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The impact of US wildland fires on ozone and particulate matter: a comparison of measurements and CMAQ model predictions from 2008 to 2012

Joseph L. Wilkins^{A,B}, George Pouliot^A, Kristen Foley^A, Wyat Appel^A, Thomas Pierce^A

^AUS Environmental Protection Agency, Computational Exposure Division, National Exposure Research Laboratory, Research Triangle Park, NC 27711, USA.

Abstract

Wildland fire emissions are routinely estimated in the US Environmental Protection Agency's National Emissions Inventory, specifically for fine particulate matter (PM_{2.5}) and precursors to ozone (O₃); however, there is a large amount of uncertainty in this sector. We employ a brute-force zero-out sensitivity method to estimate the impact of wildland fire emissions on air quality across the contiguous US using the Community Multiscale Air Quality (CMAQ) modelling system. These simulations are designed to assess the importance of wildland fire emissions on CMAQ model performance and are not intended for regulatory assessments. CMAQ ver. 5.0.1 estimated that fires contributed 11% to the mean PM_{2.5} and less than 1% to the mean O₃ concentrations during 2008–2012. Adding fires to CMAQ increases the number of 'grid-cell days' with PM_{2.5} above 35 µg m⁻³ by a factor of 4 and the number of grid-cell days with maximum daily 8-h average O₃ above 70 ppb by 14%. Although CMAQ simulations of specific fires have improved with the latest model version (e.g. for the 2008 California wildfire episode, the correlation $r = 0.82$ with CMAQ ver. 5.0.1 *v.* $r = 0.68$ for CMAQ ver. 4.7.1), the model still exhibits a low bias at higher observed concentrations and a high bias at lower observed concentrations. Given the large impact of wildland fire emissions on simulated concentrations of elevated PM_{2.5} and O₃, improvements are recommended on how these emissions are characterised and distributed vertically in the model.

Keywords

air pollution; air quality modelling; Community Multiscale Air Quality; National Emissions inventory; wildland fire emissions

Introduction

Globally, wildland fires (prescribed and wild) burn more than 330×10^6 ha year⁻¹ (1 Mha = 104 km², 1 ha = 2.47 acres), emitting vast quantities of pollutants into the atmosphere (Giglio *et al.* 2010). It is estimated that 180 000–330 000 deaths can be attributed to the air

^BCorresponding author. wilkins.joseph@epa.gov.

Conflicts of interest

The authors declare that they have no conflicts of interest.

pollution from these fires globally (Johnston *et al.* 2012; Lelieveld *et al.* 2015). With fires now occurring more frequently and burning more intensely, the exposure of humans to fine particulate matter (PM_{2.5}) and ozone (O₃) is projected to grow (e.g. Balling *et al.* 1992; Stocks *et al.* 1998; Fried *et al.* 2004; Parry *et al.* 2007; Westerling and Bryant 2008; Mitchell *et al.* 2014; Rappold *et al.* 2011, 2017; Jaffe and Wigder 2012; Liu *et al.* 2015; Aponte *et al.* 2016). The area burned by wildland fires across the contiguous United States has expanded by nearly 50% over the past 20 years, now averaging 3 Mha year⁻¹ (Liu *et al.* 2013; National Interagency Fire Center 2016). Johnston *et al.* (2012) and Lelieveld *et al.* (2015) estimate that 55 000 deaths per year are caused by outdoor air pollution and attribute ~9% of the deaths to wildland fire smoke. Fann *et al.* (2018) (and references therein for other time periods) suggest that during the 5-year period 2008–2012 between 5200 and 8500 premature deaths and illnesses in the US were related to the exposure of air pollution from fire, with a monetised impact of ~\$450 billion to the US economy. During 2008–2012, exposure to wildland fire smoke was extensive across the US, with nearly 40% of the population living in areas where the contribution of smoke to annual levels of ambient PM_{2.5} exceeded 0.75 µg m⁻³ (Rappold *et al.* 2017).

Air quality simulation models, like the Community Multiscale Air Quality (CMAQ) modelling system (www.epa.gov/cmaq), are used by environmental decision-makers to examine the impact of air pollution on human health, and to devise strategies for reducing or mitigating the exposure of humans to harmful levels of air pollution. As wildland fires become more pervasive, there is a need to assess their impact to human health in fire-prone regions during the active fire season. Models are also useful for estimating the contribution of wildland fires to O₃ and PM_{2.5} to inform States and regional agencies for designing approaches to ensure levels of air pollution deemed safe under the National Ambient Air Quality Standards (NAAQS). If the reliability of the models can be demonstrated for simulating the air quality impacts associated with wildland fires, they could possibly assist in analysing ‘exceptional event’ demonstrations for designing State Implementation Plans (Baker *et al.* 2016).

Modelling pollution from wildland fires is difficult (Jaffe and Wigder 2012) as fires vary widely in size, rate of burning, amount and type of fuel burned, and the amount and type of chemicals that are emitted (Akagi *et al.* 2012). Baker *et al.* (2016) show numerous complexities in the ways that different fires are characterised in CMAQ; model performance seems related to fire regime, with emissions slightly overestimated in some areas (e.g. prescribed burns in the Flint Hills region of Kansas) and overestimated in other areas (e.g. the 2011 Wallow wildfire in Arizona). Other studies indicate difficulties in modelling the impact of wildland fires because of changes in radiative forcing or optical impacts caused by the smoke (Wong *et al.* 2012), the attenuation of photolysis by aerosols possibly reducing O₃ production (Jiang *et al.* 2012), the treatment of aerosol volatility^A (May *et al.* 2013; Konovalov *et al.* 2015), vertical allocation of smoke plumes (Paugam *et al.* 2016; Peterson *et al.* 2017), overestimations of simulated organic aerosols (compared with observations) in some rural areas because of biomass burning (Pye and Seinfeld 2010), and the treatment of organic aerosols as semi-volatile in some models (Baker *et al.* 2016). Owing to the variability of modelling fire pollution, these studies underscore the importance of investigating model performance for wildland fires.

Multiple researchers have looked at either biomass burning patterns and/or compared the performance of air quality models to observational data for examining the impact of wildland fires on primary and secondary pollutants. The spatial scales of these studies have ranged from the entire US (e.g. Fann *et al.* 2013; Barbero *et al.* 2015), specific regions of the US (e.g. Westerling *et al.* 2003 and Dennison *et al.* 2014 for the western US; and Waldrop *et al.* 1992 and Zhang *et al.* 2010 for the south-eastern US), to individual fire events (e.g. Baker *et al.* 2016 for the Wallow fire and Flint Hills region; and Wong *et al.* 2012 for California Outbreak event). Aircraft and specialised field measurements have been used to look at the contributions of fires to O₃ (e.g. Cai *et al.* 2016; McKeen *et al.* 2002; Baker *et al.* 2016) and PM_{2.5} (Garcia-Menendez *et al.* 2013, 2014; Konovalov *et al.* 2015; Saide *et al.* 2015), and models have shown difficulty in simulating the contribution of wildland fire to O₃ (Bytnerowicz *et al.* 2016; Wigder *et al.* 2013; Pfister *et al.* 2008) and PM_{2.5} (Forrister *et al.* 2015; May *et al.* 2015; Vakkari *et al.* 2014). In addition to regional investigations of wildland fires, studies such as van der Werf *et al.* (2010) have examined specific types of fires (e.g. peat) and trends during specific time periods (e.g. Rappold *et al.* 2017 for 2008–2012; Munoz-Alpizar *et al.* 2017 for 2013–2016). For specific fire episodes, source sensitivity methods (e.g. direct decoupled method) have recently been introduced for attributing chemical processes in the model to specific sources, allowing for a clearer connection between emissions estimates and downwind impacts from wildland fires (Cohan and Napelenok 2011; Baker *et al.* 2016; Rappold *et al.* 2017).

Our study seeks to assess the ability of the CMAQ model to simulate wildland fires over a 5-year period across the US, thus capturing a wide range of fire regimes and fire types. We define a fire regime as a region sharing general patterns within a common ecosystem, e.g. acres burned, emissions' spatial and temporal allocation, and common reoccurring patterns in a typical year. Across the US, the active fire season generally occurs between May and September for wildfires, but expands to March–October when including prescribed burns (although fires can and do occur outside of that period). Here, we examine regions across the US with different types of fires, including a mega wildfire in California, reoccurring clusters of prescribed burns in the Central Plains, a peat fire in the Southeast, and a large wildfire in the Southwest.

In addition, our study responds to Rappold *et al.* (2017) and Fann *et al.* (2018), who recommend evaluating model performance for determining the reliability of modelling systems for assessing the impact of wildland fires on human health and for identifying potential areas for model improvement. In this study, the large uncertainties in the impacts of emissions from regional- and specific-fire types are explored by comparing model results with and without fire emission inputs, referred to here as a brute-force zero-out sensitivity simulation, to determine the spatial and temporal impacts on daily emissions. Previous studies have compared the brute-force zero-out version to the standard version of CMAQ with field-study measurements in an urban area (Woody *et al.* 2016), but little evaluation is available for areas heavily influenced by biomass burning (Konovalov *et al.* 2015). The goal of our study is to estimate the impact of wildland fires to elevated levels of air pollution in the US, evaluate the performance of the modelling system for this purpose, and suggest areas in the modelling system that need improvement.

Methods

Air quality model simulation details

We use version 5.0.1 of the Community Multiscale Air Quality (CMAQ) modelling system (Byun and Schere 2006; Appel *et al.* 2013, ver. 5.0; Appel *et al.* 2017, ver. 5.1), and our simulations are identical to the ones used by Rappold *et al.* (2017) and Fann *et al.* (2018). Details on the general model configuration are summarised in Table S1 (available as Supplementary material to this paper). Information used to construct the wildland fire emissions is summarised in Table 1 and other portions of modelled emissions in Table S2. Various sources of fire data included for each inventory year in SMARTFIRE ver. 2 are outlined in Table 1. For the National Emissions Inventory (NEI) years (2008 and 2011) and non-NEI years (2009, 2010, 2012), information is aggregated into the inventory based on available data. Wildland fire emission inventories estimated each year since 2002 are available at <ftp://ftp.epa.gov/EmisInventory/fires>, accessed 16 October 2016). The wildfire emission estimates used in this study were based on the following components from the BlueSky framework: SMARTFIRE2 (Sullivan *et al.* 2008) was used to reconcile the sources of fire activity data. Raffuse *et al.* (2007; 2012) describe the SMARTFIRE2 process of reconciling fires from ICS-209 reports. Once the fire reconciliation process was complete, biomass fuel consumption was calculated using the US Forest Service's CONSUME ver. 3.0 fuel consumption model (<https://www.fs.fed.us/pnw/fera/fft/consumemodule.shtml>, accessed 16 October 2016) and the Fuel Characteristic Classification System (FCCS) fuel-loading database in the BlueSky Framework (Ottmar *et al.* 2007). Emission factors were taken from the Fire Emission Production Simulator (FEPS) model (<https://www.fs.fed.us/pnw/fera/feps>, accessed 16 October 2016).

For the analysis, we pair observation data from the Interagency Monitoring of Protected Visual Environments (IMPROVE; <http://vista.cira.colostate.edu/improve/>, accessed 16 October 2016) network, the Clean Air Status and Trends Network (CASTNet; <https://www.epa.gov/castnet>, accessed 17 June 2017) and the Environmental Protection Agency's (EPA) Air Quality System (AQS; https://aqs.epa.gov/aqsweb/airdata/download_files.html, accessed 17 June 2017) to model results in space (no spatial interpolation) and time (daily or weekly depending on the network) using the Atmospheric Model Evaluation Tool (AMET; Appel *et al.* 2011) (<https://www.epa.gov/cmaq/atmospheric-model-evaluation-tool>, accessed 17 June 2017). Whereas the number of sites available for each network can vary slightly from year to year as sites are added or removed, for the 5-year period examined here, the total number of distinct sites available for analysis is 169 for IMPROVE, 91 for CASTNet and 1049 for AQS.

Data analysis

The calculated difference between the two model runs is used to represent the contribution of wildland fire emissions to ambient PM_{2.5} levels (Fire-PM_{2.5}). We investigate the impacts on air quality from wildland fires 'per grid cell' similar to Fann *et al.* (2018) and with regard to the magnitude and frequency of days with poor air quality (daily PM_{2.5} > 35 µg m⁻³; annual PM_{2.5} > 12 µg m⁻³) similar to Rappold *et al.* (2017). Although these thresholds are comparable to levels established in the US EPA's NAAQS, the model simulations analysed

here are not designed as an attainment demonstration and should not be used for regulatory purposes.

To determine the CMAQ model performance based on fire emissions input, we generate output for three critical components: the first simulation includes wildland fires 'CMAQ_{FIRE}', the second uses a 'brute-force zero-out' of fire emissions to remove fires in the simulation 'CMAQ_{NOFIRE}', and lastly, we bin the results of 'CMAQ_{FIRE} - CMAQ_{NOFIRE}' by employing a threshold metric used in Fann *et al.* (2018) of 'daily change in PM_{2.5} of 5 µg m⁻³' as an evaluation threshold to explore performance related issues. These metrics are useful for separating resulting fire impacts between large and small fires, which were found to be sensitive to low levels of model-predicted wildland PM_{2.5} concentrations (Fann *et al.* 2018).

There may be locations and times that are 'impacted by fire' emissions in the model simulations that are still categorised as 'not fire impacted' because of the selected threshold. However, we found that changing the threshold (e.g. to 1 or 10 µg m⁻³) did not affect the overall conclusions of the evaluation presented here for small *v.* large fire model performance. We do acknowledge that epidemiological studies such as Fann *et al.* (2018) have shown a sensitivity to thresholds, and there may be times and locations not included in our analysis due to omission errors with the selected threshold of 'change in PM_{2.5} of 5 µg m⁻³'.

Model evaluation

This study identifies fire-related model performance biases during a typical fire year, regionally and for select fire episodes, identified over the US during 2008–2012. We use common statistical metrics to compare the model predicted concentrations to observed values. The 2008–2012 fire seasons were, according to the National Interagency Fire Center (NIFC) database, on average slightly below normal for wildfire activity – 2.26 Mha (5.58 × 10⁶ acres) burned per year. This period contained large wildfires (in the Southeast and Northwest US), peat fires, hurricane debris burning, and large areas of prescribed burns, all representative of typical wildland fire seasons.

For regional study, three main areas are identified: (1) the Intermountain West (IW) defined as California, Oregon, Washington, Idaho, and parts of Wyoming and Montana, (2) the Southeast US (SE) defined as North Carolina, South Carolina, Georgia, Alabama and Florida, and (3) the Southcentral US (SC) defined as Texas, Oklahoma, Arkansas, Missouri and Kansas. Because the focus of the regional analysis is on typical wildfire seasons, we removed wintertime months (November–February) and constrained the analysis to the active fire season (contiguous US). Each region's active fire season is determined based on acres burned shown in the Supplementary material (see Fig. S1–S3), for the SE and SC, prescribed fires dominate in the fall (autumn) and spring, whereas in the IW wildfires dominate during the summer.

Specific fire episodes have been selected based on suspected errors in fire emission modelling. The episodes include a large anomalous wildfire event burning over 1 × 10⁶ acres (California Episode, June 2008), an annually reoccurring large prescribed fire area (Flint

Hills, March–April 2008–2012), a smouldering peat fire (Evans Road, North Carolina, June 2008), and a medium-sized (<0.22 Mha) wildfire (Wallow fire, Arizona, May–June 2011). To assist in identifying monitoring sites likely affected by the fires, we examined historical records (e.g. the SMOG BLOG <http://alg.umbc.edu/usaq/archives/002801.html>) and archived satellite data (e.g. The National Ocean and Atmospheric Administration's Smoke Text product and Hazard Mapping System Smoke and Fire Product <http://www.ssd.noaa.gov.proxy-remote.galib.uga.edu/PS/FIRE/smoke.html>).

Results and discussion

Factors affecting modelled wildland fire impacts on air quality across the US

Using simulated air quality for the period between 2008 and 2012 over the contiguous US to help identify factors affecting model performance, we compare CMAQ_{NOFIRE}, CMAQ_{FIRE}, and model difference concentrations at the grid-cell level for mean PM_{2.5} across the 5-year period (Fig. 1), daily PM_{2.5} concentrations greater than 35 µg m⁻³ (Fig. 2), and daily PM_{2.5} concentrations greater than 35 µg m⁻³ for each individual year (Fig. 3).

The first factor affecting model performance for wildland fires is the fire prone region investigated or fire regime (e.g. terrain, year, frequency of fire cycle, fuels and ecological information). Overall, we found that CMAQ produced an expected spatial pattern of Fire-PM_{2.5} for the US, which is consistent with several other model evaluations of CMAQ (e.g. Baker *et al.* 2016, Munoz-Alpizar *et al.* 2017). Rappold *et al.* (2017) showed the IW and SE frequently exhibit 10 or more Fire-PM_{2.5} grid-cell days compared with 5 for the SC and fewer for the rest of the US (see Fig. 2). Although there are fewer wildland fire affected grid-cell days outside the IW, Fann *et al.* (2018) demonstrated that for Louisiana, Florida and Georgia it is critical for modelled wildland fire impacts to be evaluated in other areas where wildland fires are not as intense. Their study demonstrated this by relating wildland fire emissions to the economy and health, and concluded that model performance in Louisiana, Florida and Georgia is especially important in addition to the IW.

Expanding upon those studies, we add additional ecological information that could have explained some of those differences found, as the land-use and land-cover impacts are an active area of research in the modelling sector. CMAQ identifies three large spatial regional footprints (or fire regimes) that are observed for Fire-PM_{2.5}. Within each regime we identify potential fuels based on the Köppen–Geiger classification (Peel *et al.* 2007) and climate conditions:

1. IW region (wildfire dominate) we simplify this regime into two main parts. (a) The northern IW, northern California to Pacific northwest expanding to the northern Rockies; fuels are heavily forested areas containing subalpine fir, lodgepole pine and Engelmann spruce typically located at higher elevations. Climate conditions are temperate or cold, steppe, and hot to warm summers that are dry but wetter than the southern portion. Compared with the southern IW, fires typically burn larger areas and are hotter (for more details see Dennison *et al.* 2014). (b) The southern IW, southern Utah to Arizona border and below;

typical fuels contain ponderosa pine and dry Douglas-fir that are generally at lower elevation and dryer than the north.

2. SE region (small or localised fires, typically prescribed) fire regime is located from New Jersey to Mississippi (we use a subset for our SE region defined above) where the typical fuel load is mixed between hardwood of oak, hickory and pine within a southern mixed forest and wetlands. The climate in the SE has a consistent temperate climate without a dry season and hot summers.
3. SC region (a mixture of IW and SE) including area within the limits of the Colorado–New Mexico borders to the Kentucky–Tennessee borders excluding Louisiana. This fire regime contains wild and prescribed fires over fuels containing crops and tall grasslands with some mixed southern forest. Areas within the western SC domain contain climate conditions of arid, steppe and cold. The eastern portion is split into two distinct climates, Southeast SC domain is temperate, without dry season and hot summer, whereas the north-east SC domain is cold, without dry season and hot summer.

The year-to-year variation of Fire-PM_{2.5} (Fig. 3) and acres burned per year (Fig. 4 with statistics in Table 3) depict the typical yearly spatial pattern dominated by wildfires in the IW and prescribed fires in the SE and SC. The CMAQ model simulations show that the contribution of fire emissions to the US daily PM_{2.5} varies annually from 7 to 13%. Furthermore, the model indicates that fire emissions can contribute between 16 and 51% to elevated daily averages of PM_{2.5} (PM_{2.5} above 35 $\mu\text{g m}^{-3}$) depending on yearly meteorological conditions. During various fire seasons, this pattern remains consistent, apart from variations in intensity (based on weather patterns) due to sporadic large wildfire influences in the SE (2008 and 2011) or anomalously large wildfires in the IW (2008 and 2012). In years with moderate to extreme drought (2008 and 2012), wildfires can dominate the PM_{2.5} signal, increasing each grid cell by 5% on average across the domain. When averaging PM_{2.5} and O₃ annually over each grid cell (Fig. S4, S5), regardless of the presence of a large wildfire, a cluster of smaller prescribed fires or a long burning smouldering fire (e.g. Flint Hills region and the SE) is required to elevate PM_{2.5} or O₃ to unhealthy levels due to fires alone.

Somewhat unexpectedly, northern Minnesota and southern Louisiana have fire contributions of 5–7 $\mu\text{g m}^{-3}$ compared an average of 3–5 $\mu\text{g m}^{-3}$ for the fire-prone region. A potential explanation of this is that wildland fires in Minnesota burn a relatively small area when compared to the total contiguous US (less than ~100 000 ha year⁻¹ compared to 2.26 Mha year⁻¹); however, the area showing high concentrations occurs over the peatlands of northern Minnesota and the Lake of the Woods. It is likely that the high emissions from peat, coupled with low plume rise from the smouldering peat fires and the stable boundary layer created by Lake of the Woods, enhance ground-level concentrations of smoke. For southern Louisiana, it is possible that sugarcane burning, hurricane debris burning (e.g. Hurricane Gustav, 2008), satellite detection error due to sun glint error over wetlands, or hot spot detection due to proximity to oceanic boundary may be the cause of high emission estimates.

The second factor affecting model performance for wildland fires is the modelling system or setup (e.g. grid-cell size, emissions inventory and plume-rise algorithm). The validity of CMAQ results can be difficult to distinguish alone; however, Munoz-Alpizar *et al.* (2017) reported comparable and consistent results with CMAQ using a different threshold air quality model setup (e.g. using FireWork for input emissions), with the only notable difference being an 11% higher US area burned during 2008–2012 compared with 2013–2016. Comparing the CMAQ results to previous ambient monitoring studies, the model estimates that fires contribute 11% to ambient $\text{PM}_{2.5}$, which is close to the 13% reported in Zhang *et al.* (2010) and within the range of Lee *et al.* (2008) who reported between 5 and 20%. When comparing model results to observations in the SE, the model shows a high bias. Although in the SE CMAQ is biased high compared with the observations used in this study (see details in the ‘Regional analysis’ section), when comparing CMAQ to Zeng *et al.* (2008), who reported in 2002 that prescribed fires in the SE contribute $>25 \mu\text{g m}^{-3}$ (50%) increase to daily ambient $\text{PM}_{2.5}$, their model shows a lower mean concentration compared with our CMAQ model average of $\sim 14 \mu\text{g m}^{-3}$ between 2008 and 2012.

Model estimates for wildland fire (Table 2) exhibit an 11% contribution to ambient concentrations of $\text{PM}_{2.5}$ for grid-cell days in the contiguous US for 2008–2012. Wildland fires’ contribution to elevated pollution ($\text{PM}_{2.5} > 35 \mu\text{g m}^{-3}$) in the daily levels increases by a factor of 4 (275%) when compared with the no-fire simulation, whereas only a 14% increase was modelled for the maximum 8-h average $\text{O}_3 > 70$ ppb and less than 1% for annual $\text{PM}_{2.5} > 12 \mu\text{g m}^{-3}$ (Table 2). When fires are included (CMAQ_{FIRE}), the area above elevated daily levels of air quality increases by 37% (3192 km² or 0.32 Mha), with the area of elevated concentrations expanding outside of city centres (e.g. rural Georgia and Indiana) (Fig. 1b). Additionally, the contribution of fires to the CMAQ $\text{PM}_{2.5}$ mean concentration per grid cell is $0.42 \mu\text{g m}^{-3}$ (an increase of 11%) and for maximum 8-h average O_3 is 0.17 ppb (an increase of 0.4%). Average $\text{PM}_{2.5}$ is significantly higher once fires are included in the Great Lakes region, Ohio Valley, and parts of the SE and IW regions, exhibited by an average increase of $3\text{--}5 \mu\text{g m}^{-3}$ in the daily $\text{PM}_{2.5}$ concentration between the years 2008 and 2012.

Additionally, we note that although general fire-detection patterns are similar, different inventories report varying numbers of areas burned and detections for wildland fires, which could affect results (see Table 3 for NIFC and NEI comparison and Larkin *et al.* 2014 for more information). Furthermore, other aspects of evaluating model performance, such as validation methods (satellite, ground-based, other models), sparsity of observations and unknown inherent errors within modelling systems, introduce additional uncertainty.

CMAQ model performance

When considering CMAQ model performance for impacts of wildland fires compared with observations, we note here that when the air quality is below the level of these thresholds it does not mean that there are no longer negative health effects. It has been well established that the ‘absolute model predictions’ without calibration compared with the level of a threshold at observational sites cannot be used for making non-attainment designations (e.g. Fann *et al.* 2018), and therefore this study focuses purely on using a model compared with observations for the purposes of a model performance evaluation. Fig. 5 compares monthly

mean $PM_{2.5}$ concentrations for the CMAQ_{FIRE} and CMAQ_{NOFIRE} at grid cells having AQS observations (with statistics shown for all available observational pairs from all networks, in Table 4). In general, CMAQ_{FIRE} concentrations are higher than the observed mean concentrations for the months with the largest model differences. When the simulation includes fires, the root-mean-square error (RMSE) increases (RMSE of 5.22 v. 5.05) whereas the mean bias (MB) improves (MB of $-0.19 \mu g m^{-3}$ v. $-0.88 \mu g m^{-3}$). The correlation between the observations and the CMAQ_{FIRE} simulation is slightly higher than the correlation for the CMAQ_{NOFIRE} simulation (r of 0.65 v. 0.61) (Table 4). It is apparent from Fig. 5 that CMAQ overpredicts $PM_{2.5}$ during the winter (November–February) season and under-predicts during the summer (June–August), which is the peak fire season, whereas the overprediction is more evident during the main fire season (March–October). When CMAQ is run in the winter, particularly for the months of January and December, it will have a positive bias and contain a larger mean error when fires are included compared with the peak fire season. Months with large differences between the two simulations correspond to periods of high fire activity (contiguous US in Fig. 4, and regions in Fig. S1–S3). The time series of CMAQ-simulated $PM_{2.5}$ for 2008–2012 (Fig. 5) indicates that episodes related to Fire- $PM_{2.5}$ in June 2008, November 2010, March 2011 and September 2012; whereas for October 2009, May 2010, March and April 2012 are indicated as non-fire related but have episodes of elevated levels for $PM_{2.5}$. This result suggests that when fires are present and detected (thus included in the emissions inventory), the model will perform well, but when the model contains fire emissions outside fire-typical situations (e.g. winter time, long smouldering, mega fire), it tends to overestimate $PM_{2.5}$.

There are many factors that may lead to an over- or underestimation of $PM_{2.5}$ in the CMAQ model. However, an attempt is made here to outline those factors relatable solely to wildland fires. The performance may be affected by the year-to-year variation in the emission inventory (Table 1). For example, two different fire inventories for acres burned (NEI and NIFC), which are based on different inputs (e.g. NEI includes satellite detects and NIFC does not), give some indication that model results can be skewed based on the inventory used. Table 3 shows acres burned for 2008–2012, during which time the NEI was on average a factor of 2 higher than NIFC. The NEI emissions were 14% lower than the NIFC for reported wildfire acres burned, and a factor of 5 (403%) higher for prescribed acres burned. For NEI years (2008 and 2011), the NEI acres burned for wildfires is 10% higher than NIFC, whereas the prescribed fire acres burned in the NEI is a factor of 6.5 (544%) higher than NIFC. However, for non-NEI years (2009, 2010 and 2012), wildfire acres burned in the NEI is 37% lower than NIFC, whereas NEI prescribed fire acres burned is a factor of 4.2 (321%) higher than NIFC. In many air quality models, acres burned is used for multiple calculations pertaining to emissions, and this could create several propagating errors in areas where this difference is large (e.g. Evans Road peat fire).

The time-series of model and observed monthly average $PM_{2.5}$ across all observational sites shows that the model tends to underestimate $PM_{2.5}$ in summer months, even when fire emissions are included. Although some of the low bias may be due to missed or undetected fire related $PM_{2.5}$, much of the underestimation is likely unrelated to misspecification of the fire emissions.

Table S3 is provided to show additional summary statistics for CMAQ model-observed PM_{2.5} fire regimes not listed in Table 4; listed in Table S3 are the normalized mean bias, the normalized mean error, and information for each fire regime including months outside the fire season. The overall model bias goes from positive to negative when excluding 52 491 (~33%) observational pairs for the winter months (November–February), whereas the error improves (RMSE of 6.22 $\mu\text{g m}^{-3}$ compared with RMSE of 5.22 $\mu\text{g m}^{-3}$) and the correlation remains approximately the same (r of 0.65). When broken down by region, the model correlation improves during the fire seasons for each specific area (e.g. summer (June–August) for the IW has an r of 0.60 compared with the yearly r of 0.56), whereas the mean error decreases and the bias goes from positive to negative for the IW. This is contrary to the negative-to-positive switch seen in the SC and SE regions, which demonstrates an overprediction from smaller fires and underprediction from larger fires based on regions.

To better separate model bias due to errors in fire emissions from bias due to other elements of the modelling system, the daily model-observation biases were divided into days with a modelled ‘change in PM_{2.5} of 5 $\mu\text{g m}^{-3}$ ’ and days where the model indicated no significant change in PM_{2.5} based on the criteria described in the ‘Methods’ section. In Fig. 6, boxplots of the daily PM_{2.5} bias for ‘change in PM_{2.5} of 5 $\mu\text{g m}^{-3}$ ’ (referred to in the figure as Fire Event) and ‘No significant change (referred to in the figure as ‘No Fire Event’) days are binned by observed PM_{2.5} concentrations. At lower observed concentrations (<25 $\mu\text{g m}^{-3}$), CMAQ_{FIRE} is biased high compared with the observed concentrations whereas CMAQ_{NOFIRE} is unbiased to slightly negatively biased. However, at higher observed concentrations (>25 $\mu\text{g m}^{-3}$), CMAQ_{FIRE} performed much better than CMAQ_{NOFIRE}, which tended to underpredict the concentrations.

The positive model bias at lower concentrations is consistent with the findings in Rappold *et al.* (2017), which state the current methods for developing fire emissions create plumes that are too dispersive and assign too high emissions rates to small fires. Additionally, Simon *et al.* (2012) showed that, for varying species, the total PM_{2.5} can have positive or negative biases, but their results agree with our analysis in that there is a common positive bias. Furthermore, the ‘no significant change in PM_{2.5}’ categorisation is based solely on model values, such that there are days when the observations are affected by fires but the ‘change in PM_{2.5} of 5 $\mu\text{g m}^{-3}$ ’ is not captured by the model, affecting the results. Further probing of individual fires with intensive measurements could help to understand the reasons for overprediction by the model at low observed concentrations.

Regional analysis

We examine model performance for different regions of US during months of elevated burn activity as listed in Table 4. For reference, daily burn area across the US is shown in Fig. 4. We selected specific time periods for each region that represent a typical fire-year by removing data outside the main fire season and windowing out episodes that having an unusually ‘large’ (>0.22 Mha acres burned) fire signal. Across the contiguous US for the months March–October, the CMAQ_{FIRE} simulation is biased high compared with CMAQ_{NOFIRE} (MB of $-0.88 \mu\text{g m}^{-3}$ v. $-0.19 \mu\text{g m}^{-3}$). In looking at specific regions for a more constrained fire period, model bias improves with the addition of fire (SE: $-1.03 \mu\text{g m}$

$^{-3}$ v. $0.75 \mu\text{g m}^{-3}$; SC: $-1.46 \mu\text{g m}^{-3}$ v. $0.09 \mu\text{g m}^{-3}$; and, IW: $-1.81 \mu\text{g m}^{-3}$ v. $-0.34 \mu\text{g m}^{-3}$). Although the model error (RMSE) increases for each region with fires included, model correlation improves in the SE ($r = 0.62$ v. 0.67) and the IW ($r = 0.37$ v. 0.60) regions, and is largely unchanged in the SC region ($r = 0.49$ v. 0.47).

The CMAQ_{FIRE} simulation does better for the IW region, which is expected, as the model is designed to handle detectable ‘middle of the road’ fires (>100 acres). However, the model overpredicts the fire emissions, with a higher bias than the CMAQ_{NOFIRE} simulation (see Table 4). This finding is consistent with our binned analysis of PM_{2.5} for fires of that size (Fig. 6). In the SC and SE, where smaller prescribed fires dominate, there is an increase in the model error, and the bias switches from negative to positive, indicating that excess emissions are being placed in the area.

In the SE region, the model significantly underperforms when wildfires are present, which is not evident in the model performance in the IW region. When compared directly to the observations, the model underpredicts PM_{2.5} in the IW by $0.33 \mu\text{g m}^{-3}$ per grid cell, and overpredicts in the SC and SE by 0.09 and $0.74 \mu\text{g m}^{-3}$ per grid cell respectively. When compared with the overall PM_{2.5} concentrations across the US, the model generally overpredicts by $0.75 \mu\text{g m}^{-3}$ per grid cell, but underpredicts by only $0.19 \mu\text{g m}^{-3}$ during the fire season. We also note that the Louisiana sugarcane burning region and northern Minnesota peaty areas were the worst performing regions in the model. Additional observations and field studies would be helpful in these areas for future model performance evaluations. Next, we investigate how the model performs for specific fire episodes within those regions.

Specific fire episodes

CMAQ model simulations are compared with observations from the IMPROVE network sites for three specific wildfire episodes, referred to here as the California Episode, Wallow Fire and Evans Road, and an annual reoccurring set of prescribed fires referred to as Flint Hills (Fig. 7; Table 5).

A comparison of observed and CMAQ PM_{2.5} daily concentrations provides evidence that including fires in the model improve performance for individual localised fires (shown in Table 5). For wildfire regions, the bias for medium-size wildfires (0.02–0.22 Mha) in the CMAQ_{FIRE} simulation remains negative (e.g. Wallow Fire MB of $-2.21 \mu\text{g m}^{-3}$ compared with $-3.05 \mu\text{g m}^{-3}$ and Evans Road MB of $-4.20 \mu\text{g m}^{-3}$ compared with $-3.04 \mu\text{g m}^{-3}$), whereas for larger wildfires (>0.56 Mha), the model bias changes from negative to positive (e.g. California Episode MB of $5.48 \mu\text{g m}^{-3}$ compared with $-19.5 \mu\text{g m}^{-3}$). With fires included, CMAQ performed well for large wildfires, and the model results show improvements from previous CMAQ model versions (e.g. California Episode r of 0.82 compared with 0.35 ; whereas Wong *et al.* (2012) calculated r of 0.68 using CMAQ ver. 4.7.1 for the same episode), which suggests that systematic biases in CMAQ are improving (these improvements maybe independent of fires). In CMAQ, larger wildfires have a higher correlation with observations ($r = 0.82$) than smaller fires (<0.02 Mha; $r = 0.51$), whereas the correlation for medium-size wildfires (<0.22 Mha) varies based on size, type and regime. Performance for medium-size fires also appear to vary by region, as model performance

improves more for the IW region (e.g. Wallow Fire $r = 0.51$ compared with 0.09) than the SE region (e.g. Evans Road $r = 0.51$ compared with 0.41).

There are known issues in emissions from air quality models that are evident from the evaluation of certain wildfire regimes for peat fires, SE wildfires and complex terrain fires. Another non-model related issue for wildfires are fires that occur in areas with no available observations. Further examination of the Evans Road fire indicates the mean modelled underestimates of emissions from this peat fire caused an underestimate in $\text{PM}_{2.5}$ concentrations by $3\text{--}4\ \mu\text{g m}^{-3}$. A similar effect is found near the peat areas of northern Minnesota, where CMAQ modelled $\text{PM}_{2.5}$ concentrations, both with and without fires, is underestimated by $>18\ \mu\text{g m}^{-3}$ compared with observations. Peat fires typically burn well past the flaming phase and can burn fairly undetected, entering long smouldering periods, which can lead to large underpredictions in models. In the Wallow Fire, errors in the model's performance of emissions estimates are more likely related to the lack of observations of $\text{PM}_{2.5}$ and O_3 and the complex terrain not being properly represented in the model. Based on the results for the wildfire regions modelled here, we suggest model performance could benefit from improvements to the model plume-rise algorithm related to wildfires, addressing issues relating to medium-size fire treatment in the model (especially peat fires), performing additional field studies on different types of fires, and adding more observational sites for evaluation.

For prescribed fires in the Flint Hills region, CMAQ_{FIRE}'s mean bias (MB) improves from $-1.68\ \mu\text{g m}^{-3}$ to $0.06\ \mu\text{g m}^{-3}$. Correlation for $\text{PM}_{2.5}$ daily concentrations also improves when adding wildland fires ($r = 0.73$ v. 0.59). The model performance improvement for prescribed fire regions may be attributable to the inclusion of multiple sites downwind. Baker *et al.* (2016) found a large overestimation of O_3 and $\text{PM}_{2.5}$ close to the fire, but a much better performance for monitors that were further away from the fire. However, the improvement in model performance for prescribed fires may be overstated due to only the highest emission months (March and April) being included. Per the regional analysis, adding subsequent months resulted in either an increase or decrease in correlation for prescribed fire regions, depending on which fire region is considered (e.g. SC r of 0.52 for March–October compared with 0.47 for March–April; SE r of 0.65 for March–October compared with 0.67 for March–April). However, if other months of the year are included, the model mean error remains lower for the prescribed fire regions when compared with the US (RMSE of $3.80\ \mu\text{g m}^{-3}$ compared with $5.22\ \mu\text{g m}^{-3}$ for March–October and $6.22\ \mu\text{g m}^{-3}$ for January–December).

Although encouraged by better performance with CMAQ when prescribed fire emissions from the Flint Hills region are included, refinements to the characterisation of these emission could further enhance model performance. In reality, prescribed fires burn for only a few hours, whereas a diurnal profile is assigned with the inventory method. In addition, the size of these prescribed fires is poorly characterised when site-specific areal information is unavailable. Specifically, these suggestions include correcting the fire inventory classifications for small (<100 acres) prescribed v. agricultural fires, correcting the burn temporal profile (small fires can burn under 1 h, whereas emissions are spread over longer time scales –1 h to 1 day), correcting the emissions allocation (or emissions point source

placement), recalculating the plume rise algorithm for small fires (fires >100 acres dynamics act differently than larger wildfires), and limiting or supplementing missed detections in the fire inventory. Incorporating these improvements into the CMAQ modelling system would require reworking the modelling system input framework (BlueSky and SMARTFIRE) and updating the fire emissions inventories (National Emissions inventory, NIFC, etc.).

Conclusions

The importance of determining the contribution of contiguous US wildland fires to PM_{2.5} and O₃ with regards to impacts on air quality of the environment and human health has been previously highlighted (e.g. Rappold *et al.* 2011, 2017; Jaffe and Wigder 2012; Johnston *et al.* 2012; Lelieveld *et al.* 2015; Munoz-Alpizar *et al.* 2017; Fann *et al.* 2018). Determining health impacts from models is a complex issue and just one example of model use, we note here that when the air quality is below the level of these thresholds mentioned that it does not mean that there are no longer any negative health effects. Thus, this study focus is purely using model compared with observations for performance evaluation as it relates to fires' contribution to ambient levels of pollution to improve model performance. As it has been well established that the 'absolute model predictions' without calibration compared with the level of a threshold at observational sites cannot be used for making nonattainment designations (e.g. Fann *et al.* 2018).

Our study provides further evidence to support wildland fire impacts for the US, by using a brute-force zero-out method to remove non-fire related effects, showing that fires contribute 11% to the mean ambient PM_{2.5}. Furthermore, adding fires to CMAQ increases the area with mean PM_{2.5} above 12 µg m⁻³ by ~1%, the number of grid cell days with maximum 8-h daily O₃ above 70 ppb by 14%, and the number of grid-cell days with PM_{2.5} above 35 µg m⁻³ by a factor of 4. Previous studies have found that CMAQ slightly underestimates domain-wide O₃ and speciated PM_{2.5}, and in some cases, CMAQ can overestimate emissions (Simon *et al.* 2012; Baker *et al.* 2016), which agrees with our overall finding here. Our results highlight that CMAQ, when coupled with wildland fire emission estimates from SMARTFIRE2, demonstrates improved performance at elevated concentrations of PM_{2.5} and O₃, although the model is biased high at lower observed concentrations. The modelled emissions performance variation is dependent on several factors (e.g. size, type, location and length of burn), as the model performs better in areas more prone to fire activity (such as those with higher frequency) in the absence of certain other conditions (e.g. complex terrain, peat fires and long smouldering fires).

Previous studies have noted numerous improvements are needed in chemical transport models to improve the simulation of fires. These include improving the fire location and size, fuel loading, emissions, plume injection height, meteorological transport and chemical transformation (e.g. Larkin *et al.* 2014; Baker *et al.* 2016; Paugam *et al.* 2016). Furthermore, it has been previously noted that more precise and robust observational datasets are needed to improve model performance. Based on our results, we recommend a focus on treating the emission rates and plume rise from 'medium-size' fires in the range of 0.2–0.22 Mha and long-smouldering peat fires. Modelling peat fires is problematic in swampy areas like northern Minnesota and eastern North Carolina, suggesting a need to better characterise their

smouldering nature with respect to enhanced emission factors and limited plume rise. In addition to peat fires, if the flaming and smouldering phases of a fire were more clearly delineated, a plume-rise algorithm could be run based on emissions emitted during the flaming phase and smouldering emissions could be limited to lower levels of the modelling system. This could help refine the simulation of dispersion and vertical transport, because emission rates and speciation $PM_{2.5}$ profiles of flaming and smouldering emissions are quite different, thus influencing the vertical distribution and downwind transport of smoke plumes.

Other recommended improvements concern the treatment of prescribed burns. These include refining the diurnal profile to capture shorter burn intervals, better estimates and classification of fire sizes. In addition, improvement in the temporal profile of the fires burned (small fires can burn under 1 h, whereas emissions are spread over longer time scales – 1 h to 1 day), and emissions allocation (or emissions point source placement), recalculation of the plume-rise algorithm for small fires (fires <100 acres dynamics act differently than larger wildfires). For regions with prescribed fires the focus should be on correcting the fire-inventory classifications of small fires (<100 acres) and in distinguishing between prescribed and agricultural fires. For example, if a fire is not detected by satellite, have some sort of lookup table for fires reported or permits for prescribed burns. Retrospectively, one could flag days where prescribed burns are not allowed and mark all fires incorrectly placed in the database as wildland fires or other. Finally, because many prescribed burns occur over fairly small areas and in the south-eastern US often in cloudy conditions under a dense forest canopy, supplementation of missed fire detections from satellite imagery is needed.

The results from this study show that CMAQ can capture the overall spatial and temporal patterns of air pollution of wildfires across the US, as well as providing evidence that model performance improves downwind of larger fires. Implementing the changes recommended above into the CMAQ modelling system could improve model performance and increase the reliability of the model to simulate the impact of fires on past, present and future air quality and human health.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1. Community Multiscale Air Quality (CMAQ) mean $PM_{2.5}$ concentrations at 12-km resolution for 2008–2012 (a) without fires, (b) with fires, and (c) the difference between the model with fires and without.

Fig. 2. Community Multiscale Air Quality (CMAQ) simulations at 12-km resolution showing the number of days with $PM_{2.5} > 35 \mu g m^{-3}$ during 2008–2012 (a) without fires, (b) with fires, and (c) the difference between the model with fires and without.

Fig. 3. Increased annual incidence of Community Multiscale Air Quality (CMAQ)-simulated days with a wildland fire contribution to emissions to ambient $PM_{2.5}$ ($Fire-PM_{2.5}$) $> 35 \mu g m^{-3}$. Refer to Table 3 for summary model statistics. $Fire-PM_{2.5} = CMAQ_{FIRE} - CMAQ_{NOFIRE}$.

Fig. 4.

Time series of daily wildland fire acres burned from SMARTFIRE2 across the contiguous United States (2008–2012). Values are reported in Millions of hectares (1M ha = 104 km², 1 ha = 2.47 acres).

Fig. 5.

Monthly mean PM_{2.5} concentrations across the contiguous US for 2008–2012 for Community Multiscale Air Quality (CMAQ) without fire (solid blue line), CMAQ with fire (solid red line), and AQS observations (dashed grey line). Only CMAQ concentrations paired with observations are included.

Fig. 6.

Bias in CMAQ_{FIRE} daily $\text{PM}_{2.5}$ concentrations across the contiguous US for 2008–2012 as a function of paired observations. Model-observed values in each observational bin are assigned (for the evaluation of model performance for fires based on emissions from large or small fires) to either a 'Fire Event Bin' = (CMAQ_{FIRE} – CMAQ_{NOFIRE}) change in $\text{PM}_{2.5}$ > 5 $\mu\text{g m}^{-3}$ (orange) or a 'No Fire Event Bin' = (CMAQ_{FIRE} – CMAQ_{NOFIRE}) where the change is deemed non-fire related < 5 $\mu\text{g m}^{-3}$ (grey).

Fig. 7. Model bias from the Community Multiscale Air Quality (CMAQ) simulation for daily $PM_{2.5}$ concentrations with four selected fire events. Observational sites associated with each fire event are shown at the top for the California wildfire episode (black dots), Wallow fire (red dots), Flint Hills fires (green dots), and the Evans Road fire (blue dots). At the bottom, boxplots showing model-observed values statistics are binned for each CMAQ simulation,

with no fire emissions (yellow) and with fire emissions (orange). Refer to Table 5 for summary statistics.

Table 1.

Source of fire data included for each inventory year in SMARTFIRE ver. 2

Fire data sources included in SMARTFIRE ver. 2 by year	2008	2009	2010	2011	2012
Geospatial Multi-Agency Coordination (GeoMac) Perimeters				✓	✓
Forest Service Activity Tracking System				✓	
US Fish and Wildlife Service fire data				✓	
National Association of State Foresters fire data				✓	
Incident Status Summary (ICS-209) reports	✓	✓	✓	✓	✓
Hazard Mapping System (HMS) fire detects	✓	✓	✓	✓	✓
Monitoring Trends in Burn Severity (MTBS)	✓			✓	
State, Local, and Tribal Fire Activity Databases				✓	
Notes				Florida and Georgia submitted their own fire emissions	

Table 2.
Impact of fire emissions on modelled O₃ and PM_{2.5} across the contiguous US for 2008–2012

Community Multiscale Air Quality (CMAQ) simulations for particulate matter (PM_{2.5}) and ozone (O₃) with fires (CMAQ_{FIRE}) and without fires (CMAQ_{NOFIRE}). ‘*n*’ is the number of grid cell days above 35 µg m⁻³ for daily PM_{2.5} and above 70 ppb for daily maximum 8-h O₃. Total number of grid cell days for each five-year set of model simulations is $\sim 1010 \times 10^5$

Model simulation	PM _{2.5} mean (µgm ⁻³)	O ₃ mean (ppb)	PM _{2.5} >35 µgm ⁻³ (<i>n</i> × 10 ⁵)	O ₃ >70 ppb (<i>n</i> × 10 ⁵)
CMAQ _{NOFIRE}	3.58	41.16	0.96	16.2
CMAQ _{FIRE}	4.00	41.33	3.60	18.5
Percentage change	10.50	0.41	275.0	14.20

Table 3.
Summary statistics for Community Multiscale Air Quality (CMAQ) contiguous US
wildfire simulations (2008–2012)

Wildland fire contributions to CMAQ ambient fine particulate matter (Fire-PM_{2.5}) are shown as the number of grid-cell days (n) above a given threshold and for acres burned (1 Mha = 10^4 km², 1 ha = 2.47 acres). Fire-PM_{2.5} is calculated by CMAQ_{FIRE} – CMAQ_{NOFIRE} using the brute-force zero-out method to isolate the wildland fire contribution to PM_{2.5}. The area burned for each fire season (2008–2012) estimated for the National Emission Inventory (NEI) is compared with the wildfire area burn estimates from the National Interagency Fire Center (NIFC). In the NEI years (2008, 2011), additional sources of information are incorporated into fire activity data. For the non-NEI years, only a few data sources are available for reconciliation. Table 1 provides the details on the data sources available for each year. Annual wildland fire emissions of PM_{2.5} from the NEI are listed in teragrams (1 Tg = 10^9 kg). The percentage increase is the CMAQ_{FIRE} simulation relative to the CMAQ_{NOFIRE} simulation

Fire season (year)	NIFC area burned (Mha)	NIFC fires >40000 acres (n)	NEI area burned (Mha)	NEI wildland fire PM _{2.5} (Tg)	Daily fire-PM _{2.5} >35 μgm^{-3} ($n \times 10^5$)	Daily fire-PM _{2.5} >35 μgm^{-3} (percentage increase)	Fire-PM _{2.5} >12 μgm^{-3} (grid cells)	Fire-PM _{2.5} contribution >12 μgm^{-3} (percentage increase)
2008	2.90	24	7.42	2.33	1.01	51.4	1293	13.7
2009	2.22	27	5.52	0.98	0.41	35.1	137	7.3
2010	1.91	9	5.44	1.04	0.42	16.3	619	8.5
2011	4.26	41	9.17	1.82	0.29	25.3	257	10.5
2012	4.45	51	4.51	2.45	0.52	40.8	307	12.4

Table 4.
Statistics summary for Community Multiscale Air Quality (CMAQ) model-observed
PM_{2.5} fire regimes 2008–2012

Comparison of observed and CMAQ modelled PM_{2.5} concentrations for different regions of the US. The Intermountain West was dominated by wildfires (WF), and South-central and Southeast was dominated by prescribed burns (Rx). Only the CMAQ grid cells containing observations from either the AQS, IMPROVE or CASTNet networks are used in the comparison

Region	CMAQ sim	Fire season (Months)	Fire regime	Obs mean (μgm^{-3})	CMAQ mean (μgm^{-3})	Obs and CMAQ pairs (<i>n</i>)	<i>r</i>	RMSE (μgm^{-3})	MB (μgm^{-3})
Contiguous US	No fire	3–10	WF and Rx	7.45	6.56	108443	0.61	5.05	–0.88
	Fire	3–10	WF and Rx	7.45	7.26	108443	0.65	5.22	–0.19
Intermountain West	No fire	6–9	WF	5.81	4.00	21053	0.37	6.03	–1.81
	Fire	6–9	WF	5.81	5.48	21053	0.60	6.43	–0.34
Southcentral	No fire	3–4	Rx	8.88	7.42	2465	0.49	5.51	–1.46
	Fire	3–4	Rx	8.88	8.97	2465	0.47	6.52	0.09
South-east	No fire	2–4,9,10	Rx	9.06	8.03	5806	0.62	4.46	–1.03
	Fire	2–4,9,10	Rx	9.06	9.80	5806	0.67	5.48	0.75

Table 5.
Comparison of observed and Community Multiscale Air Quality (CMAQ) PM_{2.5} daily concentrations for four different fire episodes

Flints Hills primarily consists of prescribed burning (Rx) and encompasses March and April for the entire 5-year period. Concentrations from corresponding CMAQ model grid cells are paired with observed data from the AQS, IMPROVE, and CASTNet networks

Fire event	CMAQ sim	Date	Fire type	Acres burned (Mha)	Model-obs (<i>n</i>)	Obs mean (μgm^{-3})	Model mean (μgm^{-3})	<i>r</i>	RMSE(μgm^{-3})	MB (μgm^{-3})
California episode	No file	20–30 June 2008	WF	0.56	77	23.4	49	0.35	25.9	−19.5
	Fire		-	-	-	23.4	28.9	0.82	19.9	5.5
Wallow	No fire	29 May–30 June 2011	WF	0.22	66	5.81	2.76	0.09	4.29	−3.05
	Fire		-	-	-	5.81	3.60	0.51	3.43	−221
Flint Hills	No file	March–April 2008–12	Rx	0.11 ^A	248	8.29	6.61	0.59	4.39	−1.68
	Fire		-	-	-	8.29	8.35	0.73	3.80	0.06
Evans Road	No file	June 2008	WF	0.02	53	15.28	11.1	0.41	7.19	−4.20
	Fire		-	-	-	15.28	12.2	0.51	6.29	−3.04

^A Annual average area burned in Flint Hills.