Practical Considerations When Using Wildfire Smoke Data in Economic Analyses

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1 Introduction

The increasing frequency and severity of wildfire smoke have widespread economic consequences (Gellman and Wibbenmeyer, 2025). Recent research documents impacts on crime (Burkhardt et al., 2019), education (Wen and Burke, 2022), health (Qiu et al., 2025), housing (Lopez and Tzur-Ilan, 2025), labor (Borgschulte et al., 2024), and recreation (Gellman et al., 2025).[1] This research typically exploits how wildfire smoke can travel hundreds of miles away from its source, which makes wildfire smoke exposure appear "as good as randomly assigned." Yet, this feature also makes measuring exposure difficult, motivating a deeper investigation of how wildfire smoke data are produced and what measurement error they may contain.

In this paper, we provide an overview of wildfire smoke datasets. We focus first on smoke plume data from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) because they are commonly used to measure wildfire smoke exposure and serve as a critical input to alternative datasets. Based on previous research, descriptive statistics, and conversations with NOAA analysts, we discuss five practical considerations for using HMS smoke plume data. We then present alternative wildfire smoke datasets, and finally, we examine key aspects of empirical analyses that researchers should consider when using these data.

2 HMS smoke plume data

2.1 Background

The 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

*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]Gould et al. (2024), Liu et al. (2015), and Reid et al. (2016) provide systematic reviews of the health impacts.

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.[2] In June 2010, analysts began assigning each plume a density — light, medium, or heavy — based on its perceived opacity in the satellite imagery.[3] Analysts generally classify plumes as "light" if they are mostly transparent and "heavy" if they are fully opaque, which introduces further subjectivity. Initially, densities were associated with approximate smoke $PM_{2.5}$ concentrations, but NOAA now recommends interpreting them qualitatively (Liu et al., 2024; NOAA, 2025). Typically, higher-density plumes overlay light plumes. For example, the presence of a medium plume implies the presence of a light plume. The presence of multiple plumes 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 in the atmosphere. Thus, they cannot determine surface-level conditions, which are relevant for most economic analyses of wildfire smoke exposure.

This begs the question: "How do smoke plumes impact 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 smoke may linger at the surface even when plumes are not observed by analysts. Consequently, plumes may underestimate surface-level conditions.

Alternatively, plumes may overestimate surface-level conditions when smoke is lofted high in the atmosphere. Liu et al. (2024) show that the correlation between plumes and surface-level smoke observations from airport monitors varies substantially by region and density. While plumes are more common than surface-level smoke throughout the United States, this pattern is strongest in the Midwest. They estimate that each year, airports in the Midwest experience 56 days with a plume but only 4 days with surface-level smoke. Dispersion models indicate that this discrepancy in the Midwest is due to smoke from distant fires that tends to be higher in the atmosphere (Brey et al., 2018). When focusing only on medium and heavy plumes, the frequency of plumes and surface-level smoke is much more similar. We caveat these findings by noting that airport monitors may not represent ground-truth. For example, airport monitors may be designed to detect dense smoke that impacts visibility and ignore lower-level concentrations. Together, these studies suggest that plumes are correlated with surface-level conditions to some extent, but they are imperfect proxies that can generate false negatives and false positives.

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

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

2.3 Consideration 2: Smoke never sleeps

HMS smoke plume data are snapshots 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 imagery is dark. Consequently, the data underestimate where plumes are located. For example, Miller et al. (2024) show that counties located within 1,000 km of a plume, but not directly under a plume, have elevated $PM_{2.5}$ concentrations.

In Figure 1, we illustrate 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 the Northern U.S., 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

Light plumes occur more frequently and widely across the country than medium and heavy plumes. Figure 2 maps the fraction of days with plumes by county. Panel (a) shows that plumes are common throughout the country, particularly the Midwest, South, and West. Approximately 15% of counties experience plumes more than one out of every four days. Surprisingly, Palm Beach County, Florida experiences the most days with plumes. Panel (b) shows that medium and heavy plumes are less common and more concentrated in the West than the Midwest and South. On days with plumes, 75% of the time there are only light plumes and no medium or heavy plumes. These findings suggest that the decision to include light plumes in analyses dramatically changes the frequency and geographic distribution of treatment, which could meaningfully alter estimates of the impacts of wildfire smoke exposure.

2.5 Consideration 4: Clouds, dust, and aerosols obscure smoke plumes

Clouds, dust, and aerosols present several challenges for plume classification. Clouds conceal plumes lower in the atmosphere. Daily HMS text descriptions accompanying the plume maps 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 mix with smoke regularly. 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 from 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. Although it is less common, the text descriptions also include a discussion of dust.

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 increase in 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).

3 Smoke $PM_{2.5}$ data

3.1 Statistical approaches

Since HMS smoke plume data do not accurately reflect surface-level conditions, several studies attempt to measure surface-level conditions by estimating the amount of $PM_{2.5}$ that is attributable to wildfire smoke, commonly referred to as "smoke $PM_{2.5}$." These studies typically differentiate smoke $PM_{2.5}$ from non-smoke background $PM_{2.5}$ by calculating deviations in total $PM_{2.5}$ at air quality monitors on "smoke days" and "non-smoke days." Here, we discuss datasets that estimate smoke $PM_{2.5}$ nationally, but we note that several papers 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 use air quality monitors from the U.S. Environmental Protection Agency (EPA) and spatial interpolation to estimate daily total $PM_{2.5}$ at a 15-km resolution. They estimate background $PM_{2.5}$ as the seasonal-median $PM_{2.5}$ on non-smoke days. Finally, they calculate daily smoke $PM_{2.5}$ as the difference between daily total $PM_{2.5}$ and background $PM_{2.5}$ in locations where plumes are overhead.

Childs et al. (2022) estimate $PM_{2.5}$ at air quality monitors and use machine learning to predict smoke $PM_{2.5}$ across the country. They first identify smoke days using smoke plumes and HYSPLIT model predictions. On smoke days, they estimate daily smoke $PM_{2.5}$ at EPA air quality monitors 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 meteorology, wildfires, 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.

Zhang et al. (2023) use transport modeling and machine learning to estimate smoke $PM_{2.5}$ based on EPA and PurpleAir air quality monitors. Like Childs et al., they combine smoke plumes with transport modeling to identify smoke days. Zhang et al.'s approach differs from Childs et al. in that they train two machine learning models. One model uses data from smoke days to predict daily total $PM_{2.5}$ at smoke-impacted locations, and another model uses data from non-smoke days to predict daily background $PM_{2.5}$ at all locations. In smoke-impacted locations, they calculate daily smoke $PM_{2.5}$ as the difference

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

between total $PM_{2.5}$ and 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 smoke $PM_{2.5}$. One strength of Childs et al. and Zhang et al. is that they mitigate measurement error from cloud cover by incorporating smoke plumes and transport modeling when identifying 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, spatial interpolation 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 there are confounders that impact these estimates regionally. Childs et al. (2024) update their analysis by incorporating spatially interpolated smoke $PM_{2.5}$ into the machine learning model directly. While this improves the estimates, predictions remain less accurate in the South and Southwest. 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 datasets through 2023, Zhang et al. have not updated their estimates after publication.

3.2 Model-based approaches

Chemical transport models, physical dispersion models, and meteorological models present alternatives to the statistical approaches above. Researchers often measure how adding wildfire 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.[5] Other tools combine several modeling approaches and provide off-the-shelf predictions of wildfire smoke concentrations. BlueSky is a U.S. Forest Service tool that includes a fire emissions model with particulate dispersion models of smoke $PM_{2.5}$ at a 3-km resolution.[6] Similarly, the High-Resolution Rapid Refresh tool models smoke $PM_{2.5}$ at a 3-km resolution using a chemical and meteorological approach.[7]

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. Notably, chemical transport models are not affected by measurement error in HMS smoke plume data, making them a potentially useful instrumental variable for smoke plumes and statistical estimates of smoke $PM_{2.5}$.

[5]Wildfire emissions measurements typically come from separate datasets, including the Global Fire Emissions Database or Quick Fire Emissions Dataset.

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

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

4 Empirical analysis

4.1 Measures of wildfire smoke exposure

First, a researcher needs to determine whether to measure the frequency or 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. document elevated $PM_{2.5}$ concentrations up to 1,000 km from plumes. Researchers must also decide how to treat plume densities. Some studies consider all plume densities (Aguilera et al., 2021; Borgschulte et al., 2024; Burkhardt et al., 2019), while others ignore light plumes in their main analyses and focus on medium and heavy plumes (Molitor et al., 2023). Ignoring light plumes may meaningfully impact analyses given the prevalence of light plumes discussed above. In contrast, statistical estimates of smoke $PM_{2.5}$ limit researcher discretion. Estimates 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, these estimates mitigate cloud-induced measurement error. 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 the intensity of exposure face their own challenges. HMS smoke plume densities approximate exposure intensity, but they do not correspond directly to $PM_{2.5}$ concentrations and may not accurately reflect surface-level conditions. Instead, continuous measures of smoke $PM_{2.5}$ provide surface-level measurements of exposure intensity. Furthermore, using a continuous measure allows comparison to other dose-response studies for $PM_{2.5}$. Since the EPA primarily considers dose-response studies in benefit-cost analyses, studies using smoke $PM_{2.5}$ could potentially support future regulatory actions. Yet, 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 coarse temporal frequencies, researchers may need to aggregate daily measures of wildfire smoke exposure within time periods (e.g., months). When using a continuous measure of smoke $PM_{2.5}$, it is common to calculate average smoke $PM_{2.5}$ within time periods (Qiu et al., 2025). Alternatively, researchers can calculate the number of days in different smoke $PM_{2.5}$ bins, characterizing the entire range of the distribution. This binning approach resembles climate research that measures temperature exposure by calculating the number of days in temperature bins (Barreca et al., 2016).

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 estimating the impacts of wildfire smoke exposure typically treats exposure as exogenous after controlling for fixed effects and common time shocks in two-way fixed effects models. Some of these specifications may be particularly susceptible to measurement error. For example, a specification that leverages variation in plume coverage within a small geographic area 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 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, which is often more plausibly exogenous than non-smoke sources like industrial manufacturing. It also 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. For example, researchers could instrument for statistical estimates of smoke $PM_{2.5}$ with model-based estimates of smoke $PM_{2.5}$ from chemical transport, dispersion, and meteorological models. This would isolate variation in estimated smoke $PM_{2.5}$ that is driven by plausibly exogenous meteorological conditions that affect pollutant dispersion, minimizing measurement error in the process.

5 Conclusion

This review surveys popular wildfire smoke datasets and highlights their key features. While HMS smoke plumes provide valuable insights regarding the geographic distribution of wildfire smoke, they are vulnerable to multiple sources of measurement error, which makes measuring wildfire smoke exposure challenging. These weaknesses have motivated statistical estimates of smoke $PM_{2.5}$ that compare surface-level $PM_{2.5}$ concentrations on smoke days to background concentrations on non-smoke days. These estimates of smoke $PM_{2.5}$ reflect surface-level conditions and mitigate cloud-induced measurement error, overcoming several weaknesses of HMS smoke plume data; however, estimating smoke $PM_{2.5}$ away from air quality monitors requires spatial interpolation that introduces non-classical measurement error.

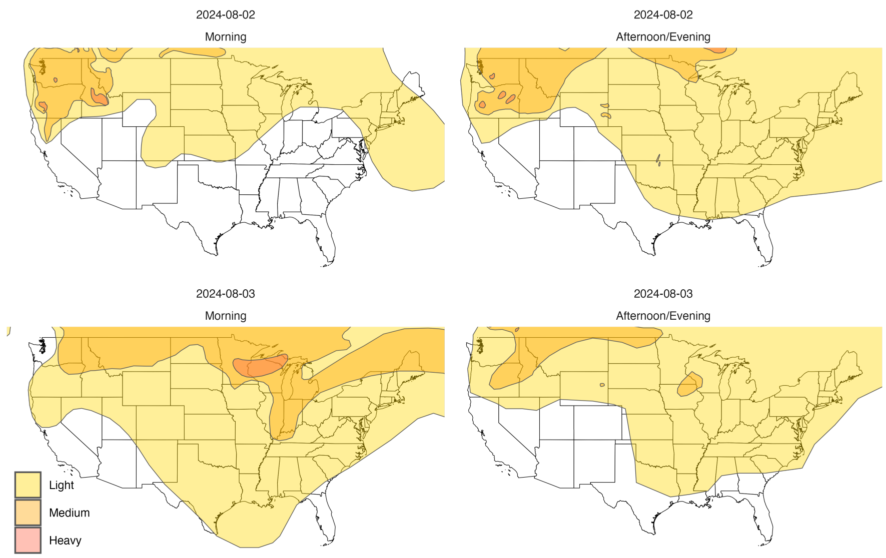
Thus far, environmental economists have paid little attention to these sources of measurement error. It is unclear how measurement error influences estimates of the impacts of wildfire smoke exposure, but estimates that depend on granular spatial and temporal variation are more vulnerable to bias. Economists have a rich history of addressing measurement error in other subfields that could inspire work in the wildfire smoke exposure literature.

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 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 (e.g., organic carbon) of $PM_{2.5}$ (Krasovich Southworth et al., 2025; Jin et al., 2025). This line of research 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 (Qiu et al., 2024). Finally, the growing availability of air quality data from private monitors (e.g., 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

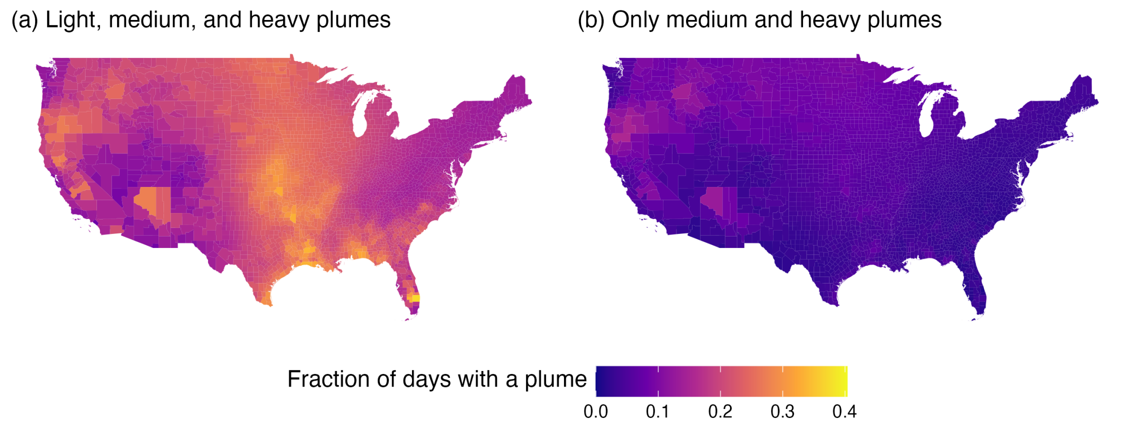
Figures

Figure 1. 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 analysts cannot track their movements continuously.

Figure 2. The frequency and geography of smoke plumes



Note: Panel (a) maps the fraction of days with a smoke plume overhead by county. This map includes plumes of any density (light, medium, and heavy). Panel (b) maps the fraction of days with a medium or heavy plume. 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.

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Appendix

A How do wildfire smoke exposure measures differ?

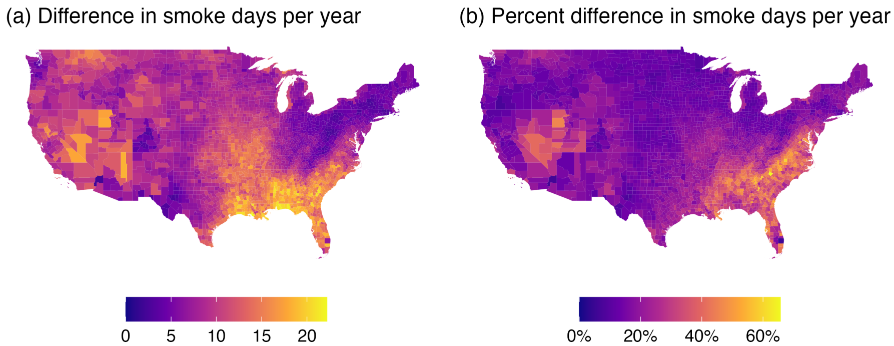
In this appendix, we compare smoke exposure measures derived from Childs et al.'s (2022) smoke $PM_{2.5}$ estimates and the HMS smoke plume data. Our sample period is 2011 through 2020—all full years where HMS smoke plumes with densities and Childs et al.'s smoke $PM_{2.5}$ estimates are available.

First, we compare the number of "smoke days" classified using the HMS smoke plumes versus Childs et al.(figure A.1). Recall that Childs et al. use the HMS plumes to identify smoke days, but they also incorporate HYSPLIT projections in areas with high cloud cover. Thus, comparing the frequency of Childs et al. smoke days and HMS plume smoke days 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 smoke days derived from either the HMS smoke plumes or Childs et al.'s smoke $PM_{2.5}$ measure. The top panel shows that 85% of days are non-smoke days according to both measures and that it is extremely rare to observe smoke plumes when Childs et al. estimate zero smoke $PM_{2.5}$. The bottom panel exposes more differences between the smoke day measures. Approximately 20% of days with non-zero smoke $PM_{2.5}$ do not have any plumes ($0.03/0.15 = 0.20$). Additionally, the decision to include or omit light plumes creates meaningful differences in the "Any plume" and "Plume $\geq$ Medium" measures, as 75% of days with a smoke plume have a light plume but no medium or heavy plume ($0.09/0.12 = 0.75$).

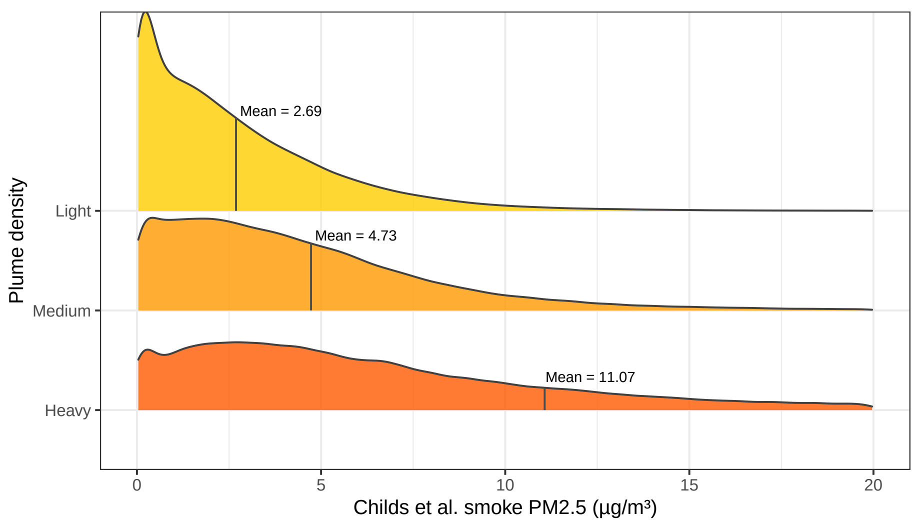
Finally, we explore how Childs et al.'s estimated smoke $PM_{2.5}$ levels vary by plume density in the HMS smoke plumes data. Figure A.2 shows that average smoke $PM_{2.5}$ increases with plume density, averaging 2.69, 4.73, and 11.07 $\mu g/m^3$ on days with light, medium, and heavy plumes, respectively. Nonetheless, there is substantial overlap in the distribution of smoke $PM_{2.5}$ levels across plume densities. For example, approximately 43% of days with heavy plumes have estimated smoke $PM_{2.5}$ levels below 5 $\mu g/m^3$. These distributions have long right tails. The maximum smoke $PM_{2.5}$ level is over 500 $\mu g/m^3$, but these extreme days are quite uncommon. Only 1% of county smoke days have predicted smoke $PM_{2.5}$ levels above 20 $\mu g/m^3$. The seeming mismatch between plume density and smoke $PM_{2.5}$ concentrations we document is likely driven by whether the plume is far overhead or at ground level.

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

	Plume $\geq$ Medium = 0	Plume $\geq$ Medium = 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

	Plume $\geq$ Medium = 0	Plume $\geq$ Medium = 1	Marginal
Any plume = 0	0.03	0.00	0.03
Any plume = 1	0.09	0.03	0.12
Marginal	0.12	0.03	0.15

Note: The table shows the joint distribution of smoke day measures. For example, 9% 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, 12% of all county-days are a Childs et al. smoke day and have a smoke plume of any density overhead.