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Practical Considerations When Using Wildfire Smoke Data in Economic Analyses

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Abstract

Estimating the impacts of wildfire smoke requires measuring wildfire smoke exposure, but several factors, such as smoke's transport through the atmosphere and gaps in air quality monitoring networks, make measuring smoke difficult. We provide an overview of the leading wildfire smoke datasets, including NOAA's Hazard Mapping System smoke plume polygons and statistical approaches that combine the smoke plume polygons with surface-level air quality observations. We discuss how these datasets are produced, highlight potential sources of measurement error, and offer advice to practitioners seeking to estimate the impacts of wildfire smoke.

JEL Codes: C55, Q53, Q54

Keywords: Air pollution, measurement error, wildfire smoke data, wildfire smoke exposure

*The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency.

1 Introduction

The increasing frequency and severity of wildfire smoke have widespread economic consequences and present profound environmental risks (Gellman and Wibbenmeyer, 2025). Recent research documents wildfire smoke impacts on crime, education, health, housing, labor, and recreation (Borgschulte et al., 2024; Burkhardt et al., 2019; Gellman et al., 2025; Gould et al., 2024; Molitor et al., 2023; Lopez and Tzur-Ilan, 2025; Qiu et al., 2025b; Wen and Burke, 2022). These impacts are amplified by wildfire smoke's ability to persist in the atmosphere and travel hundreds of miles away from its source. Because of this, many papers treat wildfire smoke exposure as plausibly random. Yet, these features also make wildfire smoke difficult to track and measure, motivating a deeper investigation of how wildfire smoke data are produced and what measurement error they may contain.

Indeed, the challenge of measuring wildfire smoke has attracted much attention. For twenty years, analysts from the National Oceanic and Atmospheric Administration (NOAA) have produced daily smoke plume data, manually inspecting satellite imagery and delineating plume boundaries. The limitations of these smoke plume data have motivated numerous alternative wildfire smoke datasets that estimate surface-level $PM_{2.5}$ concentrations attributable to wildfire smoke, commonly referred to as "smoke $PM_{2.5}$." Based on previous research, descriptive statistics, and conversations with NOAA analysts, we present five practical considerations for using smoke plume data (Section 2). We then review the alternative smoke $PM_{2.5}$ datasets (Section 3). Finally, we discuss how measurement error may impact downstream empirical analyses (Section 4) and note potential advancements in wildfire smoke datasets (Section 5).

2 HMS smoke plume data

2.1 Background

As wildfires burn, they emit particulate matter and toxic gases that conglomerate as smoke plumes and disperse through the atmosphere. NOAA's Hazard Mapping System (HMS) produces a daily map of smoke plume polygons across North America. To identify smoke plumes, NOAA analysts manually inspect visible-band imagery from GOES-East and GOES-West satellites and draw plume boundaries with geospatial software. Analysts complete training and are supervised for one year to improve the consistency and reliability of the data. Nevertheless, this plume classification process requires human judgment and subjectivity.

HMS smoke plume data are publicly available and begin in mid-2005.[1] In June 2010, analysts began assigning each plume a density — light, medium, or heavy — based on its perceived opacity in the satellite imagery, introducing further subjectivity.[2] Initially, densities were associated with approximate smoke $PM_{2.5}$ concentrations, but NOAA now recommends interpreting them qualitatively (NOAA, 2025).[3] The presence of higher

[1] https://www.ospo.noaa.gov/products/land/hms.html

[2] Plume densities were assigned inconsistently before 2010. In early years, analysts used quantitative aerosol optical depth measurements to help assign densities (Ruminski et al., 2007).

[3] Appendix figure A.2 suggests that there is significant overlap in the variation of estimated smoke $PM_{2.5}$ between plume densities.

density plumes typically implies the presence of lighter density plumes, which complicates isolating the effect of different plume densities.

2.2 Consideration 1: Smoke plumes are imperfect proxies for surface-level conditions

The presence of a plume overhead does not guarantee there is surface-level smoke; on the other hand, the absence of a plume does not rule out that there is surface-level smoke. While analysts observe where plumes are located, they are unable to measure where smoke lies vertically within the atmosphere. The height of a plume depends on a variety of factors, including atmospheric conditions, landscape, temperature, and wildfire characteristics. Thus, analysts cannot determine surface-level smoke conditions, which are relevant for most economic analyses of wildfire smoke exposure.

This raises the question: "How well do smoke plumes reflect surface-level conditions?" Borgschulte et al. (2024) find that surface-level $PM_{2.5}$ concentrations are approximately 2 $\mu g/m^3$ higher when plumes are present overhead. These areas also have elevated concentrations several days before and after plumes are present, suggesting that wildfire smoke may linger at the surface even when plumes are not detected by analysts. Consequently, plumes may underestimate surface-level smoke conditions.

Alternatively, plumes may overestimate surface-level smoke conditions when smoke is lofted high in the atmosphere. Liu et al. (2024) compare HMS smoke plume data to airport monitor observations that document the presence of surface-level smoke. They find that plumes are more common than surface-level smoke, especially in the Midwest, where smoke from distant wildfires often travels higher in the atmosphere (Brey et al., 2018). They estimate that airports in the Midwest experience 56 days with a plume each year but only 4 days with surface-level smoke. When focusing only on medium and heavy plumes, the frequency of plumes and surface-level smoke is more similar. We caveat these findings by noting that Liu et al. use an airport monitor variable that documents when smoke reduces visibility to less than 1 km. Because smoke does not always impact visibility to this extent, this definition makes their estimates of surface-level smoke conservative. In summary, plumes are correlated with surface-level smoke conditions to some extent, but they are imperfect proxies that can generate false negatives and false positives.

2.3 Consideration 2: Smoke never sleeps

HMS smoke plume polygons reflect plume coverage at specific points in time. Analysts produce two main classifications during the day, one in the morning and evening. Analysts sometimes update the morning classification in the afternoon before producing the evening classification from scratch. This process produces temporal gaps between classifications in which plumes travel unmonitored. These gaps are largest overnight when darkness prevents plume detection. As a result, HMS smoke plume data underestimate the full spatial extent of plume coverage throughout the day.

Figure 1 illustrates these temporal gaps. On the morning of August 2, 2024, there were medium and heavy plumes in the Pacific Northwest. These plumes remained in the area through the evening, while light plumes expanded across eastern states. By the morning of August 3, the medium plume covered many northern states, and a heavy plume appeared in Minnesota and Wisconsin. Since classifications cannot be generated overnight, we do not observe when this heavy plume formed and where else it traveled.

2.4 Consideration 3: The frequency and geography of smoke plumes vary by density

Because plume densities are used as a proxy for the intensity of wildfire smoke exposure, it is important for researchers to consider differences in the frequency and geographic distribution of light, medium, and heavy plumes. Figure 2 maps the frequency of plumes by density at the county level and illustrates two key facts. First, light plumes are much more common than medium and heavy plumes. From 2011 to 2024, light plumes occur on 20% of days, while medium plumes occur on 5% and heavy plumes on only 1%. Second, light plumes are common throughout the country, particularly in the Midwest, South, and West, while medium and heavy plumes are most common in the West. These facts suggest that light plumes will drive the frequency and geographic distribution of estimated wildfire smoke exposure if researchers do not allow for heterogeneous impacts across different plume densities. For example, Palm Beach County, Florida experiences the most days with a plume overhead, but its exposure to medium and heavy plumes ranks in the 48th and 9th percentiles, respectively.

2.5 Consideration 4: Clouds and other aerosols obscure smoke plumes

Clouds present several challenges for plume classification, as they conceal plumes lower in the atmosphere. Daily text descriptions accompanying the HMS smoke plume polygons include the disclaimer: "Widespread cloudiness may prevent the detection of smoke even from significant fires." Analysts mention the phrase "cloud cover" in 43% of text descriptions in 2024. The text description on May 15, 2024 offers one illustrative example: "Areas of moderate smoke were also seen covering portions of north-central Canada, north-central U.S. and the Great Lakes regions, however, a large amount of cloud cover throughout these regions are most likely concealing thicker density smoke."

Aerosols, including dust and emissions, can mix with smoke. The type and frequency of aerosols vary regionally and can differentially impact plume classification. For example, in the text descriptions, analysts often cite aerosols from gas flaring and industrial sources in Mexico that transport along the Gulf Coast. This is consistent with Brey et al. (2018), who note difficulties distinguishing smoke from aerosols in southeastern states.

2.6 Consideration 5: Improvements in satellite imagery

Several generations of GOES satellites have provided imagery for plume classification.[4] Prior to 2017, legacy satellites produced black and white imagery at a 4-km resolution. In 2017, NOAA upgraded to GOES-R satellites that use true-color imagery at a 2-km resolution. Analysts reported that the improved resolution helps identify plumes, especially from small wildfires. Additionally, color imagery helps distinguish plumes from clouds and aerosols. These improvements in satellite imagery are correlated with recent increases in estimated wildfire smoke exposure (Childs et al., 2024).

[4]For a list of satellites, see https://www.ospo.noaa.gov/products/land/hms.html#about.

3 Smoke $PM_{2.5}$ data

3.1 Statistical approaches

Several studies attempt to estimate smoke $PM_{2.5}$, the amount of $PM_{2.5}$ attributable to wildfire smoke. These studies generally measure surface-level smoke conditions using both HMS smoke plumes and air quality monitor observations. Here, we discuss studies that estimate smoke $PM_{2.5}$ nationally, but other studies produce estimates regionally (Aguilera et al., 2023; Reid et al., 2021).

O'Dell et al. (2019) estimate daily smoke $PM_{2.5}$ across the contiguous United States from 2006 to 2016. They measure total $PM_{2.5}$ from all sources at U.S. Environmental Protection Agency (EPA) air quality monitors and then spatially interpolate $PM_{2.5}$ away from monitors across a 15-km grid. For each grid cell, they estimate background $PM_{2.5}$ as the seasonal-median $PM_{2.5}$ on days without a smoke plume overhead. Finally, on days with a plume overhead, they calculate daily smoke $PM_{2.5}$ as the difference between daily total $PM_{2.5}$ and background $PM_{2.5}$.

Childs et al. (2022) take a slightly different approach, first estimating smoke $PM_{2.5}$ at EPA monitors, then predicting smoke $PM_{2.5}$ away from monitors. They use smoke plumes to identify "smoke days" when wildfire smoke is plausibly present, and when clouds are overhead, they use HYSPLIT model predictions to fill gaps in HMS smoke plume data. This approach increases the number of smoke days per year by up to 60% in some counties (appendix figure A.1). On smoke days, they estimate smoke $PM_{2.5}$ as the difference between daily total $PM_{2.5}$ and monthly-median $PM_{2.5}$ on non-smoke days over the past three years. Finally, they predict smoke $PM_{2.5}$ away from these monitors using a machine learning model that leverages data on wildfires, meteorology, HYSPLIT trajectories, aerosol optical depth, land use, and elevation. These estimates of daily smoke $PM_{2.5}$ are measured at a 10-km resolution across the contiguous United States from 2006 to 2020 and are also available for download at the ZIP code, census tract, and county levels. Childs et al. (2024) build on this work by improving the machine learning model and updating estimates through 2023.

Zhang et al. (2023) share some similarities with Childs et al. For example, they also augment smoke plumes with transport modeling to identify smoke days. They differ by measuring $PM_{2.5}$ at both EPA and PurpleAir air quality monitors and by training two separate machine learning models. One model uses data from smoke days to predict daily total $PM_{2.5}$ when smoke is present. The other model uses data from non-smoke days to predict daily background $PM_{2.5}$ at all locations, providing more sophisticated predictions of background $PM_{2.5}$. On smoke days, they calculate daily smoke $PM_{2.5}$ as the difference between daily total $PM_{2.5}$ and predicted background $PM_{2.5}$. These estimates of daily smoke $PM_{2.5}$ are measured at a 1-km resolution across the contiguous United States from 2007 to 2018.

It is challenging to assess the relative performance of these smoke $PM_{2.5}$ datasets without a ground-truth measure of surface-level smoke. One strength of Childs et al. and Zhang et al. is that they mitigate cloud-induced measurement error by incorporating smoke plumes and transport modeling to identify smoke days. Zhang et al.'s estimates are also appealing because they predict daily background $PM_{2.5}$ rather than use aggregate measures of monthly-median or seasonal-median $PM_{2.5}$.

These smoke $PM_{2.5}$ datasets share limitations. First, interpolating or predicting $PM_{2.5}$

away from monitors introduces non-classical measurement error. As a demonstration, Childs et al. (2022) examine the performance of their machine learning model by removing air quality monitors from their sample and predicting smoke $PM_{2.5}$ at these out-of-sample monitors. Their out-of-sample predictions are less accurate in the South and Southwest, which suggests the presence of regional confounders. Another source of measurement error comes from differentiating smoke $PM_{2.5}$ from background $PM_{2.5}$. If wildfire smoke affects non-smoke sources of $PM_{2.5}$, such as vehicle traffic, then smoke $PM_{2.5}$ estimates will be biased. Finally, these smoke $PM_{2.5}$ datasets are not continuously updated like HMS smoke plume data. While Childs et al. and O'Dell et al. have updated their data through 2023, Zhang et al. have not updated their data after publication.

3.2 Model-based approaches

Chemical transport, dispersion, and meteorological models present alternatives to the statistical approaches above. Researchers often measure how adding fire emissions affects simulated $PM_{2.5}$ concentrations in chemical transport models, such as the Community Multiscale Air Quality (CMAQ) model and the GEOS-Chem model. Other tools combine several modeling approaches and provide off-the-shelf predictions of wildfire smoke concentrations. For example, the BlueSky tool models smoke $PM_{2.5}$ at a 3-km resolution by combining fire emissions with dispersion models.[5] Similarly, the High-Resolution Rapid Refresh tool models smoke $PM_{2.5}$ at a 3-km resolution using chemical transport and meteorological models.[6] This suite of models has mixed results in matching surface-level $PM_{2.5}$ concentrations (Chow et al., 2022; Ye et al., 2021). Qiu et al. (2024) show that chemical transport models tend to overestimate wildfire smoke exposure in the western United States, but combining chemical transport model predictions with a machine learning model can outperform each individual method.

4 Empirical analysis

4.1 Measures of wildfire smoke exposure

Researchers have measured both the frequency and intensity of wildfire smoke exposure. One simple but common approach to measuring exposure frequency is to define binary smoke day indicators equal to one when wildfire smoke is present. It is possible to assign smoke day indicators using HMS smoke plume data, but this process requires substantial researcher discretion. For example, researchers need to decide whether plumes should fully or partially cover their spatial unit of analysis (e.g., county). While some studies require plumes to fully cover a county (Borgschulte et al., 2024), it is reasonable to define a smoke day if plumes partially cover a county (Molitor et al., 2023), given that Miller et al. (2024) document elevated $PM_{2.5}$ concentrations up to 1,000 km from plumes.[7] Researchers must also decide how to treat plume densities. Many studies consider all plume densities (Borgschulte et al., 2024; Burkhardt et al., 2019), while others ignore light plumes in their main analyses and focus only on medium and heavy plumes (Molitor

[5] https://tools.airfire.org/websky/v2

[6] https://rapidrefresh.noaa.gov/hrrr/HRRRsmoke/

[7] Similar approaches to partial coverage have been used with other wildfire smoke exposure measures like aerosol optical depth (Parthum et al., 2017).

et al., 2023). Because light plumes are so prevalent, ignoring them may meaningfully alter downstream estimates. In contrast, statistical estimates of smoke $PM_{2.5}$ limit researcher discretion. Smoke $PM_{2.5}$ data are available at the ZIP code, census tract, and county levels, which eliminates the need to make decisions regarding plume coverage and densities. In addition, Childs et al. and Zhang et al. mitigate cloud-induced measurement error by incorporating transport modeling. These advantages make using statistical estimates of smoke $PM_{2.5}$ an attractive alternative for defining smoke days relative to HMS smoke plume data.

Researchers seeking to measure exposure intensity face their own challenges. HMS smoke plume densities approximate intensity, but they do not correspond directly to surface-level smoke conditions. Instead, statistical estimates of smoke $PM_{2.5}$ predict surface-level concentrations and provide a continuous measure of intensity. Using a continuous measure allows comparison to other dose-response studies for $PM_{2.5}$ (Qiu et al., 2025a). Since the EPA primarily considers dose-response studies in benefit-cost analyses, studies using smoke $PM_{2.5}$ could potentially support future regulatory actions (Brewer et al., 2023). Despite these benefits, statistical estimates must spatially interpolate smoke $PM_{2.5}$ away from air quality monitors, which introduces non-classical measurement error.

Because outcome variables are often measured at coarser temporal frequencies than exposure variables, researchers may need to aggregate daily exposure measures within time periods (e.g., months) to match. When using binary indicators, researchers often count the number of smoke days within time periods (Borgschulte et al., 2024). When using a continuous measure of smoke $PM_{2.5}$, researchers may average smoke $PM_{2.5}$ (Qiu et al., 2025b) or sum smoke $PM_{2.5}$ (Wen and Burke, 2022) within time periods. Alternatively, researchers may calculate the number of days in different smoke $PM_{2.5}$ bins, characterizing the entire range of the distribution (Heft-Neal et al., 2023).

4.2 Empirical strategy

Our review of wildfire smoke data makes clear that measures of wildfire smoke exposure do not achieve the ideal "as good as random" assignment, as measurement error is likely correlated with confounders. Yet, previous work typically treats wildfire smoke exposure as exogenous after controlling for fixed effects and common time shocks in panel-data regression models. Some of these specifications may be particularly susceptible to measurement error. For example, a specification that leverages variation in plume coverage within small geographic areas may be almost entirely identified based on measurement error from imprecise plume boundaries. Similarly, researchers should be cautious when exploiting temporal variation given that surface-level smoke may arrive before or linger after a plume is detected overhead. These temporal spillovers may bias estimates in research designs where smoke days are compared to days immediately before or after.

Alternatively, researchers have used smoke plumes as an instrumental variable to estimate the impacts of total $PM_{2.5}$ from all sources (Borgschulte et al., 2024). This approach isolates variation in total $PM_{2.5}$ caused by wildfire smoke and produces a continuous dose-response estimate for total $PM_{2.5}$. Notably, these estimates are still susceptible to bias from measurement error in HMS smoke plume data.

Moving forward, researchers should consider empirical strategies that directly address measurement error in wildfire smoke data. In other empirical settings, studies have dealt with measurement error by averaging multiple noisy measures or instrumenting for one noisy measure with another (Ashenfelter and Krueger, 1994; Ward, 2023). The variety of wildfire smoke data and exposure measures makes both of these approaches feasible. Researchers could instrument for statistical estimates of smoke $PM_{2.5}$ with model-based estimates of smoke $PM_{2.5}$ from chemical transport, dispersion, or meteorological models. This would isolate variation in statistical estimates of smoke $PM_{2.5}$ that is driven by plausibly exogenous meteorological conditions that affect dispersion, correcting for measurement error in the process.

5 Conclusion

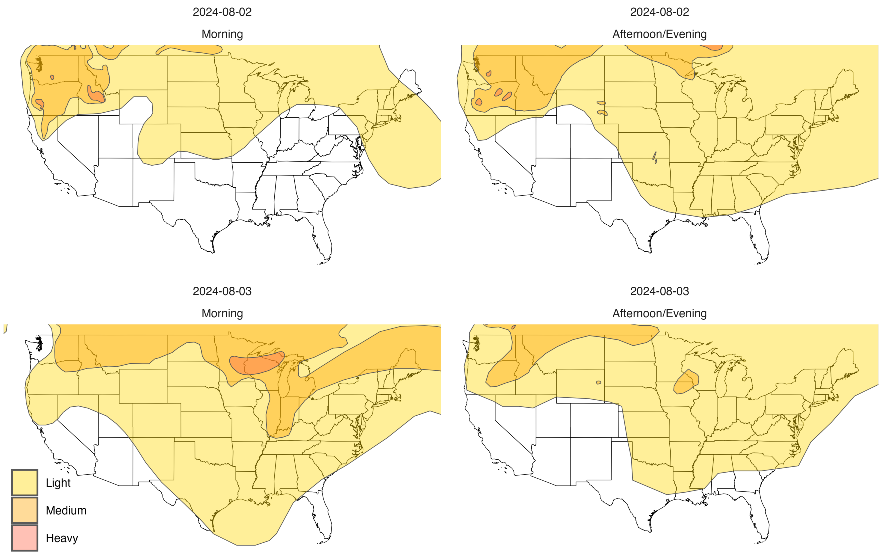
This review surveys popular wildfire smoke datasets. While HMS smoke plumes provide valuable information regarding the geographic distribution of wildfire smoke, they are imperfect measures of surface-level smoke conditions. Their weaknesses have motivated statistical estimates of smoke $PM_{2.5}$ that compare total $PM_{2.5}$ concentrations on smoke days to background $PM_{2.5}$ concentrations on non-smoke days. These estimates of smoke $PM_{2.5}$ better reflect surface-level smoke conditions and mitigate cloud-induced measurement error; however, estimating smoke $PM_{2.5}$ away from air quality monitors requires spatial interpolation that introduces non-classical measurement error.

Several ongoing efforts are poised to refine wildfire smoke data and exposure measures. First, NOAA analysts are exploring how machine learning techniques could aid the plume classification process. Since GOES satellites produce imagery every five minutes, there is potential to fill temporal gaps in HMS smoke plume data using predictions from algorithms trained on prior plume classifications. Second, new satellite products provide more information on the height of wildfire smoke in the atmosphere, allowing researchers to more accurately characterize surface-level conditions.[8] Third, recent research examines the chemical composition of smoke $PM_{2.5}$ and its contribution to different species of $PM_{2.5}$, such as organic carbon (Krasovich Southworth et al., 2025). This work supports efforts to distinguish smoke $PM_{2.5}$ from non-smoke $PM_{2.5}$. Fourth, methods for estimating smoke $PM_{2.5}$ will continue to advance, perhaps by combining statistical and model-based approaches. Finally, the growing availability of data from private air quality monitors, like PurpleAir, fills spatial gaps in the traditional air quality monitoring network, which could improve statistical estimates of smoke $PM_{2.5}$.

[8] https://www.nesdis.noaa.gov/news/wildfire-smoke-and-air-quality

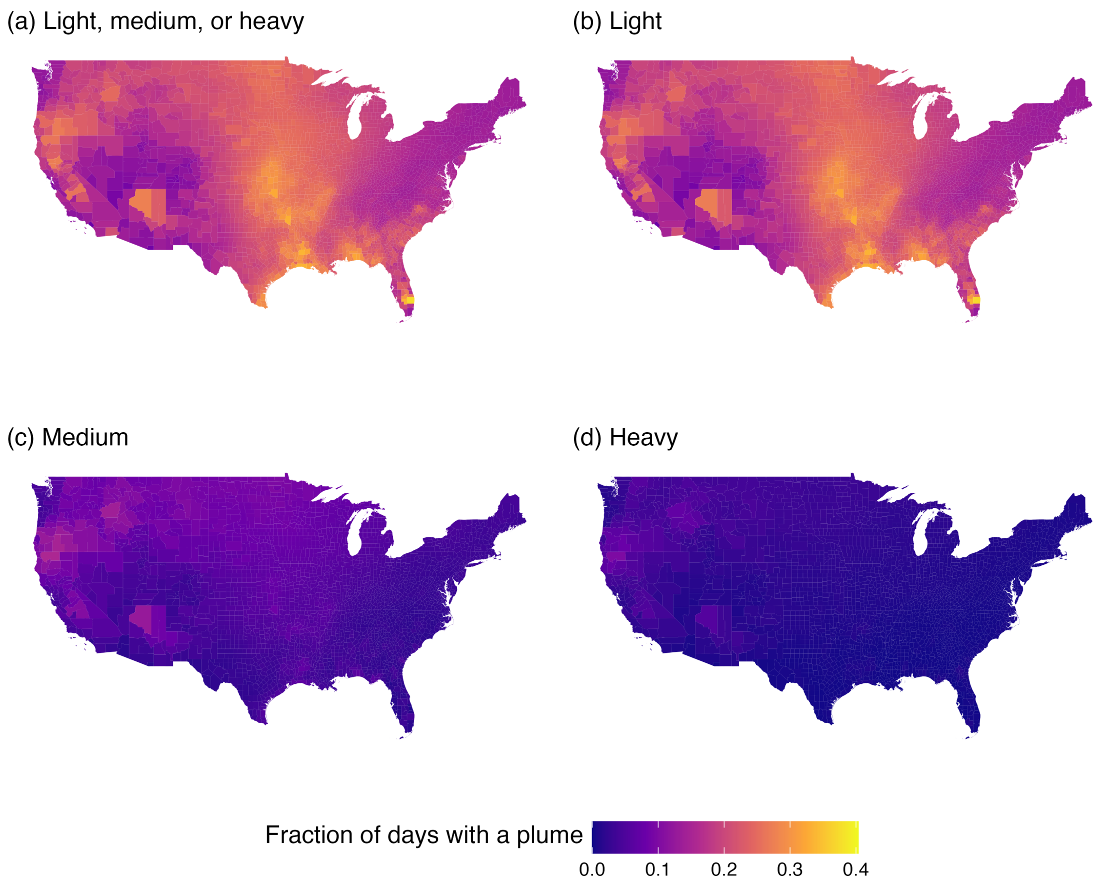
Figures

Figure 1. HMS Smoke plumes polygons do not capture continuous movements



Note: The figure maps smoke plumes from morning and afternoon/evening classifications on August 2, 2024 and August 3, 2024. Plumes travel between classifications, and NOAA analysts cannot track their movements continuously.

Figure 2. The frequency and geography of smoke plumes by density



Note: Panel (a) maps the fraction of days with a smoke plume overhead by county. This map includes plumes of any density (light, medium, or heavy). Panels (b), (c), and (d) map the fraction of days with a light, medium, or heavy plume separately. Light plumes are common across the Midwest and South in addition to the West. Medium and heavy plumes are less common than light plumes, especially outside the West. Data span 2011 through 2024.

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Appendix

A How do wildfire smoke exposure measures differ?

In this appendix, we compare wildfire smoke exposure measures derived from HMS smoke plume data and Childs et al.'s (2022) smoke $PM_{2.5}$ estimates. Our sample period is 2011 to 2020, representing all complete years when HMS smoke plumes have densities and Childs et al.'s smoke $PM_{2.5}$ estimates are available.

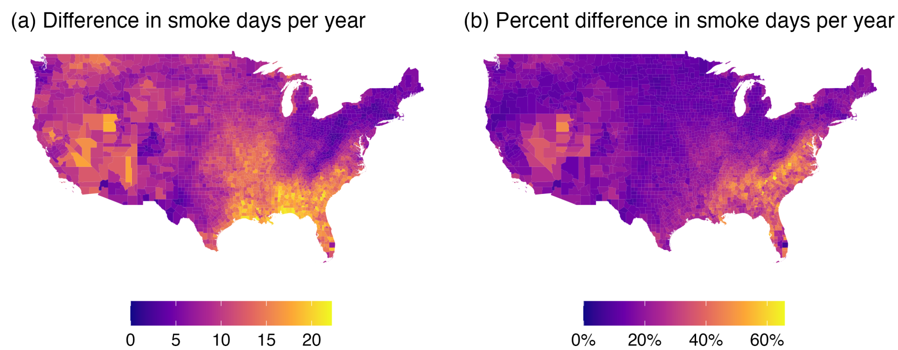
First, we compare the number of smoke days classified using only HMS smoke plume data versus Childs et al.'s smoke day measure (figure A.1). Recall that Childs et al. use smoke plumes to identify smoke days, but they also incorporate HYSPLIT projections in areas with high cloud cover. Thus, comparing the frequency of smoke days between HMS smoke plume data and Childs et al. helps gauge the importance of correcting for cloud cover. We find that Childs et al. identify substantially more smoke days per year. This is particularly true for counties in the Southeast and West where Childs et al. identify 20 or more additional smoke days per year, up to a 60% increase in total smoke days.

Table A.1 displays the joint distribution of three smoke day measures: the presence of any plume, the presence of a medium or heavy plume, and Childs et al.'s smoke day measure. The top panel shows that 85% of county-days are non-smoke days according to all three smoke day measures. Furthermore, it is rare to observe plumes overhead when Childs et al. assign a zero smoke day.[9] The bottom panel exposes more differences between the smoke day measures. Approximately 20% of Childs et al. smoke days do not have any plumes (0.03/0.15), which again suggests that cloud cover meaningfully impacts smoke detection. Additionally, the decision to include or omit light plumes creates meaningful differences in the "Any plume" and "Medium or heavy plume" measures, as 76% of days with a smoke plume have a light plume but no medium or heavy plume (0.10/0.13).

Finally, we explore how Childs et al.'s smoke $PM_{2.5}$ estimates vary by plume density. Figure A.2 shows that average smoke $PM_{2.5}$ increases with plume density, averaging 2.70, 4.75, and 11.13 $\mu g/m^3$ on days with light, medium, and heavy plumes, respectively. Nonetheless, there is substantial overlap in the distribution of smoke $PM_{2.5}$ concentrations across plume densities. For example, approximately 43% of days with heavy plumes have smoke $PM_{2.5}$ concentrations below 5 $\mu g/m^3$. These distributions have long right tails. The maximum smoke $PM_{2.5}$ concentration is over 500 $\mu g/m^3$, but these extreme days are quite uncommon. Only 1% of county-level smoke days have smoke $PM_{2.5}$ concentrations above 20 $\mu g/m^3$.

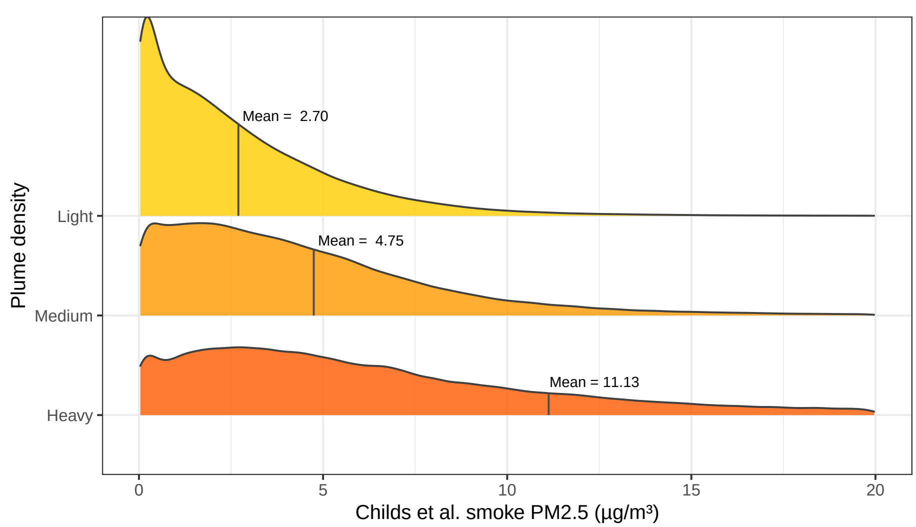
[9] Based on Childs et al.'s smoke day definition, any county-day with a plume overhead should be classified as a Childs et al. smoke day. While rare, we do find that 4,080 county-days (0.04%) have plumes but are not Childs et al. smoke days. This discrepancy is primarily caused by seven dates where plume data were unavailable for Childs et al. but have since been posted.

Figure A.1. Childs et al. identify more smoke days than the HMS plume data



Note: Panel (a) maps the difference in the number of smoke days per year identified by Childs et al. and the HMS smoke plume data by county: Childs smoke days per year minus plume smoke days per year. Panel (b) maps the average percent difference in smoke days: (Childs – plume) / plume. Both maps show that the discrepancy between Childs et al. and HMS plume smoke days is largest in the Southeast.

Figure A.2. Distribution of smoke $PM_{2.5}$ conditional on plume density



Note: The figure plots the distribution of Childs et al. smoke $PM_{2.5}$ levels on days with (1) a light plume but no medium or heavy plume, (2) a medium plume but no heavy plume, and (3) a heavy plume. We measure smoke $PM_{2.5}$ and the presence of smoke plumes at the county-level.

Table A.1. Joint distribution of smoke day measures

Childs smoke day = 0			
	Med. or heavy = 0	Med. or heavy = 1	Marginal
Any plume = 0	0.85	0.00	0.85
Any plume = 1	0.00	0.00	0.00
Marginal	0.85	0.00	0.85
Childs smoke day = 1			
	Med. or heavy = 0	Med. or heavy = 1	Marginal
Any plume = 0	0.03	0.00	0.03
Any plume = 1	0.10	0.03	0.13
Marginal	0.12	0.03	0.15

Note: The table shows the joint distribution of smoke day measures. For example, 10% of all county-days are a Childs et al. smoke day and have a smoke plume of any density overhead but do not have a medium or heavy plume overhead. The marginal columns (rows) sum across columns (rows). For example, 13% of all county-days are a Childs et al. smoke day and have a smoke plume of any density overhead