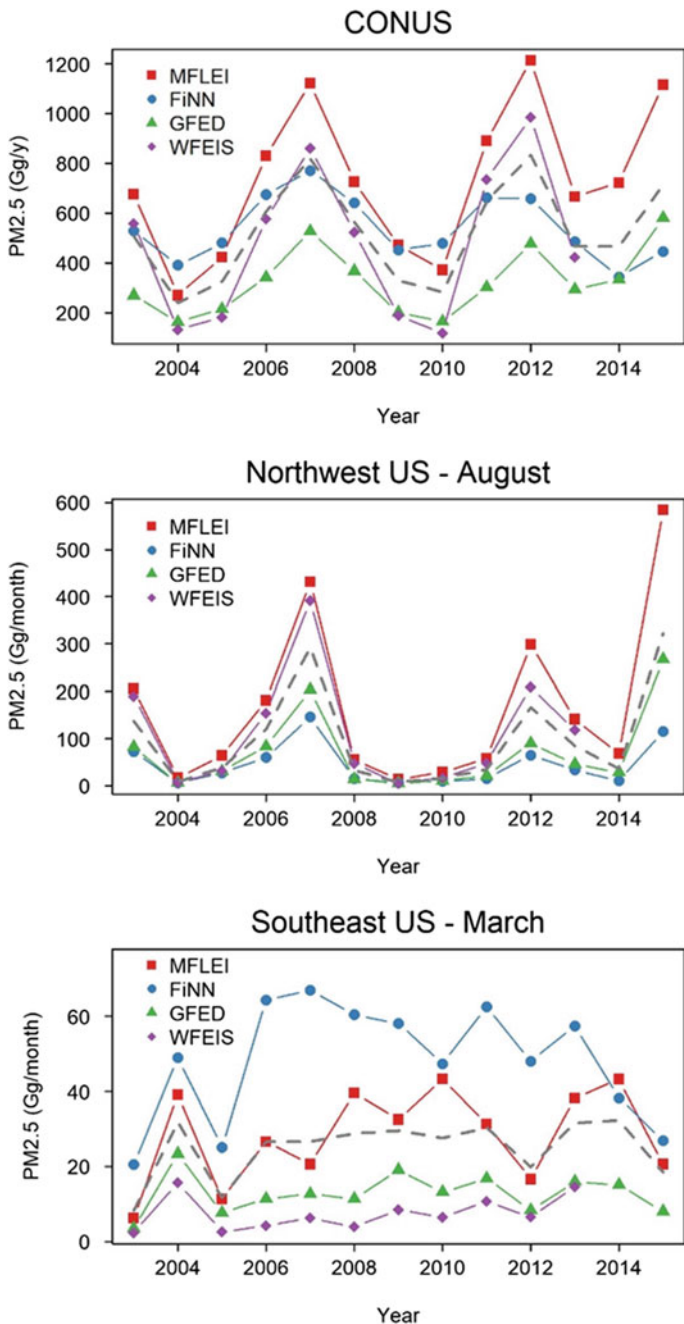


Fig. 5.12 PM_{2.5} emissions based on four different inventories: GFED, FiNN, MFLEI, and WFEIS for three regions and time periods: CONUS-wide—annual (top), northwest USA—August (middle), and southeast USA—March (bottom)

Table 5.3 Emission models for land management

Model	Availability	References
FOFEM	https://www.firelab.org/document/fofem-files/	Lutes (2019)
CONSUME	https://www.fs.fed.us/pnw/fera/research/smoke/consume	Prichard et al. (2020)
FEPS	https://www.fs.fed.us/pnw/fera/fepe	Anderson et al. (2004)
FFT	https://www.fs.fed.us/pnw/fera/fft	Ottmar (2014)
BlueSky Playground	https://tools.airfire.org/playground	Larkin (2018)

that have been sampled with detailed chemical speciation does not capture the wide range of fuels and burning conditions that occur across the USA and Canada.

EFs have not been measured from wildfires for most NMOGs known to be present in fresh smoke (based on laboratory studies). Boreal wildfire EFs for the most reactive compounds, which include nearly half the NMOG mass reported, are based on a single fire (Simpson et al. 2011). Similarly, NMOG EFs for western US wildfires are limited to only three fires and may not capture the range of wildfire emissions (Liu et al. 2017). Field studies that did not measure EFs for PM and NMOGs report an MCE range of 0.83–0.95 for 29 western USA and boreal wildfires (Hornbrook et al. 2011; O’Shea et al. 2013; Urbanski 2013). Because EFs for many species are correlated with MCE, the actual range of EFNMOG and EFPM for wildfires may be considerably broader than suggested by Liu et al. and Simpson et al., so applying these data to wildfires may introduce uncertainty in emission estimates.

5.4.2 *Connecting Laboratory Studies with Field Observations*

Comprehensive emission estimates across the spectrum of relevant fire activity require extrapolating laboratory-measured EFs to real fire conditions. EF extrapolation methods include (e.g., Selimovic et al. 2018; Sekimoto et al. 2018):

- Regression of EF versus MCE to extrapolate field MCE
- Average EF of laboratory burns according to fuels type
- Coupling of laboratory $\Delta X/\Delta CO$ with field EFCO to derive EFX at field conditions
- Pyrolysis profiles based on high- and low-temperature regimes.

These methods may also be used to extrapolate field-measured EFs to fires in different fuel types and burning conditions. A combination of the first three approaches has been used in developing global and regional EF databases that are widely used in emission models and inventories (Akagi et al. 2011; Urbanski 2014; Andreae 2019). However, an extensive evaluation of laboratory-extrapolated EFs has not been published, perhaps due to lack of field data. In a limited evaluation, Sekimoto et al. (2018) found that EFs estimated using high- and low-temperature

pyrolysis profiles analyzed with positive matrix factorization can reproduce NMOG EFs from previous field and laboratory burns with reasonable fidelity ($r \geq 0.92$). Additional field data, especially for wildfires, are needed to support a comprehensive evaluation of EF extrapolation methods.

5.4.3 *Variability of EFs with Combustion Conditions*

Long-term smoldering can result in sustained periods of poor air quality, exacerbation of health conditions among vulnerable residents, and dangerous road conditions due to reduced visibility (Chap. 7). Smoldering that persists into nighttime hours when winds tend to be light and variable, reducing dispersion, can be especially challenging when the shallow nocturnal boundary layer reduces the volume into which smoke is emitted. Nighttime subsidence drainage flows can transport smoke long distances, pooling it in valleys or low-lying areas.

Applying fuel treatments on landscapes with fuels prone to smoldering, while minimizing local smoke impacts, requires models that provide reliable temporal profiles of fuel consumption and pollutant emissions. FOFEM and FEPS are widely used to predict fuel consumption and smoke production (Ottmar 2018). However, the ability of these models to simulate fuel consumption rates for smoldering combustion has not been rigorously evaluated. In addition, the models predict temporal emission profiles using static smoldering-phase EFs.

Consumption and emission rates during long-term smoldering can differ depending on the fuel component (log, stump, basal accumulation, etc.) and fuel condition (Ottmar 2018). Likewise, EFs differ with fuel component type and smoldering characteristics (Hao and Babbit et al. 2007; Reisen et al. 2018). The absence of validated models to predict emission rates from long-term smoldering is a significant obstacle to using prescribed fire.

5.4.4 *Validation of Emission Inventories*

There are large discrepancies among the various CONUS emission inventories. In a recent study, CONUS-wide average monthly $PM_{2.5}$ emissions estimated by seven inventories, over four years, ranged from 28.2 to 485.6 Gg, with a coefficient of variation of 109% (Li et al. 2019a, b). Comparisons limited to retrospective emission inventories find large differences at fairly coarse scales (Larkin et al. 2014; Koplitz et al. 2018) and increasing variability with decreasing spatiotemporal scale (French et al. 2011; Urbanski et al. 2011).

Improving our ability to forecast smoke events and understand smoke impacts within the USA requires developing and applying thorough validation methods for emission inventories at the fire-event level. Over 10 emission inventories (near-real time and retrospective) include the CONUS, and several comparisons are found in

the literature (e.g., Larkin et al. 2014; Koplitz et al. 2018; Urbanski et al. 2018; Li et al. 2019a, b). However, none of the emission inventories has been methodically evaluated using independent data at scales relevant for assessing wildfire smoke impacts on air quality. Validation methods link satellite observations of fire emissions (e.g., aerosol optical depth, CO, NO₂) to fire activity using atmospheric models and meteorological analyses. Although these methods have been used in both forward (Ichoku and Ellison 2014; Petrenko et al. 2017) and inverse (Dubovik et al. 2008; Kopacz et al. 2010) modeling approaches to constrain fire emission inventories at global to regional scales, they have not rigorously validated emission inventories at the fire-event scale.

5.4.5 Forecasting Wildfire Emissions

The lack of reliable near-term (24 h) emission forecasts is a key obstacle to improving forecasts of wildfire smoke impacts on air quality. The main challenge is accurately predicting the growth of many active fires over the next burning period in a timely manner that is compatible with regional-to-continental smoke forecasting systems. Although several fire growth models exist, current operational smoke models use daily persistence in burned area growth to forecast emissions. Daily persistence assumes that the area burned by a given fire in the current day will be that fire's growth the following day. However, given available fuel and variable topography, daily weather plays a major role in the growth of wildfires (Chap. 3).

The sensitivity of wildfire growth to weather is evident in retrospective emission inventories that suggest that the majority of CONUS wildfire emissions occur on a small fraction of days (~5%) (Urbanski et al. 2018). The daily persistence approach will often greatly under-predict these high fire growth/high emission days, which occur during severe fire weather conditions (e.g., Jolly et al. 2019), resulting in a failure to forecast acute smoke episodes. The use of daily persistence can also overestimate fire growth over periods following extreme fire weather days, leading to an overprediction of smoke production. Improving the skill of smoke forecasts will require developing and implementing new methods for predicting short-term (24 h) fire growth and emissions. Methods based on forecast meteorological variables (temperature, relative humidity, wind speed) and fire weather indices have shown promise for improving upon daily persistence in prediction of short-term fire activity and smoke emissions (Peterson et al. 2013; Giuseppe et al. 2017).

5.4.6 Measuring and Modeling PM_{2.5}

Inaccurate PM_{2.5} measurements introduce errors in emission models used for air quality modeling and introduce uncertainty in the measurements used to validate

these models. Inaccurate ambient $PM_{2.5}$ measurements also may result in public health guidance that is either overly restrictive or not adequately protective.

Due to the semi-volatile and reactive nature of smoke, $PM_{2.5}$ concentration ratios used to calculate EFs can differ depending upon the local conditions at which they are measured. EFs are measured from fresh emissions before significant SOA formation, or other reactions have occurred and altered the chemistry of the emissions. However, at the high concentrations near the fire, the lower-volatility SVOCs will partition to the particle phase, leading to higher $PM_{2.5}$ concentrations than under more dilute conditions (Robinson et al. 2010). These volatility effects may partially explain the wide scatter observed in $EFPM_{2.5}$ across studies (Jolleys et al. 2014; May et al. 2014) and observations that $EFPM_{2.5}$ can be almost twice as high near the fire compared to downwind in a dilute plume (Holder et al. 2016).

The volatility distribution is one way to account for SVOC partitioning and is now being employed in air quality models (Lu et al. 2020). Volatility distributions have been shown to be relatively independent of fuel type and burning conditions (May et al. 2013; Hatch et al. 2018) and can explain up to a 40% loss of PM with 100:1 dilution (Hatch et al. 2018). However, volatility measurements have been limited to laboratory burns, and field measurements are still needed.

Ambient monitoring of smoke also has $PM_{2.5}$ measurement challenges. Air quality information during smoke events is generally derived from Federal Equivalent Method (FEM) monitors that provide hourly measurements. FEMs are validated against 24-h filter-based Federal Reference Measurements (FRMs) at concentrations of 3–200 $\mu\text{g m}^{-3}$ to ensure broad comparability to FRM $PM_{2.5}$ mass, which is the basis for much of the $PM_{2.5}$ health effect research (USEPA 2020). However, FEM evaluations do not purposefully include smoke-impacted times and do not cover the full range of $PM_{2.5}$ concentrations corresponding to the air quality index range.

Research to identify and resolve FEM monitor measurement accuracy for wildfire smoke is needed. Several FEMs contain measurement artifacts, which may hinder their use for assessing smoke impacts on air quality. Environmental beta attenuation monitors (EBAMs, a near-FEM grade instrument) used in temporary monitoring networks near fires are subject to a high bias at elevated relative humidity, and hourly EBAM $PM_{2.5}$ data at humidity above 40% should be used cautiously (Schweizer et al. 2016). Another FEM (Teledyne T640[®]) was found to report $PM_{2.5}$ concentrations 40–100% higher than another FEM (MetOne 1020 BAM[®]), but only when the $PM_{2.5}$ concentrations were elevated (Hassett-Sipple et al. 2020; Landis et al. 2021).

Sensor technologies are increasingly used to monitor wildfire smoke, and work is needed to identify appropriate corrections for $PM_{2.5}$ sensors and methods to ensure high-quality data during extended smoky episodes. Although some $PM_{2.5}$ sensor measurements can report concentrations up to twice as high as nearby FEMs (Mehadi et al. 2020; Holder et al. 2020; Landis et al. 2021), with correction some sensors have been found to report $PM_{2.5}$ with modest error (~20–30%) over a range of conditions (Holder et al. 2020; Barkjohn et al. 2020) and are now displayed as part of the Sensor Data Pilot on the AirNow Fire and Smoke Map (<https://fire.airnow.gov>).

5.4.7 Emissions of Hazardous Air Pollutants

PM is the major constituent of smoke associated with adverse health effects; however, numerous other hazardous air pollutants are also emitted from fires, such as hydrogen cyanide (HCN), polycyclic aromatic hydrocarbons (PAHs), and other organic compounds (e.g., formaldehyde). The contribution of these gas-phase compounds to health effects is poorly known. O'Dell et al. (2020) identified formaldehyde as the largest gas-phase hazardous air pollutant contributing to cancer risk from wildfire smoke. They also found that acrolein was the major contributor to acute and chronic hazards of young wildfire smoke (<1 day old), whereas HCN was the primary contributor to chronic hazard from aged wildfire smoke. Although O'Dell et al. (2020) estimated that health impacts from gas-phase hazardous air pollutants were small compared to PM, exposure to these pollutants may not be reduced by common actions recommended to reduce smoke exposure (e.g., portable air cleaners and N95 masks). More research is also needed on the impact of gas-phase hazardous air pollutants near fires and human health.

Toxic metals have been measured at trace levels in biomass burning PM (Chen et al. 2007; Alves et al. 2011; Hosseini et al. 2013). As other sources of toxic metal emissions to the atmosphere have decreased through regulations, fires may now be a sizable source of toxic metals to the atmosphere, and some compounds may be the leading source of these emissions to the atmosphere (Reff et al. 2009). Lead is a particular concern because it is a USEPA criteria air pollutant and regulated through the National Ambient Air Quality Standards.

When fires occur in the wildland–urban interface, burning vehicles and structures may emit toxic metals, because the “fuel” in this case may contain high concentrations of these metals (see Sect. 5.4.8). In areas where there has been environmental contamination (e.g., Superfund sites, firing ranges, areas downwind of point sources), lead and other toxic metals deposited in the soil and vegetation can be remobilized as PM, entrained ash, or soil particles (Kristensen and Taylor 2012; Odigie and Flegal 2014; Wu et al. 2017). Radionuclides were remobilized by fires in the Chernobyl Exclusion Zone (Evangelidou and Eckhardt 2020) but had limited long range transport, likely because most of the radionuclides in the fuel partition to ash (Hao et al. 2018).

The toxic metals in PM from wildland fires may be emitted from both the soil and combustion of vegetation. The larger PM size fractions (2.5–10 μm) emitted from fires are enriched in calcium, magnesium, iron, aluminum, and silicon, likely derived from soil particles entrained in the fire plume (Echalar et al. 1995; Alves et al. 2010, 2011; Popovicheva et al. 2016). Several elements (boron, manganese, zinc, copper) are micronutrients that play a vital role in vegetative physiological processes, and some plant species can hyperaccumulate heavy metals (e.g., uptake of lead by the *Brassicaceae* family (mustard family)) (Tangahu et al. 2011).

When present, the higher-volatility metals (e.g., zinc, lead, cadmium, mercury) in vegetation or soils tend to partition to $\text{PM}_{2.5}$, whereas the lower-volatility metals (e.g., cobalt, nickel, chromium, vanadium) tend to partition to ash (Narodoslawsky

Table 5.4 USEPA hazardous air pollutant metals in wildland fire smoke

Fire type	Field/lab	Sb	Cd	As	Cr	Co	Pb	Ni	Hg	Se	References
		(µg metal per g particle mass)									
Western conifer	Lab	6.5	2	23			39			2.5	Turn et al. (1997)
Western forest	Field		375		134		1102	78.3			Ward and Hardy (1989)
Southeastern forest	Field	180			29		87			97	Balachandran et al. (2013)
Southeastern forest	Field			1.9			1.5			1.2	Lee et al. (2005)
Southwestern shrub	Field	9.7	9.8	50	220	1.2	22	12	6.5	16	Chow et al. (2004)

and Obernberger 1996). Metal volatility can also be affected by local combustion conditions, such as an oxidizing atmosphere facilitating formation of low-volatility metal oxides, and the presence of other compounds like chlorine that can result in higher-volatility metal chlorides (Linak and Wendt 1993). Other compounds, such as aluminosilicates, may also act as a sorbent for some metals, causing the metals to partition to ash (Linak and Wendt 1993).

There are limited measurements of toxic metal emissions from wildland fires, owing to the lack of real-time measurement methods and the difficulty of obtaining sufficient sample mass for analysis. Table 5.4 provides a summary of field and laboratory measurements of EFs of metals on the USEPA hazardous air pollutant list. The metal contribution to PM mass can vary by one to three orders of magnitude, possibly representing the variation of the metal content in the vegetation that was burned. However, the large variation may be caused in part by analytical uncertainties due to limited sample mass. Accurate emissions for these trace hazardous air pollutants are still needed for many fuel types and regions. Measurements will require large sample masses and sensitive analytical methods to measure EFs above the detection limit.

5.4.8 Emissions from Structure Fires

Wildland fires that occur in the wildland–urban interface have the additional complication of potentially burning different fuels that release toxic emissions when combusted. Research on toxicity of emissions from combustion of building materials and vehicles has shown that numerous toxic compounds are emitted, including hydrogen cyanide, hydrogen fluoride, hydrochloric acid, isocyanates, polycyclic aromatic hydrocarbons, dioxins, NMOGs (e.g., benzene, toluene, xylene, styrene, formaldehyde), and metals (Austin et al. 2001; Lönnermark and Blomqvist 2006; Fabian et al. 2010; Reisen 2011; Stec 2017; Fent et al. 2018). Structural firefighters

use a self-contained breathing apparatus to exclude pollutant concentrations that are immediately dangerous to life or health. However, wildland firefighters responding to wildfires where structures are burned do not normally use self-contained breathing apparatus and may be exposed to high concentrations of toxic air pollutants (Chap. 7).

Several studies have quantified EFs for hazardous pollutants from building materials, vehicles, and house fires (Blomqvist et al. 2004; Lönnermark and Blomqvist 2006; Reisen 2011). The range of pollutants measured, as well as the measurement methods, differed among these studies, and substantial gaps remain on the emissions of hazardous air pollutants. In addition, limited information is available on emissions from materials that contain flame retardants or lithium batteries, or that may have highly toxic emissions.

Table 5.5 summarizes studies of emissions from combustion of structures and vehicles, compared with similar measurements from wildland fires. Although EFs for some of the most hazardous compounds are 2–1600 times greater from combustion of vehicles or building materials compared to wildland fuels, total emissions depend on the number and mass of structures or vehicles consumed in the fire. In the 2018 Camp Fire in California, nearly 20,000 structures were consumed, which may have generated sizable emissions compared to those from natural fuels.

As no inventories of emissions from structures burned in the wildland–urban interface exist, they are not included in smoke emission models. For example, in the NEI model, urban areas consumed in wildfires are assigned a default vegetative fuel loading and EFs that likely underestimate the emissions from burning structures and vehicles. Therefore, air quality forecasts estimating fire progression into populated areas may substantially under-predict smoke concentrations.

5.5 Conclusions

Because wildland fires are a major source of gases and aerosols, a thorough understanding of fire emissions is essential for addressing societal and climatic consequences of wildland fire smoke. In recent years, a large body of laboratory and field experiments has led to significant progress in characterizing the composition of fresh smoke. More than 500 gases have been identified, and our knowledge regarding the physical characteristics, chemical composition, and optical properties of aerosols has expanded greatly. Quantifying wildland fire EFs is only the starting point for characterizing emissions.

Decision support and research require emission inventories of pollutants released into the atmosphere by wildland fires. Emission inventory methods for both predictive (e.g., smoke forecasting) and retrospective (e.g., research or air quality regulation) activities have evolved by leveraging scientific advances in smoke composition, fuels and fuel consumption, and satellite remote sensing of fire activity and effects. Several wildland fire emission inventories covering the CONUS are available to support operational forecasts and retrospective analyses.

Despite recent advances, large gaps in smoke emission science remain:

Table 5.5 Emission factors for vehicle and building materials compared with those for western wildland fuels for selected hazardous pollutants

Material	PM (g kg ⁻¹)	Total PAH ^a (g kg ⁻¹)	Dioxin PCDD ^b (µg kg ⁻¹)	Formaldehyde (g kg ⁻¹)	Benzene (g kg ⁻¹)	SO ₂ (g kg ⁻¹)	HF (g kg ⁻¹)	HCl (g kg ⁻¹)	HCN (g kg ⁻¹)	References
Vehicle						10		170	2.9	Lonnermark and Blomqvist. (2006)
Vehicle	46									Reisen (2011)
Vehicle	64	1.1	2.1	1.0	3.0	5.0		13	1.6	Lonnermark and Blomqvist. (2006)
Building	50									Reisen (2011)
Building	23	0.08		0.70	2.3					Reisen et al. (2014)
Building	69					27	120	1203	9.0	Blomqvist et al. (2003)
Building						30		300	0.3	Persson and Simonson (1998)
Furniture								313	39.5	Gann et al. (2010)
Living room	1		0.01		0.7	5		0.5	1	Blomqvist et al. (2004)
Urban average	50	0.74	1.1	0.85	2.0	15	120	160	9.1	Prichard et al. (2020)
Wildland fire	20		0.3 ^a	2	0.4	1		0.1	0.4	
Urban/wildland fire EF-ratio for western wildland fuels ^b	2.5		4.1	0.60	5.0	13		1600	23	

^a Total dioxin polychlorinated dibenzodioxins (PCDDs) for forest fuels from Gullett et al. (2008)^b A unitless ratio

- There is a significant lack of EF measurements for wildfires; however, results from recent field studies may soon address this gap in our understanding of emissions.
- Even with expanded field measurements of EFs, comprehensive emission estimates across the spectrum of relevant fire activity will require extrapolating laboratory-measured EFs to real fire conditions. A thorough evaluation of the different methods used for extrapolating laboratory EFs is needed to identify best practices and quantify uncertainties of derived EF.
- EFs and emission rates from residual smoldering combustion have received only limited research attention. This knowledge shortfall has inhibited the development of reliable models for predicting local smoke impacts from prescribed fire. Field studies characterizing emissions from residual smoldering combustion are needed to provide improved modeling tools to land managers.
- Discrepancies among emission inventories for the CONUS are significant. These discrepancies are further complicated by the natural heterogeneity of wildland systems. Comprehensive evaluation of these emission inventories is needed to quantify their errors and improve their performance across operational and research applications.
- The lack of reliable near-term (24 h) emission forecasts is an obstacle to improving forecasts of smoke impacts on air quality. New methods for predicting short-term fire growth and emissions are needed to improve air quality forecast.
- Toxic metals have been measured in wildland fire PM and may be a large source of toxic metal emissions. Because toxic metal emissions depend on fuel and soil characteristics (e.g., metal content by strata) and fire behavior, understanding how wildland fires may be a source of these hazardous pollutants must be addressed.
- There is a growing need to understand the emissions from burning structures. Only limited EFs and no emission inventories are available for evaluating potential emission impacts of burned structures on the health of wildland firefighters and nearby communities.

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