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# Impacts of fire smoke plumes on regional air quality, 2006-2013

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## Abstract

Increases in the severity and frequency of large fires necessitate improved understanding of the influence of smoke on air quality and public health. The objective of this study is to estimate the effect of smoke from fires across the continental U.S. on regional air quality over an extended period of time. We use 2006-2013 data on ozone ($O_3$), fine particulate matter ($PM_{2.5}$), and $PM_{2.5}$ constituents from environmental monitoring sites to characterize regional air quality and satellite imagery data to identify plumes. Unhealthy levels of $O_3$ and $PM_{2.5}$ were respectively 3.3 and 2.5 times more likely to occur on plume days than on clear days. With a two-stage approach, we estimated the effect of plumes on pollutants, controlling for season, temperature and within-site and between-site variability. Plumes were associated with an average increase of 2.6 ppb (2.5, 2.7) in $O_3$ and 2.9 μg/m$^3$ (2.8, 3.0) in $PM_{2.5}$ nationwide, but the magnitude of effects varied by location. The largest impacts were observed across the southeast. High impacts on $O_3$ were also observed in densely populated urban areas at large distance from the fires throughout the southeast. Fire smoke substantially affects regional air quality and accounts for a disproportionate number of unhealthy days.

### Keywords

Fire Smoke; Air Quality; AQI; HMS

## INTRODUCTION

Exposure to particles and gasses found in wildfire smoke are linked to adverse health outcomes, ranging from worsening of health symptoms, to respiratory and cardiovascular hospitalizations and even mortality (1-6). Since the 1970's, the number of large wildfires (1000+ acres, ~400+ he) in the U.S. has doubled, while the number of very large wildfires

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(10,000+ acres, ~4,000+he) has increased fivefold (7). These trends are exacerbated by prolonged droughts, increasing spring and summer temperatures, earlier snowmelt, population growth, and land-use practices (8-10). Wildfire smoke plumes are transported long distances, degrading air quality as well as contributing to public health burdens. However, the impact of long-range transport of plumes on air quality is not characterized on the national scale and over an extended period of time. Trends in recent large wildfire activities necessitate improved understanding about the impact of smoke plumes on air quality to facilitate the development of health risk communication tools.

In this manuscript, we examine the utility of the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) to characterize the impact of wildfire smoke plumes on regional air quality over an eight-year period, 2006-2013. We use the HMS to determine geographical extent of smoke plumes, and concentrations of ozone ($O_3$), fine particulate matter ($PM_{2.5}$), and species of $PM_{2.5}$ measured at monitoring sites across the continental U.S to characterize regional air quality. HMS smoke plumes are drawn daily using data from multiple environmental satellites and are one of the few available tools used to determine regions impacted by smoke in real time across the U.S. We summarize the frequency of smoke plumes in the U.S., assess plume impacts on the Air Quality Index (AQI), and quantify the average effect of HMS smoke plumes on regional air pollution.

We estimate absolute and relative change in air pollution concentrations with a two-stage approach that takes into account both the spatially-correlated nature of smoke plumes and monitoring data. In the first stage, we estimate a monitor-specific plume day effect, quantifying the change in pollutant concentrations on days impacted by smoke plumes while accounting for confounding effects of season and temperature. In the second stage, we combine monitor-specific plume day effects with a spatial hierarchical model and estimate a pooled, nationwide average effect (11-13). The results of this analysis include site-by-site and overall estimates of the change in concentrations for $O_3$, $PM_{2.5}$ and the constituents of $PM_{2.5,}$ organic and elemental carbon (OC and EC), as well as a characterization of the smoke impacts on the number of unhealthy air quality days at each monitoring site in the study.

## DATA & METHODS

### Smoke Plume Data

We obtained shape files of smoke plumes that define the geographic extent of smoke from the NOAA Hazard Mapping System (HMS). The HMS incorporates data from seven NOAA and NASA environmental satellites and indicates the extent of smoke as seen by animated visible band satellite imagery. Nearly all of the smoke plumes in this study were detected and generated using the two NOAA Geostationary Operational Environmental Satellites (GOES), GOES-East and GOES-West.

### Air Pollution Data

We obtain $O_3$, total $PM_{2.5}$ and $PM_{2.5}$ constituent measurements for 2006 to 2013 from the U.S. Environmental Protection Agency's (EPA) Air Quality System database. We use daily average 8-hour $O_3$ measurements, daily average concentrations of $PM_{2.5}$ measured by Federal Reference Method (FRM, $PM_{2.5}^{FRM}$) and daily average of $PM_{2.5}$ species from the Interagency Monitoring of PROtected Visual Environments (IMPROVE, $PM_{2.5}^{IMP}$) network (14,15). The species of $PM_{2.5}$ included sulfate, nitrate, potassium, mercury, elemental carbon (EC) and organic carbon (OC). In this study, we only consider EC and OC. Ozone concentrations were measured daily, while total $PM_{2.5}^{FRM}$, $PM_{2.5}^{IMP}$ and speciated $PM_{2.5}^{IMP}$ readings are typically collected every third or sixth day. We did not include gases associated with wildfires (carbon monoxide and carbon dioxide) due to the sparseness of these monitoring networks. We used daily temperature recorded at the nearest NOAA stations within 50 km of the $O_3$ and $PM_{2.5}^{FRM}$ monitoring sites (16,17). For IMPROVE sites, we used mean daily temperature recorded at the monitoring sites.

We denote ‘plume days’ as days on which visible smoke plumes are detected in the vertical column above a monitoring site. The geographical distribution of environmental monitors and HMS smoke plumes on June 14th, 2008 is displayed in Figure 1. Multiple smoke plumes observed by geostationary and orbiting satellites on June 14th, 2008 are overlaid in gray-shaded polygons with darker regions implying multiple plumes at the same locations.

## Air Quality Index

To quantify the impact of smoke plume days on unhealthy air quality, we used Air Quality Index (AQI) values for $O_3$ and $PM_{2.5}^{FRM}$. AQI is a public health tool published daily by the EPA to inform the public about air quality and associated health risks (18). For each pollutant, AQI classifies air quality into one of six health risk categories (“Good,” “Moderate,” “Unhealthy for Sensitive Groups,” “Unhealthy,” “Very Unhealthy,” and “Hazardous”) and codes each with a distinct color (green, yellow, orange, red, purple, and maroon). For $O_3$, the AQI values consistent with the 2008 $O_3$ standard (https://www.epa.gov/criteria-air-pollutants/naaqs-table) were downloaded with the monitoring data. AQI values for daily $PM_{2.5}^{FRM}$ were calculated from the data (19). We did not identify any Hazardous “Maroon” days. We summarize the percent of days with smoke-plumes for each AQI category as well as the odds ratio of each color code observed on smoke-plume days versus no-smoke-plume days in Table 1.

## Methods

We examined the impact of smoke on regional air pollution with a two-stage analysis for each pollutant ($O_3$, $PM_{2.5}^{FRM}$, $PM_{2.5}^{IMP}$, EC, OC). In the first stage, we estimated the plume effect on pollutant concentrations at each monitoring site in the study separately and defined standard errors at each site. In the second stage, site-specific estimates are pooled to estimate an overall plume effect, taking spatial variability into account (11-13).

In the first stage, we use a generalized additive model to estimate a plume effect at each site, accounting for seasonality and temperature,

$$Y_{s,t} = \alpha_s + \beta_s plume_{s,t} + h_s(t) + g_s(T_t) + \epsilon_{s,t}. \quad (1)$$

The response, $Y_{s,t}$, is daily air pollutant concentrations at a monitoring site $s$ on day $t$. The intercept term, $\alpha_s$, denotes background pollutant concentrations at site $s$. The variable $plume_{s,t}$ is an indicator of HMS-detected smoke plumes in the vertical column of monitor $s$ on day $t$. The $plume_{s,t}$ regression coefficient or 'plume effect', $\beta_s$, is the expected change in pollutant concentration at site $s$ on days with plumes, adjusted for seasonality and meteorological conditions. Seasonal trends were modeled with the smooth function, $h$, using natural splines with four degrees of freedom (df) per year or 32 df in total. The effects of daily temperature ($T_t$) were accounted for with the smooth function, $g$, using natural splines with two df. We compared several choices and found that two df minimized BIC (Swartz 1978). We assumed the errors, $\epsilon_{s,t}$, are normally distributed with zero mean and a constant variance for each site.

The first stage analysis therefore provides us with the site-specific estimate of the plume effect, $\hat{\beta}_s$ , and associated standard errors, $\nu_s$. Controlling for seasonality and temperature in this stage ensures that the effect of plume presence is not confounded with the (smoothly varying) seasonal effect or any nonlinear changes due to effects of temperature, which are typically associated with high $O_3$ values.

In the second stage, we pool site-specific plume effects to estimate the overall effect, $\mu$, via a 2-level hierarchical model:

$$\hat{\beta}_s = \tilde{\beta}_s + \nu_s e_s,$$
$$\tilde{\beta}_s = \mu + \varepsilon_s.$$

In level 1, we have stage one estimates of the plume effect, $\hat{\beta}_s$ , as the response, which are centered around true but latent plume effect, $\tilde{\beta}_s$ , with error $\nu_s e_s$, where $\nu_s$ are standard errors of the plume effect from stage one and the random errors, $e_s$, are Gaussian. In level 2, we model the true plume effects with overall mean $\mu$ where the random error term, $\varepsilon_s$, captures variation in the true effect.

For each pollutant, we considered two models (spatial and non-spatial) by specifying distribution of error terms ($e_s$ *and* $\varepsilon_s$) capturing different scales of spatial dependence and giving us four possible model formulations. Namely, in the non-spatial models, $e_s$ and $\varepsilon_s$ are independent between sites (indexed by s), whereas in the spatial models, we specify spatial correlation among the within-site errors ($e_s$) and spatial variation among the true unobserved plume effects ($\varepsilon_s$). The first form of spatial dependence captures the spatial variability of the plume effect that may be introduced as spatially correlated measurement error, such as the error induced by smoke plumes covering multiple sites simultaneously. The second form of spatial variability captures the spatial heterogeneity of true plume effects. The true plume effects may exhibit variations because the properties of burning vegetation, climate, and other factors vary regionally. Correlation between the errors at any two locations decays exponentially as the distance between them increases. Parameters of the decay function were estimated from the data. Further details of the model can be found in Appendix A.

In the results, we report stage two estimates of the plume effects, $\tilde{\beta}_s$ , for $O_3$ (ppb) and for $PM_{2.5}^{FRM}$ ($\mu g/m^3$) and comment on the spatial patterns displayed. A positive estimate of $\tilde{\beta}_s$ is evidence for increased pollutant concentrations during plume episodes as compared to clear days. A negative estimate indicates the converse. In Table 2, we record the model of best fit for all four pollutants using BIC and report an estimate of the overall mean, $\mu$. Viewing stage two as a meta-analysis of smoke plume impacts on all sites in the US, the overall mean estimate serves as summary of impacts. We also present these estimates in terms of relative change, procured by implementing the analysis on log-transformed pollutant concentrations.

# RESULTS

## Distribution of Days by AQI on Smoke Plume vs. Clear Days

The frequency of each AQI code on both clear and smoke plume days is given in Table 1. At $O_3$ monitoring sites, “Good” air quality days (green) occurred most commonly; they were observed on 89.5% of clear days and 70.3% of plume days. “Very Unhealthy” days (purple) occurred least commonly; they were observed on only 0.0057% of clear days and 0.0277% of plume days. For $PM_{2.5}^{FRM}$, “Good” days were also the most common, accounting for 70.6% of clear days and 46.4% of plume days. Incidence of “Very Unhealthy” days at the $PM_{2.5}^{FRM}$ monitoring sites was low for both clear (0.0004%) and plume days (0.0061%).

Plume days accounted for a larger percentage of unhealthy days than healthy days (Table 1). For $O_3$, only 6.1% of “Good” days were observed on plume days whereas 18% of “Moderate” air quality days (yellow), 25.8% of “Unhealthy for Sensitive Groups” days (orange), 30.1% of “Unhealthy” days (red), and 28.8% of “Very Unhealthy” days (purple) were observed on days with plumes. The odds of observing yellow, orange, red, and purple coded days were, respectively, 3.1, 4.3, 5.2, and 4.8 times higher on plume days than on clear days.

Similarly, for $PM_{2.5}^{FRM}$, plumes were observed on 4.2% of “Good” days, 10.6% of “Moderate” days, 15.8% of “Unhealthy for Sensitive Groups” days, 16.5% of “Unhealthy” days, and 50% of “Very Unhealthy” days. We did not identify any “Hazardous” days (maroon). The odds of observing yellow, orange, red and purple coded days were, respectively, 2.7, 2.9, 3.0, and 15.0 times higher on plume days than on clear days.

## $O_3$ and $PM_{2.5}^{FRM}$

We summarized daily smoke plume activity from 2006 to 2013 at environmental monitors located within the continental U.S. Figure 2 provides the distribution of days with smoke plumes across $O_3$ monitoring sites (panel a) and $PM_{2.5}^{FRM}$ monitoring sites (panel b). Monitors are color coded by quartiles of the daily smoke plume frequency distribution. The median percent of days with smoke plumes at $O_3$ sites was 6.85% and 5.4% at the FRM sites ($O_3$: $25^{th}$ = 4.5%, $50^{th}$ = 6.85%, $75^{th}$ = 11%, $100^{th}$ = 36.3%; $PM_{2.5}$: $25^{th}$ = 3.7%, $50^{th}$ = 5.4%, $75^{th}$ = 8.3%, $100^{th}$ = 30.1%). Both $O_3$ and FRM monitoring stations in the Great Lakes region, Central and Northwest U.S., and Northern California had the highest proportion of days of HMS-detected plume cover. Ozone and $PM_{2.5}^{FRM}$ monitoring stations in the Northeast, Southwest and Florida peninsula had the lowest proportion of days with plume coverage. The spatial distribution of plume coverage across the two monitoring networks largely agreed despite differences in the temporal frequency of data collection for each pollutant.

The stage-two plume effects on $O_3$ and $PM_{2.5}^{FRM}$ exhibited strong spatial patterns across the continental U.S. Among the four stage-two models, we found the one with spatial correlation among site-specific error terms and spatial variation in the true unobserved plume effect best fit both pollutants. In Figure 3, we present plume effect estimates from the model of best fit for $O_3$ (panel a) and $PM_{2.5}^{FRM}$ $_5$ (panel b) by quartiles. For $O_3$ we estimated the following absolute (relative) change: $25^{th}$ = 1.66 ppb (6.5%), $50^{th}$ = 2.56 ppb (9.07%), $75^{th}$ = 3.69 ppb (12.3%), $100^{th}$ = 7.45 ppb (24.7%); and for $PM_{2.5}$: $25^{th}$ = 2.35 μg/m$^3$ (22.3%), $50^{th}$ = 2.9 μg/m$^3$ (26.1%), $75^{th}$ = 3.45 μg/m$^3$ (34.7%), $100^{th}$ = 8.48 μg/m$^3$ (78.4%).

The plume effect on $O_3$ was the largest in the Southeast, scattered sites in the Northeast (Connecticut, Massachusetts, and Maine) and West Coasts, and around St Louis, Missouri. The lowest plume effects on $O_3$ were found in the Southwest and West. For $PM_{2.5}^{FRM}$ concentrations, smoke plumes had the highest impact in the Southeastern, Western, and Northwestern regions. The lowest plume effects on $PM_{2.5}^{FRM}$ were found in the Great Lakes Region (Minnesota, Michigan and Wisconsin) and parts of South West. Nationally, the average impact of fire plumes on $O_3$ and $PM_{2.5}^{FRM}$ was estimated at 2.6 (2.5, 2.7) ppb and 2.9(2.8, 3.0) μg/m$^3$, respectively, as summarized in Table 2 where we also present estimates of relative change.

### Speciated $PM_{2.5}^{IMP}$ from IMPROVE Network

Concentrations of $PM_{2.5}^{IMP}$ components measured at IMPROVE sites also increased during plume events. We observed a 0.09 μg/m$^3$ increase for EC and a 0.7 μg/m$^3$ increase for OC. The model of best fit for EC was the fully non-spatial model and the model of best fit for OC was the fully spatial model.

## DISCUSSION

Our analysis demonstrated impacts of smoke plumes on regional daily air quality from 2006 through 2013. Smoke-plume days accounted for a disproportionate number of days with elevated AQI levels, indicating that moderate increases in regional air pollution due to large fires and long distance transport of smoke can tip the air quality to unhealthy levels. Unsurprisingly, due to use of visible imagery of smoke, $PM_{2.5}$ concentrations increased more than $O_3$ in relative terms (33.1% vs 11.1%). However, a striking finding here was that smoke plumes accounted for a disproportionate number of unhealthy $O_3$ days compared to unhealthy $PM_{2.5}$ days. Namely, while only 6.3% of $PM_{2.5}^{FRM}$ monitoring days and 7.7% of $O_3$ monitoring days had plumes, these days accounted for 16% of days categorized as unhealthy (code orange, red and purple combined) for $PM_{2.5}^{FRM}$ and 27% of unhealthy days for $O_3$ (code orange, red and purple combined). Unhealthy days for $O_3$ and $PM_{2.5}^{FRM}$ were 3.3 and 2.5 times more likely to occur on plume days than on non-plume days, respectively. With a two-stage statistical model, we accounted for spatial heterogeneity of plume effects and determined that $O_3$ concentrations on days with visible plumes were on average 2.6 ppb or 11.1% higher than on the clear days, and $PM_{2.5}^{FRM}$ concentrations were on average higher by 2.9 μg/$m^3$ or 33.1%. Organic and elemental carbon concentrations were elevated as well (OC: 0.7 μg/$m^3$ or 30.6%; EC: 0.09 μg/$m^3$ or 21.3%).

The results of our analysis suggest consistent increase in concentrations of both $PM_{2.5}$ and $O_3$ across all sites and in some regions, concentrations of both pollutants increased (e.g. Southeast) on smoke days. Health impacts studies of wildfire exposures do not typically consider multi-pollutant exposures or the impacts of secondary pollutants formed downwind such as $O_3$. However, there is strong scientific evidence implicating both pollutants in respiratory and cardiovascular health risks (20,21). Both epidemiologic and clinical research suggests that the two pollutants do not share the same biological mechanism leading to adverse health outcome and may occur at different temporal scales suggesting that the effects of multi-pollutant exposures should be considered to adequately protect public health (22). Some studies have previously reported that the joint effect of these two pollutants on health is lower than a combination of the two taken together but larger than either alone (23,24) while others reported additive effects (25-27). Controlled exposure studies in humans and animals have recently demonstrated that combined gaseous (with $O_3$ in particular) and particle exposure (e.g., diesel) have a synergistic impact on both the respiratory and cardiovascular health risk (28,29). Therefore, frequent and simultaneously high exposures to both pollutants during fire episodes may require additional health risk messages to adequately protect health in susceptible populations.

We also observed that regional plume transport increased $O_3$ concentrations over several densely populated urban areas far removed from large fires; the Massachusetts and Connecticut areas, the entire Southeast, and the Illinois, Indiana, and Kansas areas. Enhanced $O_3$ production over urban areas has previously been reported in case studies and hypothesized to be due to fire-related VOC's being transported into NOx-rich urban areas (30-33). Using similar data as in our analysis, an impact of smoke-plume days on $O_3$ concentration in the urban areas along the Eastern seaboard and Southeast was also noted by Brey and Fischer (34). The authors found a larger increase of up to 35 ppb in comparison to our analysis 3.69-7.45 ppb (Figure 3a) however they defined plume days differently. Enhanced $O_3$ production in urban areas is a concern because of the population size potentially impacted and because air pollution levels could be already elevated due to local and mobile sources.

Despite our study's consistent and robust estimates of air quality changes in the presence of HMS smoke plumes we note several limitations. First, HMS smoke plumes are drawn by an analyst using visible satellite imagery and represent only smoke plumes that were seen in the images. The use of visible imagery is problematic because smoke cannot be visibly detected at night and clouds can hinder or completely obscure smoke plumes limiting the number of smoke plumes drawn; thus, the number of plumes drawn can be considered conservative. Additionally, the total areal coverage represented by all of the plumes is also likely to be conservative because the plumes are typically drawn once or twice per day and the total area covered represents a period of a couple of hours.

In this study, we utilize the geographical extent of smoke plumes to characterize impacts of fire on unhealthy air quality across continental U.S. With the introduction of new generation satellites, such as GOES-16, which distribute data in five minute increments and in near real time, satellite-based imagery may have the potential for wider use, including public health messaging of risk during wildfire episodes. Satellite imagery is by far the easiest tool to use for the general public and public health professionals, and is readily accessible at NOAA, AirNow and the websites of a number of state-level departments of environmental quality. Additionally, satellite imagery is particularly useful for visualizing and capturing smoke impacts coming from distant fires. Using satellite data for public health messaging may, however, demand equally important research on the estimation of plume density. While HMS utilizes an atmospheric model to estimate $PM_{2.5}$ concentrations and classifies smoke into light (range 0-10 μg/m3), medium (range 10.5-21.5 μg/m3) and dense (range 22+ μg/m3) levels for most of the years analyzed here, it does not estimate the $PM_{2.5}$ and $O_3$ concentrations from anthropogenic sources. Additionally, we only observed a small proportion of dense plumes across all monitoring systems ($O_3$: 0.2%; FRM: 0.1%; IMPROVE: 0.1%), resulting in what would be a prohibitively diminished number of monitors to analyze. A further limitation, our analysis relied on a determination of whether a plume is detected in the vertical column above the monitoring site; it did not account for the height of the plumes. Estimating how the planetary boundary height impacts the probability of unhealthy air quality at the regional level, particularly when smoke is coming from distant fires, may improve specificity of public health messaging where monitors are not available. Public health messaging may also require incorporating data on planetary boundary height in addition to plume presence. The results of our analysis support the need of ground-to-model data validation for such purposes (35).

As noted earlier, a large wildfire in the Western U.S., Canada, and Alaska can produce large smoke plumes that travel thousands of kilometers from the source fire and remain aloft for many days or over a week. This typically results in very large plumes that are lofted well above the surface, perhaps as high as 20,000-30,000 ft (~6,000-9,000m). Often, as the smoke drifts to the Eastern and Southeastern U.S., it becomes more diffuse and mixes with regional haze pollution. It can be very difficult for an analyst to distinguish between smoke and haze pollution or even to know when the smoke may have completely dissipated, bringing uncertainty to the actual spatial extent of the smoke. Generally speaking, the greater the distance travelled, the lighter the winds and the longer the time since the smoke was generated, the more difficult it is to distinguish between smoke and haze pollution. In our analysis, undetected smoke plumes or plumes that are aloft and not visible could have resulted in lower estimated effect sizes. However, our statistical model is robust, combining uncertainty within and between sites, so we expect the ramifications of missing plume data to be small or negligible.

We used HMS to capture the long-range transport of visible plumes over an extended spatial and temporal domain and regional air quality data from the environmental monitoring sites. The plume effect therefore is representative of the impacts on regional air quality and not on air pollutant concentrations near fires. The impacts of fire smoke on air quality near fires are undoubtedly larger by orders of magnitude. Moreover, the plumes from HMS contain an aspect of subjective judgment by the operator and are not intended to prove impacts of a specific fire on a specific monitor; instead, we are interested in the average impact of these plumes relative to the clear days. Dispersion and chemical transport model predictions could be used as an alternative way of specifying plume transport; however, these are modeled predictions and are subject to their own uncertainties and limitations.

The results of the current analysis show that smoke plumes bring consistent and non-marginal increases in $O_3$, $PM_{2.5,}$ and $PM_{2.5}$ components and account for a disproportionate number of unhealthy air quality days. We observed that $PM_{2.5}$ and $O_3$ impacts are not uniform across all geographic locations and that the additional $O_3$ production by plume is present over densely populated regions. As the frequency of large fires increases and emissions from all other sources decrease, fire smoke is expected to account for a growing portion of air quality related public health concerns, which may require new health risk communication tools in near future.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

## Acknowledgments

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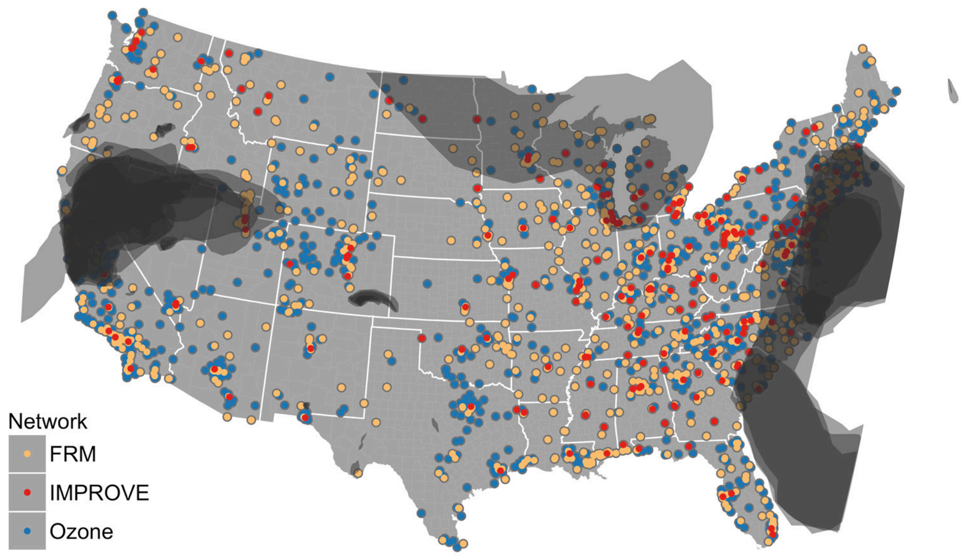
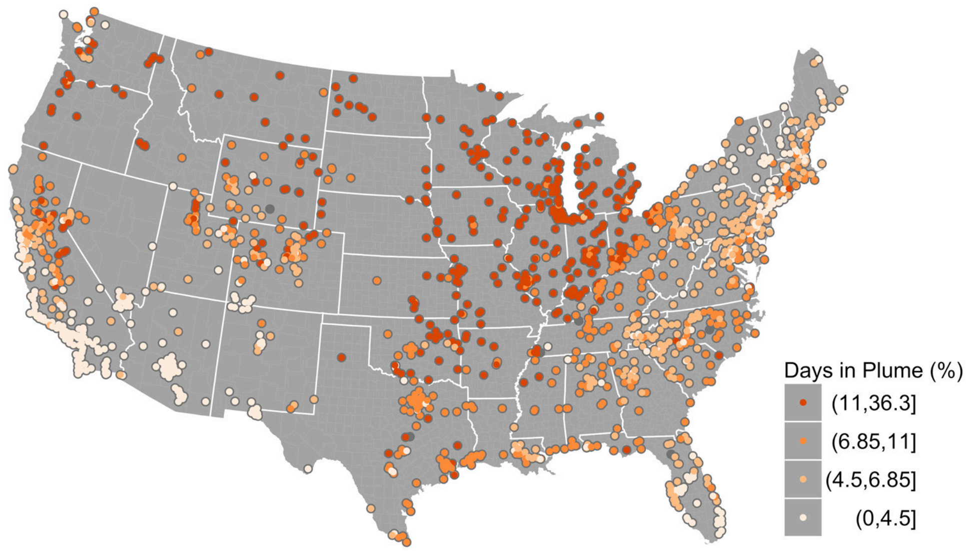



**Figure 1.**
Geographic distribution of environmental monitoring sites for $O_3$, $PM_{2.5}$, species of $PM_{2.5}$, and HMS smoke plumes on June 14th, 2008. HMS depicts smoke observed by multiple geostationary and orbiting satellites. The geographic extents of the smoke plumes are drawn with gray-shaded polygons with darker regions denoting multiple plumes at the same locations.



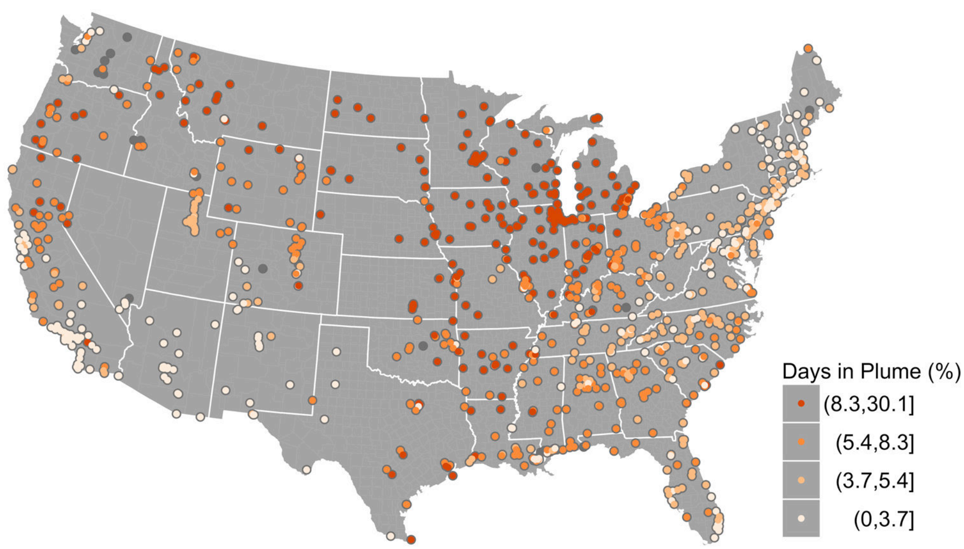




**Figure 2.**

Frequency of days with HMS smoke plumes visible above $O_3$ monitoring sites (panel a) and above $PM_{2.5}^{FRM}$ monitoring sites (panel b). Monitoring sites are colored by the quartiles of the frequency distribution with red denoting locations that experienced a frequency of smoke plume days in the top quartile.

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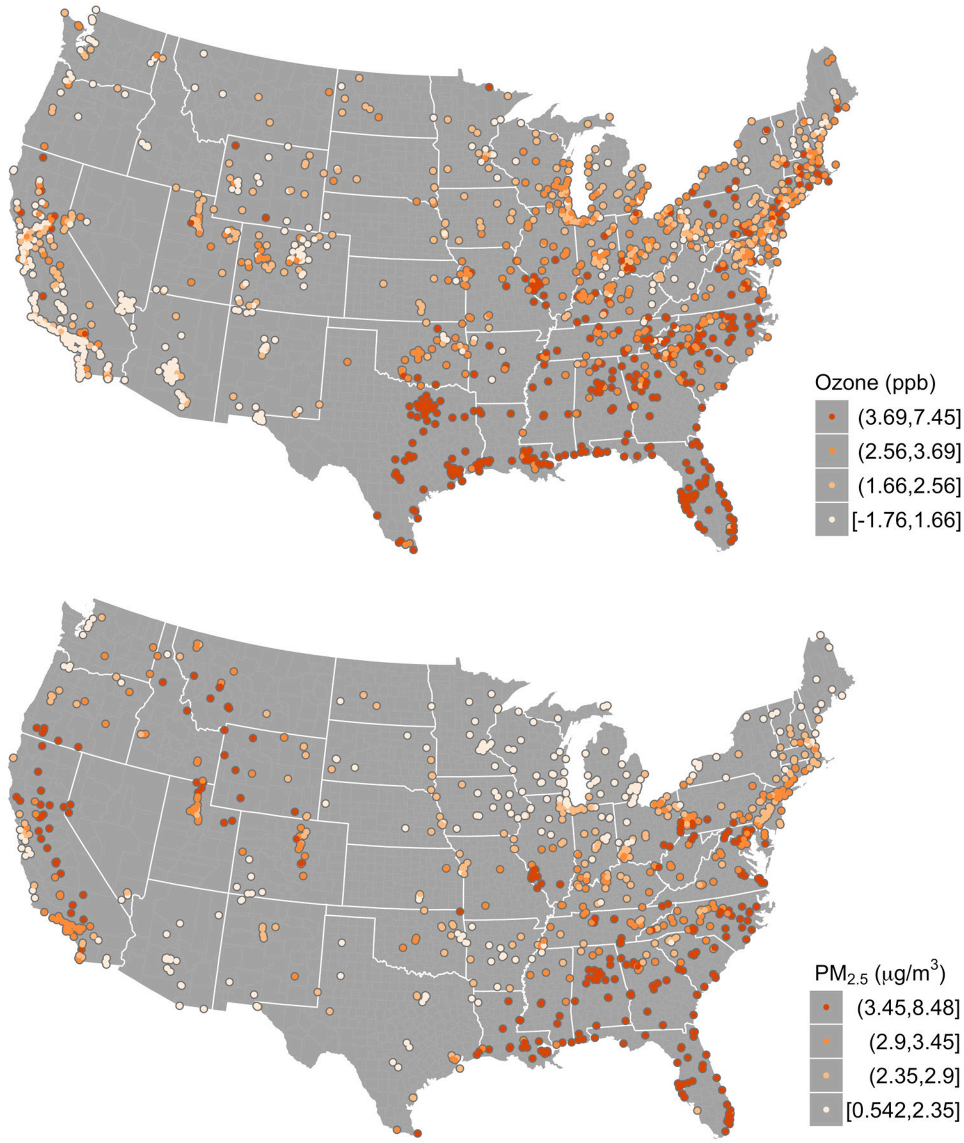


**Figure 3.**

Geographic distribution of the estimated change in pollutant concentrations on plume days for $O_3$ monitoring sites (panel a) and $PM_{2.5}^{FRM}$ monitoring sites (panel b) by quartiles of distribution. These estimates are calculated from the best fitting second stage model.

**Table 1.**

**Distribution of days by Air Quality Index.**

Percent of AQI days on clear and plume days for each AQI category and the odds ratio of each AQI color code observed on a plume day versus a clear day. Green, yellow, orange, red, and purple AQI color codes denote “Good”, “Moderate”, “Unhealthy for Sensitive Groups”, “Unhealthy”, and “Very Unhealthy” air quality respectively.

| Pollutant | | AQI Color Code | | | | |
|---|---|---|---|---|---|---|
| | | Green | Yellow | Orange | Red | Purple |
| Ozone | % of AQI codes on clear days | 89.5% | 9.15% | 1.26% | 0.082% | 0.0057% |
| | % of AQI codes on plume days | 70.3% | 24.0% | 5.27% | 0.425% | 0.0277% |
| | % Plume Days for each AQI code | 6.1% | 18.0% | 25.8% | 30.1% | 28.8% |
| | Odds Ratio | 0.278 | 3.13 | 4.34 | 5.20 | 4.82 |
| $PM_{2.5}^{FRM}$ | % of AQI codes on clear days | 70.6% | 28.8% | 0.58% | 0.083% | 0.0004% |
| | % of AQI codes on plume days | 46.4% | 51.7% | 1.65% | 0.25% | 0.0061% |
| | % Plume Days for each AQI code | 4.2% | 10.6% | 15.8% | 16.5% | 50.0% |
| | Odds Ratio | 0.360 | 2.65 | 2.88 | 3.02 | 15.0 |

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## Table 2.

### Summary of models and national estimates for each pollutant.

Summary statistics represent the average pollution contribution from fire smoke by species as well as the estimated relative increase over background levels of each pollutant over the whole nation. The confidence limits presented demonstrate that all national effects are plausibly non-zero at a significance level of 0.05. These estimates control for temperature, seasonal variation and spatial variation. The relevant spatial variation for each pollutant is described under Model Settings. The best model settings are given for the average plume effect model as well as the model for relative change.

| Pollutant | # of Sites | Model Settings | | National Summary (95% Confidence Limits) | |
|---|---|---|---|---|---|
| | | Spatially Correlated Measurement Error | Spatial Variation in True Plume Effect | Average Plume Effect | Relative Plume Effect |
| Ozone (ppb) | 1,489 | Yes | Yes | 2.6 (2.5, 2.7) | 11.1% (6.4, 15.8) |
| $PM_{2.5}^{FRM}$[a] ($\mu g/m^3$) | 1,096 | Yes | Yes | 2.9 (2.8, 3.0) | 33.1% (24.7, 41.5) |
| $PM_{2.5}^{IMP}$[b] ($\mu g/m^3$) | 224 | Yes | Yes[*] | 2.7 (1.5, 3.9) | 24.6% (22.1, 27.2) |
| EC[b] ($\mu g/m^3$) | 188 | No | No[**] | 0.09 (0.07, 0.12) | 21.3% (18.9, 23.6) |
| OC[b] ($\mu g/m^3$) | 188 | Yes | Yes | 0.7 (0.5, 0.8) | 30.6% (23.3, 37.9) |

[a] FRM sites,

[b] IMPROVE sites

[*] No for relative change,

[**] Yes for relative change