

Article

Daily Fine Resolution Estimates of the Influence of Wildfires on Fine Particulate Matter in California, 2011–2020

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Abstract: Worsening wildfire seasons in recent years are reversing decadal progress on the reduction of harmful air pollutants in the US, particularly in Western states. Measurements of the contributions of wildfire smoke to ambient air pollutants, such as fine particulate matter (PM_{2.5}), at fine resolution scales would be valuable to public health research on climate vulnerable populations and compound climate risks. We estimate the influence of wildfire smoke emissions on daily PM_{2.5} at fine-resolution, 3 km, for California 2011–2020, using a geostatistical modeled ambient PM_{2.5} estimate and wildfire smoke plume data from NOAA Hazard Mapping System. Additionally, we compare this product with the US Environmental Protection Agency (EPA) daily and annual standards for PM_{2.5} exposure. Our results show wildfires significantly influence PM_{2.5} in California and nearly all exceedances of the daily US EPA PM_{2.5} standard were influenced by wildfire smoke, while annual exceedances were increasingly attributed to wildfire smoke influence in recent years. This wildfire-influenced PM_{2.5} product can be applied to public health research to better understand source-specific air pollution impacts and assess the combination of multiple climate hazard risks.

Keywords: wildfire smoke; fine particulate matter; air pollution modeling; source-specific air pollution



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1. Introduction

Decadal progress on the reductions of harmful air pollutants, such as fine particulate matter (PM_{2.5}), in the United States has been derailed by the increasing contributions from wildfire emissions in recent years [1]. In the Western United States, worsening wildfires have become the primary driver for exceedances of PM_{2.5} [2–5]. One study found that 71.3% of total PM_{2.5} is attributable to wildfires on days exceeding the US Environmental Protection Agency (EPA) regulatory standard for daily PM_{2.5} (35 µg/m³), from 2004 to 2009 [2]. Wildfire frequency and severity continues to worsen due to changes in climate and landscape management, leading to repeated record-breaking seasons in recent years. Researchers examined one such year, 2020, and showed that the contribution of wildfires to ambient air pollution exceedances was much higher in the Western US (43%) compared to the contiguous US (23%) [3].

Wildfire smoke contains a mixture of harmful pollutants, such as PM_{2.5} and volatile organic compounds, associated with adverse respiratory, cardiovascular, and cerebrovascular health outcomes [6–8]. A variety of metrics have been used to characterize wildfire smoke exposure in these studies, including estimates of ambient air pollutants during episodes of wildfire or wildfire smoke [6]. However, assessment of source-specific contributions of wildfire smoke is limited. Understanding source-specific effects of air pollutants is important to guide public health actions and policy makers. The diverse contributions to ambient air pollution often require different strategies for monitoring and management. Additionally,

source-specific emissions can have different toxicities, interactions, and drivers [9]; thus, leading to differential health effects.

An *in vitro* toxicology study shows biomass burning emissions ranked high in toxicity; it ranked third overall following diesel and gasoline engine exhaust, suggesting concentrations of these pollutants may have differential human health effects [9]. The differential source-specific impacts are further supported by a study finding wildfire-specific PM_{2.5} is up to 10 times more harmful to respiratory health than non-wildfire PM_{2.5} [10]. However, effects of wildfire PM_{2.5} relative to other sources may vary by health endpoint. For instance, asthma has a strong association with ambient PM_{2.5}; yet, there are studies on effects attributable to wildfire episodes, which do not find significant associations [11–13]. Sources of air pollution can also affect the psychological responses and willingness to reduce exposures or emissions [14]. For instance, Creer et al. found perceptions of air pollution was strongly related to whether individuals had economic dependencies on the emissions source.

Wildfires present additional complications for air quality regulations, as the source of emissions are often beyond the regional air quality jurisdiction. Traditionally, air quality standards focused on location-specific emission sources controlled by human activities [1]; and reduction of health impacts has primarily been achieved by targeting emission sources [15]. National air quality standards established by the EPA under the Clean Air Act, however, have limited applicability to control smoke emissions impacting areas far from the wildfire source. Disentangling the contributions of wildfires to ambient air pollutants may be useful for guiding regional air quality regulations. Air quality exceedances can be granted exception due to wildfires, a designation which is granted more frequently in the western US [16]. Despite regulatory lenience, the threats to public health remain and this designation does not encourage reduction of the frequency or impacts of exceptional events.

Alternatively, the focus may shift from reducing emissions at the source to mitigating public health impacts through exposure reduction. The contribution of wildfire smoke to air pollution is expected to increase due to climate change [17]. Thus, it is important to develop tools to assess wildfire-specific exposure and consider strategies for exposure reduction. Furthermore, there is growing concern relating to compound climate risks, i.e., the combination of two hazardous events in time and/or space. The fifth National Climate Assessment beckons for experts to address the evolving risks of wildfires as well as compound hazards [5,18]. To do so, researchers may use estimates of wildfire-related PM_{2.5} to assess the specific contributions of wildfire hazards to compound risks.

Methods applied to estimate the contributions of wildfire smoke to air pollution burdens have varied in the literature. Some studies adjust the modeled estimates of total PM_{2.5}, which may be derived from a variety of ground monitor networks or modeled using a geophysical or geostatistical approach [19–21]. On the other hand, one study trained a model to predict wildfire smoke PM_{2.5} directly, rather than adjusting total PM_{2.5} estimates [20]. Prior studies also differ in the study regions, timeframe, and spatial resolution of data. Nonetheless, wildfire smoke data from the National Oceanic and Atmospheric Administration's Hazard Mapping System's Smoke Product (HMS SMOKE) is commonly used to determine the influence of wildfire emissions. Our study aims to produce daily estimates of wildfire-influenced fine particulate matter for 2011–2020 at fine-resolution, 3 km, for California, to be applied in public health research. We then compare this product to other wildfire-influenced PM_{2.5} estimates available in the same time frame.

2. Materials and Methods

Using two established datasets on air pollution over California, we created a set of estimates for daily (average) fine particulate matter (PM_{2.5}) that describes the influence of wildfire on local air quality for 2011–2020.

2.1. $PM_{2.5}$ Estimates

The daily $PM_{2.5}$ exposure estimation dataset that we used in this study were originally generated from continuous spatial surfaces of daily $PM_{2.5}$ on a 3 km grid for the entire State of California from the year 2011 to 2020 using the geostatistical surfacing algorithm of Al-Hamdan et al. (2009, 2014) [22,23]. The development of this daily $PM_{2.5}$ gridded dataset for California was part of a bigger project that was funded by the National Aeronautics and Space Administration (NASA) Health and Air Quality Applied Sciences (HAQAST) Program [24,25]. This data fusion geostatistical surfacing algorithm uses environmental data from the U.S. EPA ground observation Air Quality System (AQS) database and NASA Moderate Resolution Imaging Spectroradiometer (MODIS) instrument onboard the Aqua Earth-orbiting satellite [22,23,26,27]. Use of remotely sensed data can help to fill the temporal and spatial gaps found with ground-level monitor data. This spatial surfacing algorithm estimates daily 3 km gridded $PM_{2.5}$ concentrations and it includes regression models, B-spline and Inverse Distance Weighted (IDW) smoothing models, a quality control procedure (QC) for the EPA AQS data, and a bias adjustment procedure for MODIS/Aerosol Optical Depth (AOD)-derived $PM_{2.5}$ data [22,23].

As explained in detail in previous studies [22,23], the QC procedure uses observations from surrounding sites in a non-parametric rank-order spatial analysis, while the bias adjustment procedure was developed to account for potential biases in the MODIS-derived $PM_{2.5}$ estimates due to the indirect nature of the observation and the imperfect relationship between AOD and $PM_{2.5}$. We also used the MODIS AOD data that is associated with the MODIS retrieval algorithm quality assurance flag of 3, which is designated for “Very Good” retrievals with the highest confidence levels for the available/retrieved MODIS data, which are reported only if the values are less than 5.0 [28]. Thus, our geostatistical algorithm data fusion geostatistical surfacing algorithm uses a combination of EPA AQS data and MODIS-derived data so that they would supplement each other [22,23]. Previous studies also showed that merging MODIS remote sensing data with surface observations of $PM_{2.5}$ not only provides a more complete daily representation of $PM_{2.5}$ than either dataset alone would allow, but it also reduces the errors in the $PM_{2.5}$ -estimated surfaces [22–24,26,27]. Example maps of the AQS $PM_{2.5}$ data, MODIS-derived $PM_{2.5}$ data and estimated $PM_{2.5}$ concentrations on a 3 km grid are given in other studies [22–27].

For this study, data for one date (18 May 2020) was excluded due to reading/reporting errors corrected by EPA later after the ground observation AQS data were originally obtained.

2.2. HMS Data

Information on air pollution specifically connected to wildland fires was obtained from the National Oceanic and Atmospheric Administration’s (NOAA) Hazard Mapping System’s Smoke Product (HMS SMOKE). This dataset provides smoke plume information recorded by NOAA analysts using visible satellite information (GOES) tied to fires on the Earth’s surfaces remotely detected by satellite. Plumes are assigned categorical densities based on AOD. Plumes are recorded at multiple times each day during daylight hours.

2.3. Defining Smoke Days and Expected Smoke-Free Values

We spatially intersected the centroid for each grid cell for the $PM_{2.5}$ estimates with HMS SMOKE information for the same day. The presence of plumes over a centroid at any point in the day resulted in the centroid receiving an assignment for that plume’s smoke density. For example, if a grid cell was under light, and medium smoke plumes in a single day, but not heavy smoke, it would be assigned as both light and medium for that day (light = 1, medium = 1, heavy = 0). Using the combination of $PM_{2.5}$ estimates with plume information, a data set of smoke-free observations ($PM_{2.5}$ estimates grid cells on days with no plume overhead) were obtained for the entire study window (2011–2020).

These smoke-free $PM_{2.5}$ estimates, for each grid cell and day of the year (DOY), are used as input data to a Generalized Additive Model (GAM). These methods were adapted from previous work using HMS Smoke data and coarser estimates of $PM_{2.5}$ to

predict expected smoke-free values and estimate the frequency of departures from the norm [21]. Preisler et al. used ground-based air quality monitoring data to measure $PM_{2.5}$, coupled with additional inputs for weather conditions to predict expected smoke-free values. However, the advanced geostatistical modeling of $PM_{2.5}$ at fine resolution, estimated by the NASA Data Fusion product, does not require the additional inputs for weather conditions in this analysis. All modeling is done using R Software and the Mixed GAM Computation Vehicle with Automatic Smoothness Estimation (mcgv) Package. Leap days (Feb 29, 2012, 2016, 2020) were excluded from modeling. Each DOY- and location-specific GAM is then used to predict mean smoke-free estimates (with 95% confidence intervals) for every grid cell and DOY over California. Models use a smooth spline function for DOY (degrees of freedom = 199) to account for seasonal variations.

The mean expected smoke-free $PM_{2.5}$ values are then appended to the combined HMS Smoke and $PM_{2.5}$ estimates. For any grid cell and day (2011–2020) when the $PM_{2.5}$ estimate exceeds the expected smoke-free upperbound (95%CI of the mean expected smoke-free value) and there is a smoke plume present over the grid cell, that $PM_{2.5}$ estimate is assumed to be impacted by wildfire smoke ('WFInfluenced'). The difference between the expected smoke-free mean and the $PM_{2.5}$ estimate for any 'WFInfluenced' observation is calculated to be the additional $PM_{2.5}$ for that location and day from wildfire smoke. We then assess how frequently observed values are 1.64 standard deviations above the expected and anticipated to be 5%. Departure from the norm is estimated by location, DOY, and HMS smoke plume density. The distribution of the departure from the norm is then plotted by smoke density.

We analyzed the geographic and temporal distribution of wildfire smoke influence on $PM_{2.5}$ in California at the grid level and within California Air Basins, a geographic unit established by the California Air Resources Board (CARB) for air resource management.

2.4. Sensitivity Analysis

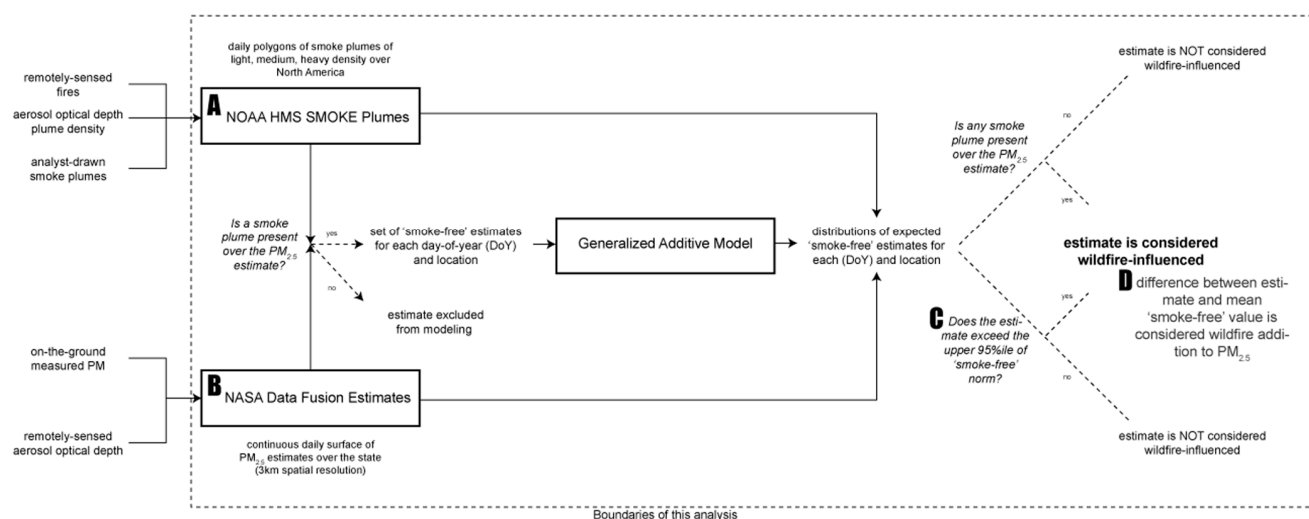
Logistic regression was used to examine the likelihood of above normal $PM_{2.5}$ values (exceedances) in the presence of each density of HMS smoke plume—low, medium, heavy, and none. We also tested the sensitivity of the WFInfluenced $PM_{2.5}$ using the US EPA's daily and annual standards for $PM_{2.5}$ exposure. We produce descriptive maps showing the number of days a gridded estimate exceeds the Primary 24-h standard, over $35 \mu g/m^3$, from 2011 to 2020, and where the annual average exceeds the Primary Annual standard, over $12 \mu g/m^3$ at the time of this study period, for each year. We differentiated between WFInfluenced estimates and smoke-free $PM_{2.5}$ values.

Additionally, WFInfluenced $PM_{2.5}$ estimates were aggregated to the county level by averaging estimates of grids within each county. Then, county level estimates were compared with the products from Childs et al. for 2011–2020. These authors developed a machine learning model to estimate wildfire-driven $PM_{2.5}$ across the contiguous US at 10 km resolution [20].

3. Results

Our approach to classifying wildfire-influenced estimates of $PM_{2.5}$ shows HMS smoke plumes influence $PM_{2.5}$ values in California (Figure 1). Examples for 23 August 2020, during a large wildfire episode, show widespread smoke with heavy smoke plumes in the Central Valley up through Northern California. The majority of above normal $PM_{2.5}$ concentrations were distributed in smoky regions, primarily covered by heavy HMS smoke plumes (Figure 1D). However, there were some areas around Los Angeles to Santa Barbara with above normal $PM_{2.5}$, but no smoke plume present. Similarly, inland Southern California had a light HMS smoke plume present but not above the normal $PM_{2.5}$ estimates on this day.

Methods Framework



August 23, 2020 Examples

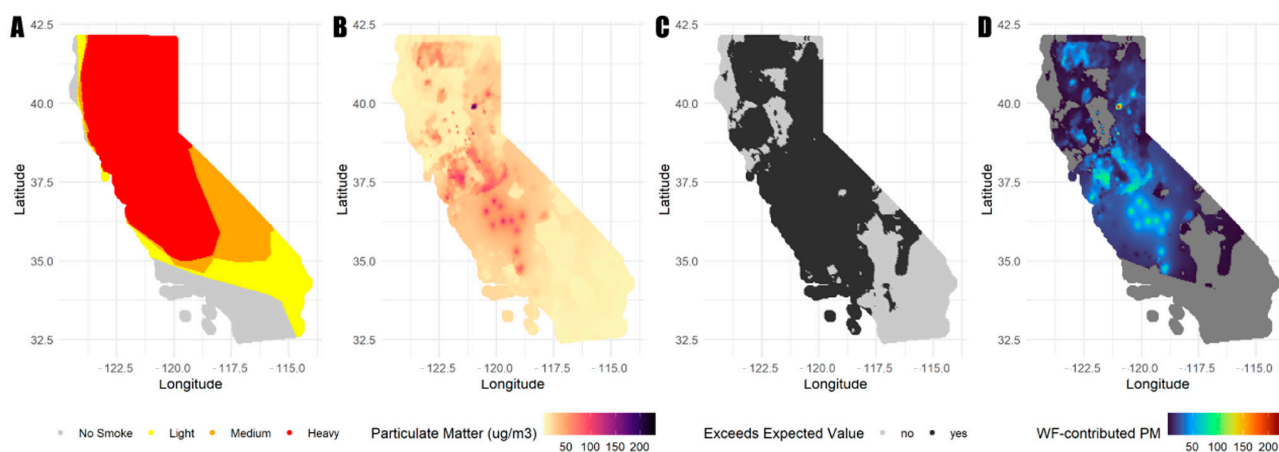


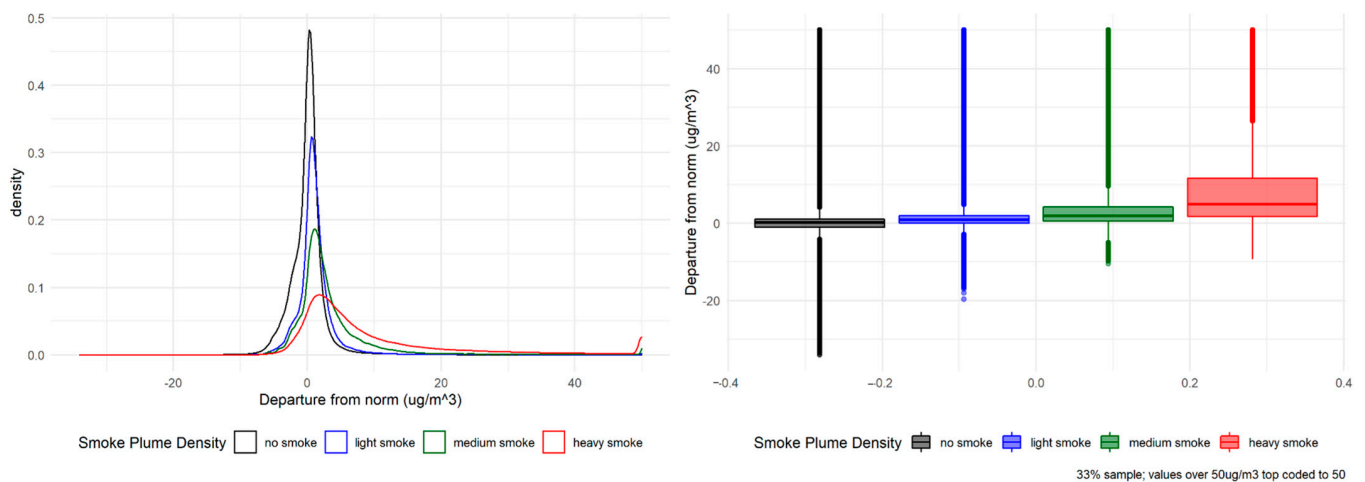
Figure 1. Methodological Framework for identifying wildfire-influenced $PM_{2.5}$ values with examples from (23 August 2020), Wildfire-influenced $PM_{2.5}$ is estimated using a combination of (A) NOAA Hazard Mapping System (HMS) smoke plume data, and (B) NASA Data Fusion estimates of $PM_{2.5}$. (C) Exceedances of expected smoke-free $PM_{2.5}$ estimates and (A) HMS smoke plume present on the same day results in (D) wildfire-influenced $PM_{2.5}$ estimates.

The contributions of wildfire smoke led to a higher average estimate of WFInfluenced $PM_{2.5}$ ($19.5 \mu\text{g}/\text{m}^3$) compared to the average ambient $PM_{2.5}$ estimates ($10.2 \mu\text{g}/\text{m}^3$) for the same period, 2011–2020 (Table 1). Density of wildfire smoke plumes affected the concentration of above normal $PM_{2.5}$ observed as well. The average above normal $PM_{2.5}$ concentrations were highest for days with heavy smoke ($25 \mu\text{g}/\text{m}^3$), and lowest for days with light smoke ($15.2 \mu\text{g}/\text{m}^3$). HMS smoke was shown to influence $PM_{2.5}$ values in plots of the distribution of the residuals (departures from the norm). Days with heavy, medium, and light smoke plumes each showed a heavier tail distribution of increasing $PM_{2.5}$ with plume density (Figure 2).

Table 1. Summary statistics of the ambient PM_{2.5}, background PM_{2.5}, and WF-PM_{2.5} data.

Number of Observations *						
	Normal PM Value		Above Normal PM Value		Total	
Smoke	#	Row %	#	Row %	#	Col %
no smoke	108,675,050	96.8%	3,634,335	3.2%	112,309,385	91.7%
light smoke	5,448,265	83.8%	1,050,082	16.2%	6,498,347	5.3%
medium smoke	1,202,713	60.6%	781,708	39.4%	1,984,421	1.6%
heavy smoke	535,571	32.5%	1,110,822	67.5%	1,646,393	1.3%
any smoke	7,186,549	70.9%	2,942,612	29.1%	10,129,161	8.3%
All	115,861,599	94.6%	6,576,947	5.4%	122,438,546	
Average PM Values *						
	Normal PM Value		Above Normal PM Value		Total	
Smoke	Average PM (Range)		Average PM (Range)		Average PM (Range)	
no smoke	9.6 (0, 36.4)		18.2 (9.047, 318)		9.9 (0, 318)	
light smoke	10.2 (0, 24)		15.2 (9, 557)		11.0 (0, 557)	
medium smoke	10.3 (0, 19.5)		17.5 (9.7, 409.7)		13.1 (0, 409.7)	
heavy smoke	10.4 (0, 21.1)		25 (9.6, 824.1)		20.2 (0, 824.1)	
any smoke	10.2 (0, 24)		19.5 (9, 824.1)		12.9 (0, 824.1)	
All	9.7 (0, 36.4)		18.8 (9, 824.1)		10.2 (0, 824.1)	

* Data from 18 May 2020 were excluded due to errors corrected by EPA after data were collected.

**Figure 2.** Distribution of the residuals (departures from the norm) for PM_{2.5} by HMS smoke plume density.

The odds of a PM_{2.5} estimate being beyond the expected smoke-free value were greatly increased in the presence of smoke. The odds of an estimate being above normal also increased as the density of the smoke plume was greater. Locations and days with light smoke plumes present were nearly six times more likely (OR = 5.8; CI: 5.7, 5.9) to be beyond the 95th percentile of expected smoke-free PM_{2.5} values. Estimates under medium (OR = 19.2; CI: 18.8, 19.6) and heavy (OR = 61.3; CI: 59.9, 62.8) smoke plumes were even more likely to be above normal and considered WF-influenced.

We also show substantial variability in the distribution of WFInfluenced PM_{2.5} across California as well as over the years, 2011–2020, and months. Concentrations of WFInfluenced PM_{2.5} were highest in more recent years, 2018 and 2020. We show Northern California was consistently impacted by wildfire smoke over the ten years, and Central Valley was burdened by the highest concentrations of WFInfluenced PM_{2.5} in 2020. Figure 3

shows wildfire smoke influenced spikes of $PM_{2.5}$ concentrations, primarily across Northern California air basins, from 2011 to 2020. Southern California regions show lesser influence of wildfire smoke, although 2020 was an impactful year of wildfires statewide.

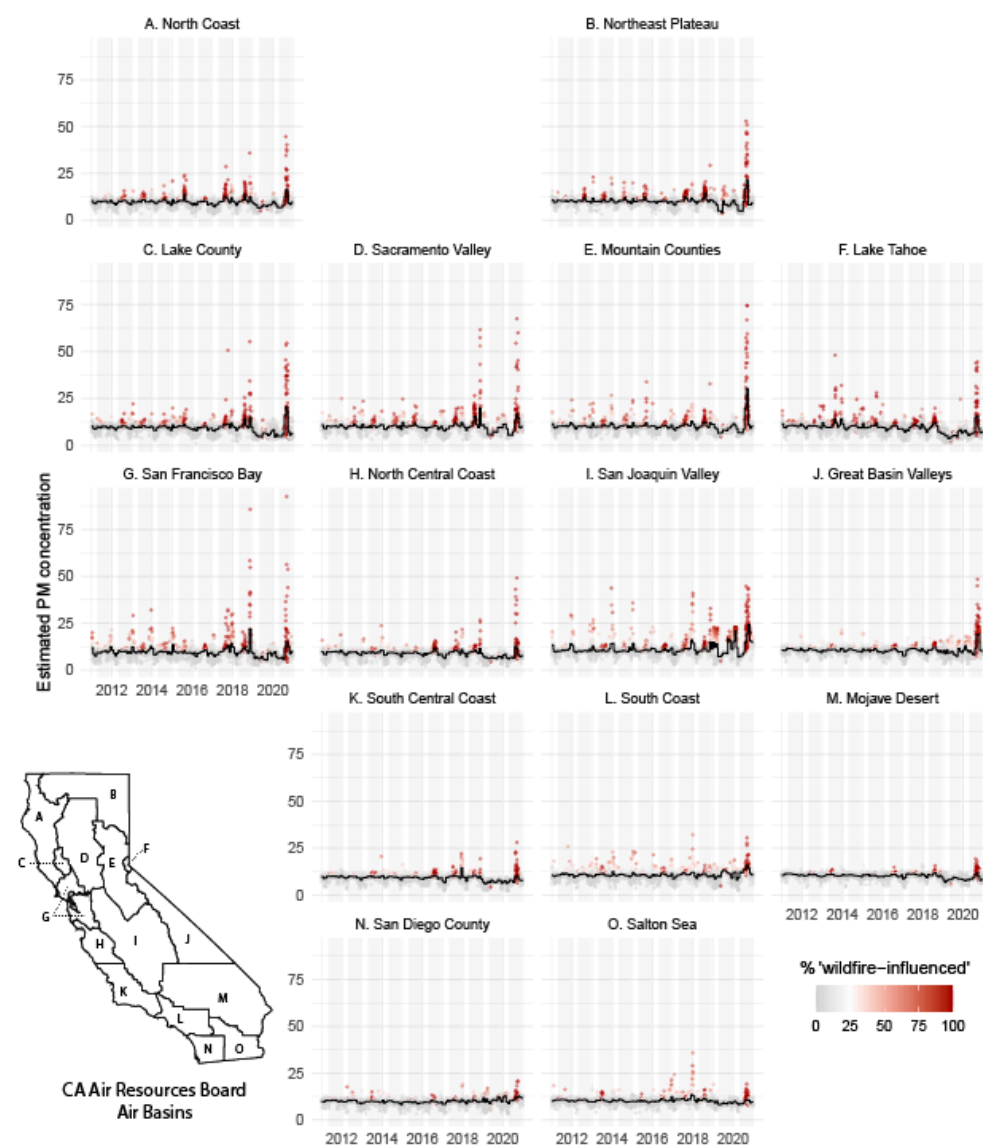


Figure 3. The line shows monthly averages of daily fine particulate matter ($PM_{2.5}$; $\mu g/m^3$) for California Air Basins (A–O), 2011–2020. The vertical gray bands show wildfire months, May–November. Points represent daily air basin averages of $PM_{2.5}$; the color corresponds to the percent of daily observations within the air basin influenced by wildfire smoke, determined by the presence of NOAA Hazard Mapping System (HMS) smoke plumes and exceedance of smoke-free expected values. The map shows the corresponding location of each air basin.

Aside from spikes due to wildfires, estimates of total $PM_{2.5}$ decreased in 2019 and 2020, particularly in the Lake County air basin (Figure 3C). We crosschecked EPA/AQS monitor data and found all monitors in California had lower values of $PM_{2.5}$ (the average of all monitors' measurements in California in 2019 was $7.61 \mu g/m^3$, compared to $9\text{--}12 \mu g/m^3$ in other years). Lake County may be more dramatically impacted by low monitor values because the only available data is from a 6-day monitor. While the modeled $PM_{2.5}$ estimates reflect this decrease, the modeling is supplemented with satellite data, and we do observe large impacts due to wildfires for these years as well.

Over 50% of $PM_{2.5}$ estimates were considered wildfire-influenced at the peak of the 2020 wildfire season for each air basin, with nearly 100% wildfire-influenced estimates in many Northern California air basins (Figure 4). We also show wildfire seasons are most impactful to $PM_{2.5}$ from July to September (Figure 4). However, there is minimal influence of wildfire smoke during wintertime except in the San Joaquin Valley Air Basin, which shows a large influence of wildfires during winter months in more recent years.

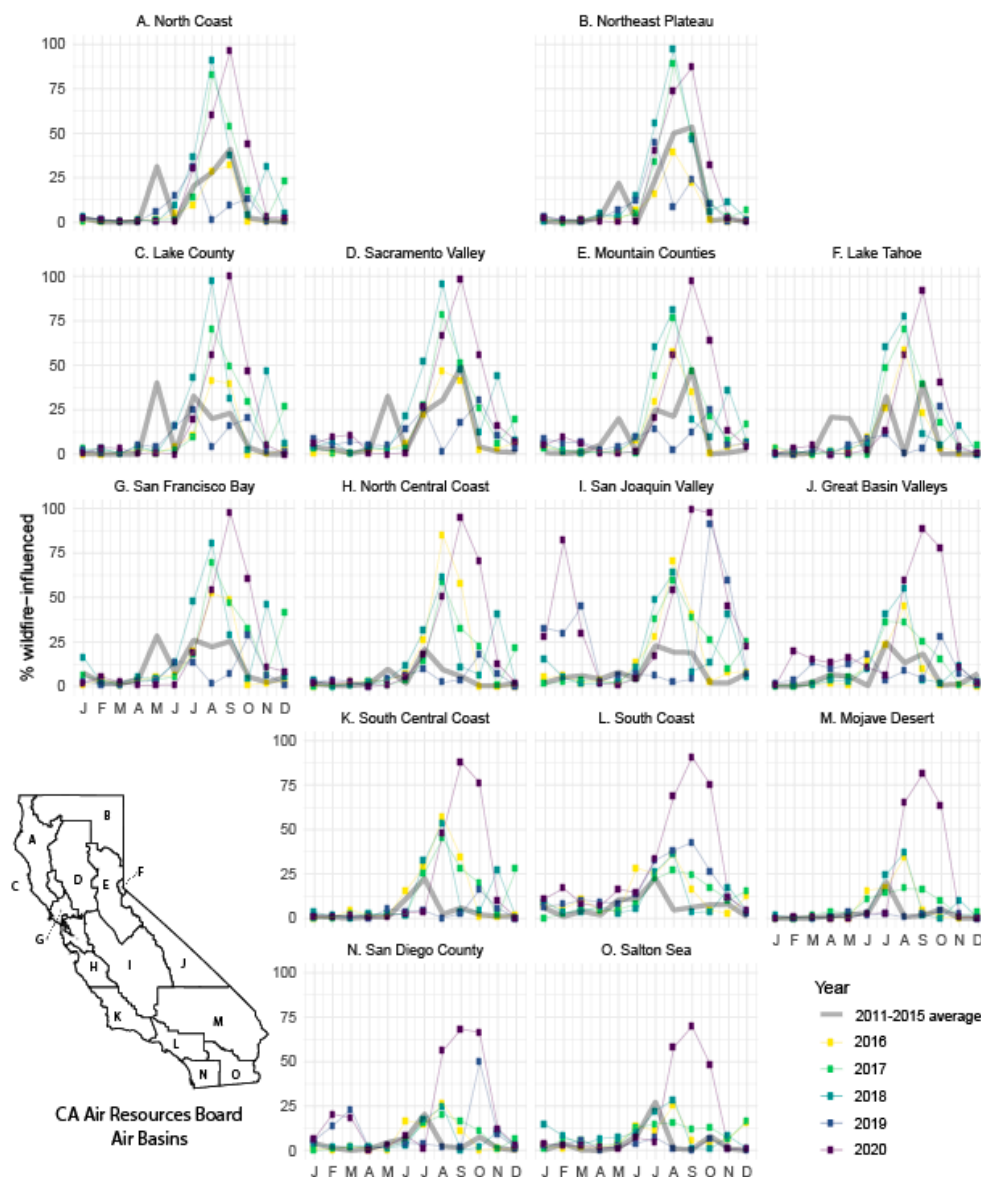


Figure 4. The percent of $PM_{2.5}$ observations influenced by wildfire smoke within California Air Basins (A–O) by month for each year, 2016–2020, and the average over 2011–2015. The map shows the corresponding location of each air basin.

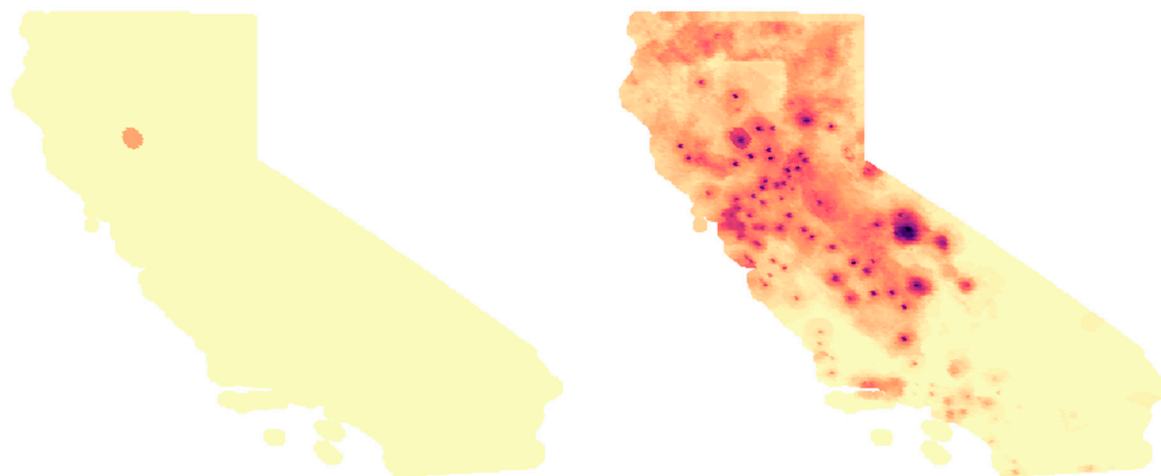
Daily exceedances of the US EPA 24-h standard for $PM_{2.5}$ ($35 \mu\text{g}/\text{m}^3$) at the grid level were nearly all influenced by wildfire smoke (Figure 5). Smoke-free $PM_{2.5}$ above the daily standard was limited to a small region in Northern California, and the highest number of days a grid exceeded the daily standard without wildfire smoke was 9 days. However, exceedances of the daily standard by WFIInfluenced $PM_{2.5}$ shows some grid cells experienced more than 50 days above the standard, with an average across the state of 6.42 days over the standard. Wildfire smoke influenced exceedances were primarily distributed through Northern and Central California.

Assessment of Primary 24-hour Standard for PM_{2.5}

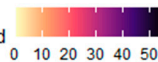
35.0 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$)

days over standard (smoke-free)

days over standard (wildfire)

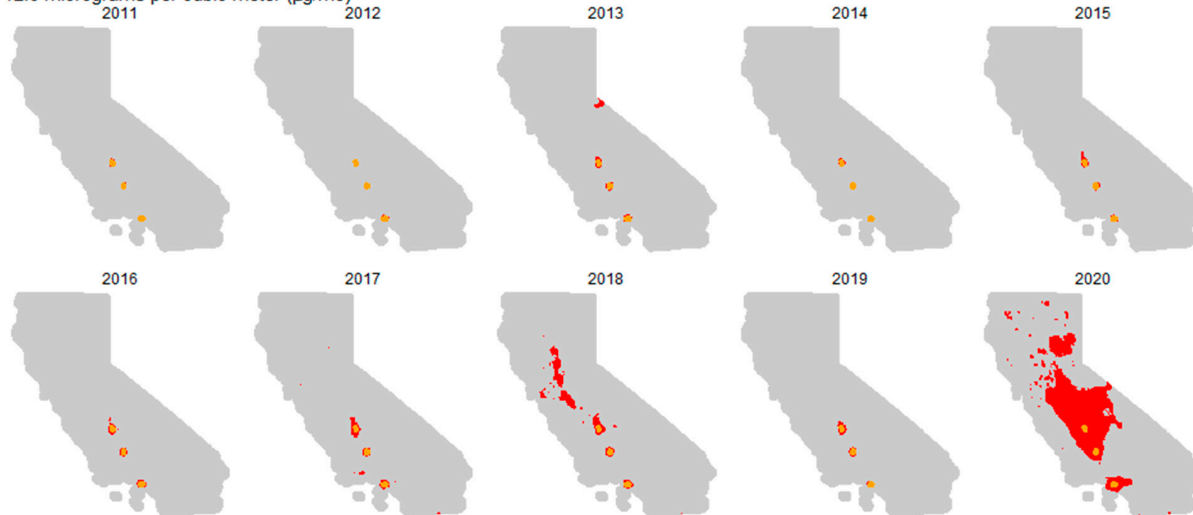


Days exceeding the Primary 24-hour PM_{2.5} Standard



Assessment of Primary Annual Standard for PM_{2.5}

12.0 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$)



Primary Annual PM_{2.5} Standard • fails standard due to WF smoke • fails standard even without WF Smoke • meets standard despite WF smoke

Figure 5. Comparison of smoke-free and wildfire influenced PM_{2.5} estimates to US EPA's 24 h (top) and annual (bottom) PM_{2.5} Standards.

Similarly, we show exceedances of the annual standard for PM_{2.5} ($12 \mu\text{g}/\text{m}^3$) from 2011–2020 (Figure 5). Wildfire smoke had minimal to no influence on the exceedance of annual PM_{2.5} standards earlier in the study period. However, in recent years, particularly 2018 and 2020, wildfire smoke had a bigger impact on annual PM_{2.5} exceedances across the state. Across all years, three regions consistently exceeded the annual standard without wildfire smoke influence. These hot spots may be influenced by other emission sources, such as power plants and traffic-related air pollution, which were not included in this analysis.

4. Discussion

Wildfire smoke has meaningfully contributed to concentrations of PM_{2.5} in California, even driving some regions beyond the daily and annual regulatory standards for this pollutant. Central and Northern California exceeded these standards more frequently

in recent years due to the increasing contributions of wildfires. Other studies, similarly, emphasize the role of wildfires in $PM_{2.5}$ exceedances across the Western US [1–4,21]. As progress is being made to reduce harmful air pollutants, our study shows record-breaking wildfire seasons are worsening adherence to $PM_{2.5}$ regulatory standards.

Our approach to classifying smoke-free and WFIInfluenced estimates of $PM_{2.5}$ is adapted from Preisler et al., who study the impact of wildfire smoke on site-specific ground monitored $PM_{2.5}$ values in the Sierra Nevadas. In contrast, we examined all of California with finer-resolution estimates of $PM_{2.5}$. We show that fine-resolution, 3 km, estimates of $PM_{2.5}$ are effective for detecting impacts of wildfires on regulatory compliance, providing a granular view on the role of wildfire smoke across the state. We observed exceedances of the daily standard ($35 \mu\text{g}/\text{m}^3$) across Northern and Central California from 2011–2020. Preisler et al. found exceedances of the daily National Ambient Air Quality Standards (NAAQS) were limited to a few sites in the Sierra Nevadas and only a few of the study years, primarily in 2008. In contrast, we studied a later period (2007 to 2013 in Preisler et al., and 2011–2020 in our study). We show more recent years, 2018 and 2020, had the largest impact of wildfires on exceedances of the annual standard ($12 \mu\text{g}/\text{m}^3$ at the time of this study period). Worsening wildfires influenced by climate change and landscape management decisions are likely factors in the larger impacts of wildfires on compliance in recent years.

Similar to other studies, we show that wildfire smoke plumes can influence large increases of $PM_{2.5}$ values in California [19–21], and the relationship is dynamic with the density of the HMS-detected smoke plumes [21]. In our study and others, HMS data is an effective tool to demonstrate the impact of wildfires on $PM_{2.5}$ values [19–21]. These results are also consistent with the expected $PM_{2.5}$ concentrations of HMS smoke plume densities. Light, medium, and heavy density plumes correspond to 0–10, 10–21, and 22+ $\mu\text{g}/\text{m}^3$, respectively [29]. Our results show average WFIInfluenced $PM_{2.5}$ falling similarly within these ranges for medium and heavy smoke, however, concentrations linked to light smoke plumes are higher than the expected HMS plume density.

Other studies have used alternative approaches to define the contribution of wildfire smoke to concentrations of $PM_{2.5}$ [19–21]. For instance, Childs et al. modeled wildfire-specific $PM_{2.5}$, similarly using HMS data to determine the influence of wildfires but also applying speciated $PM_{2.5}$ data to confirm the smoke source [20]. Additionally, the authors constructed a model to predict smoke $PM_{2.5}$ directly, rather than adjusting a total $PM_{2.5}$ estimate for the expected contribution of smoke. Comparing estimates for 2011–2020 at the county level, we find similar temporal patterns; however, the smoke $PM_{2.5}$ estimates from Childs et al. are consistently higher than our WFIInfluenced estimates. Both datasets use HMS data to identify wildfire contributions, which may explain the similarities in data over time, while differences may stem from our approach to estimate the influence on $PM_{2.5}$ using a total $PM_{2.5}$ estimate and adjusting for expected smoke-free values. Importantly, both studies show wildfire smoke greatly adds to the burden of $PM_{2.5}$ in California.

We utilized a fine-resolution, 3 km, estimate of $PM_{2.5}$ for California; however, states across the Western US face a growing threat of wildfires. Childs et al. show wildfire smoke $PM_{2.5}$ at coarser resolution, 10-km, has increased across much of the contiguous US, and primarily in Western states [20]. Therefore, estimation of wildfire-related $PM_{2.5}$ at fine-resolution across broader geographies and time frames would provide a fuller picture on the role of wildfires on air pollution in the US.

Estimating the influence of wildfire smoke on air pollutants at fine resolution can also improve public health assessments of wildfire emissions and accurate analysis of wildfire smoke exposures across the diverse populations within California. Estimates of wildfire related $PM_{2.5}$ can be used to identify modifiable risks which predict exposure to wildfire smoke. Thus, identifying opportunities to improve social and place-based conditions for exposure risk mitigation. Amidst growing concern for compound climate hazards, it is also essential to have hazard-specific measures to estimate the impacts of wildfire smoke in combination with other climate-related public health threats [18]. Importantly,

a better understanding of the wildfire influence on $PM_{2.5}$ can guide future development, particularly in Wildland Urban Interfaces (WUI), in a smart, climate-conscious, and risk-reductive approach. As wildfires worsen due to climate change, their contribution to overall air pollution is expected to increase. Studies suggest wildfire related air pollutants contain differential toxicities compared to other emission sources. Aguilera et al. show higher risk of respiratory hospitalization for wildfire related $PM_{2.5}$ compared to non-wildfire sources of $PM_{2.5}$ [10]. Therefore, it may also be important to consider applications for a wildfire specific air quality guideline to tailor risk communication for public health.

Fine tuning estimates of wildfire-related air pollution and understanding the factors which affect contributions of wildfire smoke to concentrations of harmful air pollutants, such as $PM_{2.5}$, will help to build better tools to forecast wildfire smoke and anticipated health risks. It is important to consider factors mediating the relationship between wildfire smoke and concentrations of $PM_{2.5}$ posing a threat to public health, such as climate conditions, fuel and ignition factors, and proximity to wildfires. The mobility of smoke plumes can impact air pollution distant from fires, complicating regional-based regulatory capabilities; thus, it is important to consider the role of transboundary smoke on air pollution and the spatial extent between the influence of wildfires on air pollution and proximity to fire source. Additionally, Santa Ana Winds (SAWs), strong wind events that have led to raging wildfires, also influence transport of wildfire smoke and related $PM_{2.5}$ [30]. Aguilera et al. (2020) show SAWs in Southern California during periods of wildfire smoke can have polluting effects, driving $PM_{2.5}$ from inland fires toward highly populated coastal regions. Incorporating data on SAWs, or fuel and ignition factors, such as lightning strikes, can enhance our ability to predict the impacts that wildfire smoke may have on population exposures to harmful air pollutants.

This study has some limitations. While our results show HMS smoke categories influence above normal $PM_{2.5}$, there was substantial variability among $PM_{2.5}$ concentrations within levels of smoke and no smoke. Other studies show that HMS smoke plume density does not always correspond to the same patterns with $PM_{2.5}$ concentrations [31]. It is likely that concentrations for no smoke and light smoke are associated with a large range of estimates because they capture larger geographic regions, even with a mutually exclusive assignment of grid days. Additionally, modeled total $PM_{2.5}$ estimates are not optimized for assessing the contribution of smoke to $PM_{2.5}$ concentrations. Assessing the influence of wildfires post-hoc with the HMS data allows for an efficient use of an existing fine-resolution gridded daily $PM_{2.5}$ product. However, the inputs of the total $PM_{2.5}$ model were not constructed to directly predict wildfire-related conditions, such as distance to fire. Additionally, on 7 February 2024, EPA lowered the annual standard for $PM_{2.5}$ from 12 to 9 $\mu g/m^3$ [32]. We use the standard set during the time of our analysis (12 $\mu g/m^3$), which reflects the regulatory guidelines during the study period. However, this may underestimate the number of exceedances by the new annual standard.

5. Conclusions

The influence of wildfire emissions on harmful $PM_{2.5}$ concentrations has become more substantial in recent years as climate change worsens wildfire events. Adherence to regulatory standards is complicated by the transboundary nature of wildfire smoke. Thus, tools to evaluate wildfire-related $PM_{2.5}$ are necessary for public health actions, including assessments of compound climate risks and development of wildfire smoke advisories or forecasting tools. Epidemiologic studies can be advantageous for measures like the one provided here to better understand source-specific risks and improve mitigation strategies for vulnerable communities, tailored to the hazard type.

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