Note: this non-peer reviewed preprint. It has been submitted to a peer-reviewed journal for publication.

Growing wildfire-derived $PM_{2.5}$ across the contiguous U.S. and implications for air quality regulation

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August 18, 2025

Abstract

Growing wildfire activity across North America generates large amounts of smoke that can travel long distances. Characterizing the influence of this smoke on surface air quality is critical for regulation of air quality and protection of public health. Here we provide granular, daily estimates of smoke fine particulate matter ($PM_{2.5}$) concentrations across the contiguous U.S. and use them to assess the influence of wildfire smoke on surface $PM_{2.5}$ from 2006 to 2024, using a combination of surface measurements, satellites, and machine learning. Each year from 2020 to 2024, population-average smoke $PM_{2.5}$ exposures were 2.6–6.9 times higher than the 2006 to 2019 average and exposure periods were more than twice as long. Despite wildfire smoke being historically more common in the Western U.S., the worst 5 days for population-average smoke exposure in our sample period all occurred in 2023, a year with limited Western exposure. We estimate that 34% of monitoring stations are currently above the recently-updated ambient air quality standards but would be below them absent smoke, necessitating increased use of extreme event exemptions to remain within regulatory limits; we show that such use is already rare on attainment-relevant days and could become increasingly challenging. Absent wildfire smoke, we estimate that $PM_{2.5}$ concentrations would have continued to improve throughout the contiguous U.S.

Recent years have seen a dramatic increase in wildfire activity across North America, a result of climate-driven increases in fuel aridity combined with a century of fire suppression and increasing human activity in wildlands (1–5). The smoke from these fires is having a demonstrable negative impact on surface air quality (6–9) and public health (10–15). Prior studies estimate that wildfire smoke accounted for 25% of U.S.-wide $PM_{2.5}$, and over 50% in some Western states, in previous extreme wildfire years (7, 16, 17).

While wildfire smoke exposure has historically been more common in the Western U.S., there have been recent increases in wildfire smoke in other parts of the U.S., for example as a result of the transport of smoke from Canadian fires in 2023 into the Central and Eastern U.S. (18). Rapid recent changes in both the seasonal timing and geography of smoke exposure, along with recent strengthening of U.S. ambient air quality standards, motivate the continued development, improvement, and deployment of tools that can accurately and rapidly assess the contribution of wildfire smoke to surface air quality at a high temporal and spatial resolution. Such estimates are an important component of understanding whether existing approaches to air quality regulation, which have been successful in reducing many non-wildfire sources of air pollutants but exempt wildfire smoke from regulation, are likely to maintain air quality and protect public health. Such estimates are also a key input into an improved understanding of the health impacts of wildfire smoke—analyses that often require long time series of spatially resolved exposure data to accurately characterize public health risks.

Here, building on previous work, we use statistical approaches to estimate $PM_{2.5}$ from wildfire smoke by combining data from ground monitoring stations and satellite-based smoke plume identification (6, 7, 9). In contrast to process-based chemical transport models (CTMs), these statistical approaches do not attempt to parameterize the physical processes driving wildfire smoke, but rather derive ground-based measures of wildfire smoke in observed monitoring station data and then train a statistical model to directly predict these measures from a range of inputs. Statistical approaches have been shown to have better agreement with surface observations in predicting wildfire smoke relative to CTM-based approaches (19), especially under extreme smoke levels (e.g., western US in 2020), in part because CTMs depend on a number of inputs—in particular, emissions inventories and plume injection heights—which are difficult to empirically constrain (20, 21).

While previous estimates of daily wildfire smoke have covered through at most 2020 (7, 9, 22, 23), recent large-scale wildfire activity and smoke exposures throughout North America (24) motivate updated concentration estimates and assessment of population exposure to wildfire smoke $PM_{2.5}$. Additionally, statistical methods for attributing and predicting wildfire smoke impacts on air quality are in their infancy, particularly in comparison to a better-established literature on measuring overall concentrations of key air pollutants (25, 26), suggesting improvements over existing methods are likely possible. Finally, the confluence of growing wildfire smoke exposure and the recent tightening of ambient air quality standards for particulate matter in the U.S. (from 12 to 9 $\mu g/m^3$ for annual mean concentrations) (27) has unclear implications for whether and how these standards will be achieved. Wildfire smoke is exempted from regulation under these standards, but jurisdictions must apply for these exemptions by demonstrating that wildfire caused a jurisdiction to exceed its statutory limit. Such demonstrations require making complex, causal claims about the influence of wildfire smoke on ambient air quality (28). There is little comprehensive evidence on how exemptions are being used in response to rapidly growing smoke risk, and thus it is unknown the extent to which this growing risk threatens attainment of increasingly strict standards.

We estimate daily concentrations of surface-level smoke $PM_{2.5}$ at ground monitoring stations in the contiguous U.S. (CONUS) by first estimating a counterfactual non-smoke concentration that accounts for location and season-specific averages as well as trends in non-smoke $PM_{2.5}$ over time, using satellite- and analyst-derived smoke plumes to distinguish which days were smoke influenced. Surface-level smoke $PM_{2.5}$ at each monitor is then estimated as the difference between this background and observed $PM_{2.5}$ when a smoke plume is overhead. To produce estimates of surface smoke $PM_{2.5}$ that then fill spatial and temporal gaps in monitoring data, we train a machine learning model to predict monitor-level smoke $PM_{2.5}$ using a range of candidate features shown to be useful in previous work, validating model prediction on held-out monitors not used in model training (Fig. S1). Our approach builds on earlier work (6, 7, 9, 23, 29, 30) and shows how a combination of satellite and ground monitor data can be combined to efficiently produce accurate measures at scale, outperforming previous approaches.

We then use our trained model to produce daily, 10 km estimates of wildfire smoke from 2006 to 2024, and use these estimates of smoke $PM_{2.5}$ to understand patterns and trends in ambient smoke $PM_{2.5}$ concentrations, particularly focusing on shifting population exposure. Finally, given the rapidly growing concentrations of wildfire smoke $PM_{2.5}$, the current exemption of wildfire smoke $PM_{2.5}$ under U.S. air quality regulations, and the recent strengthening of the National Ambient Air Quality Standards, we use station-level smoke $PM_{2.5}$ data and flags for exceptional events to understand how smoke may influence whether locations can remain in attainment of these new standards and whether jurisdictions are using and will be able to use exceptional event exemptions to meet standards.

Results

Model performance For our best performing model, out-of-sample performance measured with spatial cross validation was an R^2 of 0.72 at the daily level (Fig. S2a, Fig. S3a). Within R^2, an estimate of the explained variance after controlling for monitor-specific averages and annual changes over time common to all monitors, was largely similar to the overall R^2 computed using variation both within and between monitors, suggesting that the model estimates are capturing temporal variation in smoke $PM_{2.5}$ within locations and not just spatial patterns in averages smoke $PM_{2.5}$ levels (Fig. S2a). We also evaluated whether models can perform well out of sample temporally by training models on January 2006 to June 2023 data and predicting smoke for July 2023 through December 2024. We find that the performance of our model in predicting temporally held-out data is similar to its performance in predicting spatially held-out data (Fig. S2b). We also validate the model performance in comparison to non-reference-grade PurpleAir monitors that are not used in the model training, and find that model performance is slightly lower (R^2 = 0.53, Fig. S4).

Model performance was somewhat better at low smoke $PM_{2.5}$ concentrations than at high smoke $PM_{2.5}$ concentrations, with underestimation at high concentrations and a smaller magnitude of overestimation at low concentrations (Fig. S2). Performance also varied by location, with model performance as measured by station-specific R^2 using out-of-sample predictions highest in the Northeast, Midwest, West, and Northwest and lowest in the Southwest (Fig. S3b). This variation in model performance is consistent with previous estimates of total and fire-specific $PM_{2.5}$, which have also shown poorer performance in the Southwest and at high concentrations (22, 26, 31, 32), and in part reflects the low smoke variance and sometimes short and noisy time series of some stations in this region (7). In comparison to a model without interpolated smoke $PM_{2.5}$ from nearby stations, a highly predictive feature used in the current work (Fig. S3c) but not previous work (7), the preferred model that includes interpolated smoke $PM_{2.5}$ improves performance throughout the CONUS, even at stations in the western states that are relatively far from other stations used in interpolation (Fig. S3d).

Finally, we assessed how updated smoke estimates altered inferences in two existing downstream applications (12, 13) that used earlier modeled smoke $PM_{2.5}$ estimates to quantify drivers and impacts of wildfire smoke. This important but infrequently implemented exercise is statistically distinct from the more customary characterization of how new predictions alter estimated population exposures, but is crucial for understanding how updates to existing datasets alter established scientific findings derived from those datasets. We find in both replications that prior inferences were robust to data updates (Fig. S5).

Patterns and trends in smoke $PM_{2.5}$ We aggregate our daily predictions to larger temporal periods to understand patterns and trends in smoke $PM_{2.5}$. We calculate annual average smoke $PM_{2.5}$ over the contiguous U.S. at the grid-cell level and find that recent years have had some of the highest smoke $PM_{2.5}$ concentrations (Fig. 1), with many locations experiencing levels of annual average smoke $PM_{2.5}$ that exceed the new annual average ambient air quality standard for total $PM_{2.5}$ (updated to 9 $\mu g/m^3$ in 2024). While 2017, 2018, and 2020 showed high concentrations of smoke $PM_{2.5}$ primarily in Western states, recent years (2021–2024) have had more elevated levels of smoke $PM_{2.5}$ in Eastern states as well.

Using these annual average estimates, we then fit location-specific trends in smoke $PM_{2.5}$ over the 19-year period, and find annual increases in smoke $PM_{2.5}$ of over 0.4 $\mu g/m^3$ per year in some locations (Fig. S6c); such increases are large relative to background concentrations. These increases in smoke $PM_{2.5}$ are largest in the Western states, but almost all locations experienced increases over this time period. While most locations with high annual average smoke $PM_{2.5}$ experienced large increases from 2006 to 2024, some locations, including the Northern Rockies and Northern Cascades, saw more modest increases despite high annual average smoke $PM_{2.5}$, a result of higher smoke $PM_{2.5}$ in some earlier years in our study period (in particular, in 2012; Fig. S6, Fig. 1). In addition to annual averages, the number of days with extreme smoke $PM_{2.5}$ (>50 $\mu g/m^3$) per year has also increased, although these increases are primarily concentrated in Western states (WA, OR, CA, MT, ID, and NV), where some locations have seen an increase of one additional extreme day per year; the Upper Midwest and Ohio Valley have seen smaller increases. We find these trends match observed trends at monitoring stations despite the predicted nature of the smoke $PM_{2.5}$ estimates and changes in station reporting (Fig. S7, Fig. S8)

Population exposure to smoke $PM_{2.5}$ While increases in smoke $PM_{2.5}$ concentrations in the West have been larger, the more recent and slightly smaller increases in smoke $PM_{2.5}$ concentrations in the Midwest and East (Fig. 1) are particularly notable given the high population density throughout the region. To understand how population-average exposure to smoke has changed over time—interpretable as the change in smoke exposure for the average resident in the CONUS—we estimate population-weighted cumulative exposure to wildfire smoke $PM_{2.5}$ for each year over the CONUS and find that exposures from 2020–2024 were 2.6, 3.6, 3.0, and 6.9, and 3.8 times higher, respectively, than the 2006–2019 average (Fig. 2a). These notably higher population-average smoke $PM_{2.5}$ concentrations in 2020-2024 are congruent with high annual biomass burning emissions and burned areas observed in those years (Fig. S9). These extreme wildfire conditions in 2020-2024 throughout the US and Canada were driven by extreme weather conditions including large scale extreme heat and drought in those years, which increased fire risks and synchronized fire dangers that further challenged the suppression of those fires (33, 34). Since 2021, the average "smoke season" was also notably longer, with meaningful CONUS-wide population-level exposures (defined here as days with $>1 \mu g/m^3$ smoke $PM_{2.5}$) beginning in spring rather than summer and lasting until late fall—in total, over three times as long in the 2021–2024 period as compared to the 2006–2019 average smoke season (Fig. S10). We find that changes in station reporting over time is unlikely to have contributed to these large-scale increases in population exposure to wildfire smoke $PM_{2.5}$ or the lengthening "smoke seasons" (Fig. S11).

We calculate the individual days with the highest population-average smoke exposure in our 2006–2024 sample period. All 10 of the highest smoke exposure days fell within the last 4 years (Fig. 2b). On the worst day on record (June 7, 2023), over 155 million people were exposed to wildfire smoke $PM_{2.5}$ above 10 $\mu g/m^3$, with an average exposure over the entire CONUS population for that day of 29.2 μg/m^3 . Remarkably, seven of the 10 worst days occurred in June 2023 when smoke from Canadian wildfires affected Midwest and Eastern states—a period in which the Western U.S., historically the recipient of extreme exposures, was unaffected. The remainder occurred in September 2020 when wildfire smoke covered much of the Western states (Fig. 2b).

These increases in average population exposure have also corresponded to an increase in exposure to days with extreme smoke $PM_{2.5}$ concentrations (Fig. 2c). In 2023 alone, over 135 million people were living in locations with at least one day where concentrations from wildfire smoke alone exceeded 50 μg/m^3 , and of those, over 83 million people had at least one day over 100 μg/m^3 . While 2023 stands out for the number of people experiencing at least one day over 50 or 100 μg/m^3 , the most extreme exposures over 200 μg/m^3 were greatest in 2020, when 6.6 million people experienced at least one day over 200 μg/m^3 , mostly in the Western U.S.

Impacts of smoke on air quality regulation We use our station-level reconstructions of daily wildfire smoke concentrations, coupled with observed measurements of total daily $PM_{2.5}$ from the same stations, to assess the relative contribution of smoke to overall air quality and how changing concentrations of wildfire smoke $PM_{2.5}$ contribute to whether localities are above or below recently-updated National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$ set by the Environmental Protection Agency (EPA). These standards are now 9 μg/m^3 for annual average $PM_{2.5}$ (recently lowered from 12 μg/m^3), and the unchanged 24-hour standard of 35 μg/m^3 (27). Our goal in this analysis is not to estimate whether localities are "in attainment" of these updated standards. Not only is this designation officially made at a more aggregated "area" level (including, variously, at the city, county, or air basin level), but attainment designations are explicitly allowed to exempt wildfire smoke: jurisdictions are allowed to apply for "Exceptional Events" exemptions of monitor–day readings for which they believe unusual or naturally occurring events outside of local agency control (including wildfire smoke) have led to nonattainment, with those readings excluded from attainment calculations if the exemption request is concurred by the EPA (28). Instead, our goal is to understand the extent to which local jurisdictions will need to rely on exceptional events exclusions in order to remain in attainment of ambient standards—and whether, given recent trends, the current approach to air quality regulation (which exempts wildfire smoke) is likely to keep local air quality below thresholds the EPA has deemed important to protect public health.

At the national and regional level, we find that recent trends in overall (smoke + non-smoke) $PM_{2.5}$ concentrations, which saw multi-decadal improvements through around 2015 and then subsequent stagnation and reversal of progress (8), are substantially driven by recent changes in wildfire smoke $PM_{2.5}$ (Fig. 3). We estimate that absent smoke $PM_{2.5}$, overall $PM_{2.5}$ concentrations would have continued to decline through 2024 in almost all regions of the country (blue lines, Fig. 3). With smoke, overall ambient $PM_{2.5}$ concentrations have stagnated or risen in recent years throughout the country.

Consistent with these regional trends, we find that the number and proportion of stations with ambient $PM_{2.5}$ concentrations above the updated 9 μg/m^3 standard fell steadily through about 2016, before leveling off. Prior to 2016, we estimate that the vast majority of stations with ambient concentrations above 9 μg/m^3 would still have had concentrations above 9 μg/m^3 in the absence of wildfire smoke (Fig. 4a). Put another way, wildfire smoke was not the reason why concentrations at these stations exceeded current ambient standards. Beginning 2016 and following, not only have the number of stations with concentrations exceeding annual standards stagnated, but wildfire smoke has increasingly been a contributing factor. In the last 5 years (2020–2024), 32% of stations (or 416 out of 1297 stations) had annual levels above 9 μg/m^3 in at least one year. Of these 416 stations, 61% would have had annual $PM_{2.5}$ concentrations below 9 μg/m^3 for all years absent wildfire smoke. Similar to the annual standard, wildfire is increasingly a contributor to stations exceeding the 24-hour regulatory limit (Fig. 4). From 2008 to 2019, on average, 6% of all stations were over the 24-hour regulatory limit each year and 38% of those exceedences would not have occurred absent smoke. But in the last 5 years, the number of stations exceeding the 24-hour standard has almost doubled to 10% of stations on average each year. In total, 17% of stations were over the 24-hour standard in at least one of the last five years and 91% of those would have otherwise been under the regulatory limit if not for wildfire smoke.

The stations where attainment status is increasingly affected by smoke are located throughout the country, and illustrate the pattern of both smoke $PM_{2.5}$ and background, non-smoke $PM_{2.5}$ concentrations. In the West, wildfire smoke is helping push a large number of stations in California, Oregon, Washington, and Idaho over the regulatory limit for both annual averages and daily extremes (Fig 4b). In contrast, in the East and South where background $PM_{2.5}$ levels are higher (Fig 3), smoke is contributing to exceedences for annual averages, but has had little influence on daily extremes. In total, 34% of stations have exceeded regulatory limits in one of the last 5 years but would not have absent smoke, with 9% of stations exceeding limits for both annual averages and daily extremes (Fig. 4).

Understanding where smoke is a key contributor to $PM_{2.5}$ concentrations rising above ambient standards does not precisely answer where the exclusion of smoke-affected days from air quality standard compliance calculations, as is done through exceptional events rulings, would result in compliance with these standards. While jurisdictions can legally request the exclusion of high smoke $PM_{2.5}$ days from attainment calculations, this approach can be challenging as jurisdictions face longer smoke seasons with more days with elevated $PM_{2.5}$ from smoke throughout the year, as well as prolonged periods with lower levels of smoke $PM_{2.5}$ for which exclusion is more difficult to justify due to its classification as a “Tier 2” or “Tier 3” event (35). To estimate how many smoke days different jurisdictions (again proxied by monitoring stations in our data) would have to exclude from the record to have stayed below ambient standards in recent years, we simulate a setting in which jurisdictions sequentially exclude smoke days, starting with the day with the highest smoke $PM_{2.5}$ concentration and iteratively dropping lower days until they are below both the annual $PM_{2.5}$ standard and 24-hour $PM_{2.5}$ standards. We then compute the number of days that were needed to be dropped, and the smoke concentration on the final dropped day.

We find that for a subset of monitors, only a few extreme smoke $PM_{2.5}$ days would need to be excluded in recent years to bring both annual and 24-hour values back below ambient standards (Fig. 5, Fig. S12). In many others, however, nearly a month or more of days would need to be excluded to meet the standards, with many dropped days having relatively low smoke $PM_{2.5}$ which could be harder for regulators to identify and justify. These locations where more days at lower smoke $PM_{2.5}$ levels must be excluded are primarily in locations where average non-smoke $PM_{2.5}$ is close to the ambient air quality standards and where many days are affected by wildfire smoke (Fig S13). In particular, 2023 stands out as the year in which excluded smoke days would have the greatest benefit for attainment in terms of the number of stations benefited (251 stations, Fig. S12)—a result of widespread smoke exposure in the Midwest and East and an ongoing decline in non-smoke $PM_{2.5}$. Given many days of relatively low smoke exposure during 2023, most of these stations would have to exclude relatively low smoke days, and often many of these days, to remain in attainment. We estimate that 27% of stations above the 9 $\mu g/m^3$ annual standard with smoke in 2023 that could become compliant with exclusions would need to exclude over 5% of days from the record to remain compliant (Fig. S12).

Are local jurisdictions actively seeking these exclusions, and on what days? We examine all smoke days since 2019 at regulatory monitors and calculate the proportion of days at different smoke values when local jurisdictions "informed" the EPA of potential wildfire influence or applied for a wildfire-related exemption. We focus on monitor–days when smoke $PM_{2.5}$ was plausibly relevant to attainment designation—i.e., days when we calculate that including or not including a $PM_{2.5}$ reading could affect a monitor's attainment designation for that year.

We find that on these "relevant" days, jurisdictions are more likely to inform or apply for exemptions at higher smoke levels, as expected (Fig. 6). However, the likelihood of either are quite low on low- to moderate- smoke days, which make up a substantial proportion of total exposure, and applications are currently infrequent at even fairly high smoke levels, with only about 20% of days with smoke $PM_{2.5}$ above 100 $\mu g/m^3$ requested for exclusion.

Discussion

We provide updated, granular estimates of wildfire smoke $PM_{2.5}$ across the contiguous U.S. from 2006–2024. These updated estimates show improved agreement with ground observations as compared to previous work, with improvements in model performance across geographies and at both high and low smoke exposures. Resulting estimates indicate rapidly growing population exposure to ambient smoke particulate matter across the U.S., and suggest that these growing exposures could represent substantial ongoing and future challenges to air quality regulation.

These estimates complement a growing body of literature estimating wildfire smoke $PM_{2.5}$ (7, 9, 22, 23, 36–39) by providing up-to-date estimates through 2024. The inclusion of recent years (2021-2024) highlights the widening geographic area, particularly in the eastern U.S., affected by wildfire smoke $PM_{2.5}$. In contrast to some other estimates (38, 39), we focus on daily predictions of wildfire smoke $PM_{2.5}$ due to the large day-to-day variation in concentrations. We improve on earlier work (7) by integrating interpolated smoke $PM_{2.5}$ as an additional feature to improve model performance. With the addition of interpolated smoke $PM_{2.5}$, predicted AOD anomalies no longer contribute large improvements to model performance and can be removed to reduce computation.

Our estimates could likely be further improved in multiple ways. For example, NOAA Hazard Mapping System (HMS) smoke plumes, which determine which days are identified as possibly smoke-influenced and are commonly used in smoke analyses, have uncertainty and data gaps that could impact our (and other) smoke $PM_{2.5}$ estimates. Prior work has found that the presence of smoke plumes outside the Western U.S. is less correlated with surface pollution levels, especially under light smoke conditions (40). However, as our approach relies on other features—primarily interpolated smoke $PM_{2.5}$ and aerosol anomalies (Fig. S3c)—to determine smoke $PM_{2.5}$ concentrations at ground level, our method can identify the days where smoke plumes may be overhead but have little impact on surface concentrations. On the other hand, the HMS smoke plumes may also miss smoke-affected areas especially under cloudy conditions (41). Thus, our current estimates are likely conservative estimates of wildfire smoke $PM_{2.5}$. In addition, several new satellite sensors launched in the last few years—e.g., TROPOspheric Monitoring Instrument (TROPOMI) or Tropospheric Emissions: Monitoring of Pollution (TEMPO)—could provide information that further improves statistical-based estimates of smoke $PM_{2.5}$. However, given the importance for many applications in having a long panel of observations—for instance, to evaluate trends in exposure or to accurately estimate health impacts—an ongoing challenge will be whether and how to integrate these new data streams with earlier sensors to achieve the dual goals of consistency over time and having the highest-quality possible measures at any given time step. Further improvements in the estimation of non-smoke $PM_{2.5}$ background, either through more sophisticated statistical modeling or with the aid of transport models (9, 19), could also potentially improve our smoke $PM_{2.5}$ estimates. Future work could also focus on improving performance of estimates at high $PM_{2.5}$ concentrations and in regions such as the Southwest where model performance is lower, settings with persistently poor performance in total and fire-specific $PM_{2.5}$ estimates (22, 26, 31, 32). Finally, we focus solely on $PM_{2.5}$ and future work could characterize and estimate other air pollutants affected by wildfire smoke, including ozone and nitrogen dioxide (22, 42).

While we have referred to our estimates as "wildfire smoke $PM_{2.5}$ ", our approach does not aim to isolate the pollution effects from wildland fires from other types of fires, such as agriculture fires and prescribed fires. Our smoke $PM_{2.5}$ estimates are based on HMS smoke plumes and satellite-derived anomalies in aerosols and other fire information. Therefore, our estimates include some $PM_{2.5}$ from large prescribed fires and agriculture fires, if these fires are large enough to be detectable by satellites. Specifically, in the Southeast, we find that our smoke $PM_{2.5}$ estimates capture some prescribed fire but underestimate the total prescribed fire impact(Fig. S14). Our estimates may miss the effects from smaller fires, which are predominantly prescribed and agriculture fires, especially if these fires last less than one day (43). The influence of these agricultural and prescribed burns is likely small, especially in locations where wildfire smoke has historically been highest. For example, recent estimates suggest approximately 4% of smoke $PM_{2.5}$ in California, Oregon, and Washington is from agricultural fires from 2014-2020 (36). This dominance of wildfire in estimated smoke $PM_{2.5}$ is least clear in the Southeast where prescribed and agricultural fires have historically been more common and contributed substantially to annual average $PM_{2.5}$ concentrations (37, 44). But in comparison between prescribed fire $PM_{2.5}$ and our smoke $PM_{2.5}$ in the Southeast, we find increasing smoke $PM_{2.5}$ concentrations during summer months when prescribed and agricultural burning were historically lower, which may suggest a growing influence of wildfires (Fig. S15). Given the smaller contributions of these prescribed and agricultural fires to air quality and population exposure at the national scale, their influence on our overall findings regarding trends, population exposures, and implications for policy is likely small. However, future research could improve the characterization of these small fires by using recently-available geostationary satellite products or other inputs.

The growing influence of wildfire smoke on ambient air quality poses substantial challenges for the regulation and improvement of air quality. Our results indicate that growing wildfire smoke is helping push total $PM_{2.5}$ concentrations above recently tightened ambient air quality standards for $PM_{2.5}$ at monitoring stations around the country; given the strong links between climate conditions and smoke $PM_{2.5}$, these effects are likely to increase in coming years (8, 13). These changes could lead to two possible scenarios. In the first, jurisdictions could succeed in getting enough smoke $PM_{2.5}$ exempted from local measurements to stay in attainment with these new air quality standards. In this scenario, jurisdictions would remain compliant with the Clean Air Act, but air quality would worsen absent other successful interventions to mitigate wildfire activity, likely harming public health. In the second scenario, jurisdictions would not exempt enough smoke and would increasingly fall out of Clean Air Act attainment, perhaps requiring the mitigation of additional stationary-source non-smoke $PM_{2.5}$ emissions. Such mitigation could be cost effective in many regions where abatement costs remain low relative to the benefits of further air quality improvements (45), but could become onerous if wildfire smoke concentrations continue to grow, as is expected under a warming climate (13).

We find in recent years that local jurisdictions appear to rarely recognize (at least officially flag) the influence of wildfire on air quality and even less frequently use exceptional events demonstrations (EEDs) to request the exclusion of smoke-affected days from air quality standards attainment calculations, even when removal of those days appears may be consequential for attainment status (Fig. 6a). Further, on even the most extreme smoke days, very few requested exclusions are concurred by the EPA. If days with low smoke $PM_{2.5}$ become more common (Fig. 6b), distinguishing and demonstrating "exceptional" events among an increasing number of days with elevated smoke $PM_{2.5}$ may become even more difficult. As wildfire smoke contributes to more jurisdictions exceeding ambient standards, air quality agencies with no prior experience with Clean Air Act nonattainment may have to develop the technical expertise to submit EEDs, or else more heavily regulate local stationary sources of pollution.

Difficulty in controlling smoke concentrations through existing air quality regulations suggests that alternate approaches will likely be needed to maintain air quality and protect public health. These include measures to reduce the extreme wildfire activity that increasingly generates regional or continent-wide wildfire smoke exposures, as well as measures to protect communities when smoke events do occur. Understanding what measures are effective in both settings is incomplete, and is a critical area for future research.

Methods

Our approach to estimating smoke $PM_{2.5}$ proceeds in four steps: attributing a portion of observed $PM_{2.5}$ to smoke at EPA monitoring stations, developing a set of candidate features that might predict surface-level smoke $PM_{2.5}$ estimates at these stations, training a model to predict the ground data with candidate features which is evaluated on held-out ground data, and finally selecting and tuning a final model to produce predictions over all locations in the CONUS. Unless otherwise noted, analyses were performed in the R programming language (46).

Smoke $PM_{2.5}$ attribution at monitoring stations

To attribute $PM_{2.5}$ to smoke at monitoring stations, we combine data on the location and timing of smoke plumes from satellite imagery with ground measurements of $PM_{2.5}$ from EPA monitoring stations. Our approach builds on that of Childs et al. 2022 (7). We use satellite plume data from the NOAA Hazard Mapping System (HMS), which are boundaries of smoke plumes identified by analysts using geostationary satellites. We classify a grid cell–day as smoke-affected if the grid cell intersects with any smoke plume on that day, and assign EPA monitoring stations smoke day classifications based on the grid cell in which they fall.

We then calculate location- and month-specific non-smoke medians to estimate a counterfactual measure of how much $PM_{2.5}$ would be expected if there was no smoke:

$$\overline{PM}_{imy}^{NS} = \text{median}(\{PM_{IDMY} | I = i, M = m, y - 1 \leq Y \leq y + 1, \text{smoke}_{idmy} = 0\}), \tag{1}$$

and estimate anomalies from the median on smoke days in each location:

$$\widetilde{PM_{idmy}} = (PM_{idmy} - \overline{PM}_{imy}^{NS}) * \text{smoke}_{idmy}, \tag{2}$$

where PM_{idmy} is the $PM_{2.5}$ at station i on day d in month m and year y and smoke_{idmy} is a binary indicator for smoke day classification. These medians use a month-specific, 3-year window in order to flexibly account for seasonal patterns and trends in non-smoke $PM_{2.5}$ over time in each location. When training the machine learning model, we bottom code these $PM_{2.5}$ anomalies at zero before using them as labels. When calculating smoke and non-smoke $PM_{2.5}$ at monitoring stations for analyses about attainment thresholds, we use all anomalies in $PM_{2.5}$ on smoke days for smoke $PM_{2.5}$ (not just positive anomalies) and define non-smoke $PM_{2.5}$ as total $PM_{2.5}$ minus smoke $PM_{2.5}$. Using speciated $PM_{2.5}$ data, previous analyses with a similar approach found these $PM_{2.5}$ anomalies from non-smoke medians corresponded to increases in smoke-associated species (organic carbon) but not non-fire-associated species (dust and elemental carbon) (7). For $PM_{2.5}$ data from the EPA monitoring stations, we use data from the Air Quality System (AQS) for all years, and additionally use data from EPA AirNow (https://docs.airnowapi.org/) for 2024 where data is missing in AQS since it can take up to 6 months or more from the time data is collected until it is available through the AQS API. For AirNow data, we limit to the same set of monitors and stations that are in the AQS data.

Predicting gapless smoke $PM_{2.5}$

While our approach allows us to estimate smoke $PM_{2.5}$ at stations on days with reporting, in order to produce daily continuous estimates over the CONUS, we predict smoke $PM_{2.5}$ using a machine learning model. We use a 10 km grid covering the CONUS, where CONUS is based on TIGER/Line county borders (47). We process and develop a set of candidate features for the machine learning model, and harmonize to the 10 km grid. These features include meteorology, derived fire variables, land use, elevation, direct aerosol measurements, predicted aerosol optical depth (AOD) anomalies, interpolated smoke $PM_{2.5}$, month of year, latitude, and longitude (Table 1). Below we describe the approach for interpolating smoke $PM_{2.5}$ and details on model selection and model performance. Additional information on data processing and the remaining features are included in the Supplementary Materials.

Table 1: Smoke $PM_{2.5}$ Model inputs

Feature	Source
Interpolated smoke $PM_{2.5}$	Dereived from Environmental Protection Agency (EPA) Air Quality System (AQS) Data Mart (48, 49) and EPA AirNow (https://docs.airnowapi.org/)
Aerosol optical thickness (AOT) anomalies (current, 1-day, 2-day, and 3-day lagged)	Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) (50)
Predicted aerosol optical depth (AOD) anomalies (min, max, mean, 25th, 50th, 75th percentiles)	trained on Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-angle Implementation of Atmospheric Correction (MAIAC) AOD retrieved through Google Earth Engine (GEE) (51)
Elevation (mean and standard deviation in grid cells)	National Elevation Database (NED) US Geological Survey (USGS) retrieved through GEE (51)
Percent of area in each Level 1 land cover class (water, developed, barren, shrubland, herbaceous, cultivated, forest, wetlands)	National Land Cover Database (NLCD) USGS retrieved through GEE (51)
Distance to nearest fire cluster	Derived from HMS fire points (52)
Size of nearest fire cluster (area and number of constituent fire points)	Derived from HMS fire points (52)
Meteorology (daily mean, max, and min planetary boundary layer, average sea level pressure)	European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis version 5 (ERA5) Global (53)
Meteorology (total precipitation, average 2m air temperature, average eastward and northward wind speed, average surface pressure, average 2m dewpoint temperature)	ERA5 land (54)

Smoke $PM_{2.5}$ interpolation We perform inverse-distance weighted interpolation using the smoke $PM_{2.5}$ from EPA monitoring stations. We use all observations of smoke $PM_{2.5}$ (including zero smoke $PM_{2.5}$ at stations without a plume over head) at EPA monitor locations to interpolate smoke $PM_{2.5}$ for each day. We tune the inverse distance weighting power, the maximum number of nearest observations to use, and the maximum distance away from a location to look for observations. We tune these parameters using Bayesian optimization with 8 initial points and 6 iterations, evaluating spatial out-of-sample performance (i.e. performance on held-out monitors) to evaluate parameter sets. We split the sample of monitors into N folds and evaluate the performance of a parameter set by leaving each fold out in turn, interpolating with the remaining N-1 folds, and extracting interpolated values for the left out fold at the centroid of the associated 10km prediction grid cell. We then calculate R^2 using the out of sample predictions on smoke days for all stations for a parameter set. This performance metric is intended to evaluate the interpolations at the task relevant to the overall smoke $PM_{2.5}$ estimates: predictions at new locations unobserved in monitoring stations.

Because these interpolations are a feature in the machine learning model where we will subsequently again be using nested spatial cross validation for model evaluation, we prevent data leakage by using the same folds as in the full model training and consider this parameter tuning part of the interpolation process. We perform this interpolation process both for all stations (using 5 folds) as well with each fold held out of the process entirely (using the same 5 fold split but with parameter tuning occurring over 4 folds).

Model selection and validation As we aimed to predict smoke $PM_{2.5}$ for locations without monitoring stations, we take a similar approach to (7), and assess model performance using spatial nested cross validation with model hyperparameter tuning occurring in the inner loop. We split our stations by the coarsest input (MERRA-2, 0.5° latitude x 0.625° longitude, ~50 km) to define five disjoint spatial folds – i.e. all monitors in a given MERRA cell are assigned the same fold. We then fit gradient boosted trees (55), using Bayesian optimization to tune to the hyperparameters with 24 initial rounds and 16 iterations. We treat this hyperparameter tuning as part of the model training process, and train five models, each with one of the spatial folds held out. We train these models using data from January 2006 to June 2023 to evaluate both the spatial and temporal out of sample performance. We calculate all evaluation metrics using out of sample predictions from these cross-validation models. We repeat this process with 3 sets of candidate features: (1) all available features, (2) all features except interpolated smoke $PM_{2.5}$ —most closely resembling the features used in Childs et al. (7), (3) all features except predicted AOD anomalies, a computationally-expensive input derived from a separate model trained to fill spatial and temporal gaps in AOD observations. We select among these three sets of features using out-of-sample performance and train the final model using the selected feature set, all 5 spatial folds, and data from 2006–2024. This final model is used to produce predictions over CONUS.

Model performance We found that the model with the highest performance on spatially cross-validated data (i.e., entirely held-out monitors) included interpolated smoke $PM_{2.5}$ but no AOD anomaly predictions. Across almost all performance metrics, the preferred model performed slightly better than a model with interpolated smoke $PM_{2.5}$ and AOD predictions, and much better than both the interpolated smoke $PM_{2.5}$ alone and a model with AOD predictions but no smoke $PM_{2.5}$ interpolations (Fig. S3a). While AOD is generally recognized as an important feature to predict surface $PM_{2.5}$, our results suggest that the interpolated $PM_{2.5}$ and AOT anomalies derived from reanalysis data likely provide enough information to predict surface pollution levels, and the AOD anomaly predictions introduce further uncertainty from the gap-filling process.

The most important feature in the preferred model was interpolated smoke $PM_{2.5}$, followed by AOT anomalies and derived fire features (Fig S3c). In comparison, previous estimates found that predicted AOD measures were the most important features (7), which are no longer included in the preferred model. Despite this change in most important features, these updated estimates are very similar to previous estimates, with an R^2 between the two sets of estimates of 0.84 (Fig. S16). The estimates are even more similar at larger spatial aggregations (e.g., $R^2 = 0.88$ at the county–day level) or longer temporal aggregations (e.g., $R^2 = 0.95$ at the county–month level) (Fig. S16). Improved performance of current estimates over previous estimates appears to come mainly from our new model's improved ability to accurately predict smoke on low- to moderate-smoke days—compared to previous work, CV R^2 rose substantially on days with smoke $PM_{2.5}$ $<50\ \mu g/m^3$, and modestly on days with smoke $PM_{2.5}$ $>50\ \mu g/m^3$ (Fig. S3).

Quantifying smoke influence on air quality regulatory limits

To understand the impact of wildfire smoke on whether locations are above or below NAAQ regulatory limits, we calculate 3-year annual averages similar to the EPA defined design values (56):

$$\overline{\text{average}PM}_{iy} = \frac{1}{3}\sum_{Y=y-2}^{Y=y} \text{average}PM_{iY}, \tag{3}$$

where

$$\text{average}PM_{iy} = \frac{1}{N_{iy}}\sum_{j=1}^{j=N_{iy}} PM_{iyj}, \tag{4}$$

is the annual average over all available daily $PM_{2.5}$ observations with N_{iy} indicating the number of observations for station i in year y. Similarly, to calculate the 24-hour value, we similarly use a 3-year average across the yearly 98^{th} percentile:

$$\overline{98^{th}\ \text{percentile}PM}_{iy} = \frac{1}{3}\sum_{Y=y-2}^{Y=y} 98^{th}\ \text{percentile}PM_{iY}, \tag{5}$$

where 98^{th} percentilePM_{iy} is the 98^{th} percentile of daily $PM_{2.5}$ from station i in year y as described in (57). We use only stations with at least 50 observations for each of 3 years.

To quantify whether smoke has affected whether a station is above or below the new NAAQS thresholds, we calculate the annual and 24-hour values (Eqs. 3 and 5) for total $PM_{2.5}$ and estimated non-smoke $PM_{2.5}$. We then classify stations relative to the 9 $\mu g/m^3$ annual value and 35

μg/m^3 24-hour value, depending on whether the total and non-smoke values exceed the relevant thresholds.

Simulating smoke exemptions To understand how a location might seek to exempt smoke-affected days from NAAQS calculations, we simulate exemptions by dropping total $PM_{2.5}$ observations beginning with day with highest smoke $PM_{2.5}$ first, and iteratively dropping days until the station is below the regulatory limit. For each dropped day, we re-calculate the 3-year annual and 24-hour values to identify whether a station has met the NAAQS. For each station and 3-yr average, we track the smoke $PM_{2.5}$ level above which days must be dropped and the number of days that must be dropped in order to meet the annual and 24-hour thresholds.

Identifying wildfire-related flags and policy relevance of air quality monitor readings When submitting data to the EPA for NAAQS compliance monitoring, air quality agencies can flag individual observations to indicate that they reflect a deviation from normal operating conditions. When this deviation is the result of wildfire smoke, the air monitoring agency can apply two broad classes of flags: "inform" flags, which are solely informational and have no implications for NAAQS compliance; and "request exclusion" flags, which indicate to the EPA that the air monitoring agency would like to exclude the flagged observations from the set of monitor readings that are used to determine NAAQS compliance. When the EPA concurs a request for exemption of $PM_{2.5}$ monitoring data, it excludes all observations of that station–day from compliance calculations, so we treat flags as binary by station–day. Inform and request exclusion flags are current as of 22 April 2025 and are taken from the EPA AQS; the last full year of EPA AQS data is 2023, limiting the time period of our analysis. Data for concurred exclusion requests were obtained via a Freedom of Information Act request to the EPA and are current as of 11 December 2024.

To determine the "policy relevance" of individual observations, we reconstruct from raw monitor data each station's daily average $PM_{2.5}$ values as well as its annual average of quarterly averages ("annual standard") and annual 98^{th} percentile ("daily standard") values for the preceding two years. We label a station–day observation as "policy relevant" for a NAAQS standard if it exceeds the value that would have to be achieved in that monitoring year for the 3-year running average station value to be under that standard's NAAQS limit. We then compute the proportion of these days on which jurisdictions flagged or requested exclusions as a function of observed smoke $PM_{2.5}$ on that day.

Acknowledgments Some of the computing for this project was performed on the Sherlock cluster, and we would like to thank Stanford University and the Stanford Research Computing Center for providing computational resources and support that contributed to these research results. We thank the Keck Foundation for funding. MLC was supported an Environmental Fellowship at the Harvard University Center for the Environment and by NIH training grant T32 ES007069.

Data and code availability Code to replicate results in the main text and supplementary materials is available at https://github.com/echolab-stanford/smokePM-version1.1. Due to privacy concerns and our data use agreement with the California Department of Health Care Access and Information we cannot share ED visit data. Researchers can apply for access at: https://datarequest.hcai.ca.gov/csm?id=csm_login. Purple Air monitor data cannot be shared per our data use agreement, but can be accessed at: https://www2.purpleair.com. All other data are publicly available.

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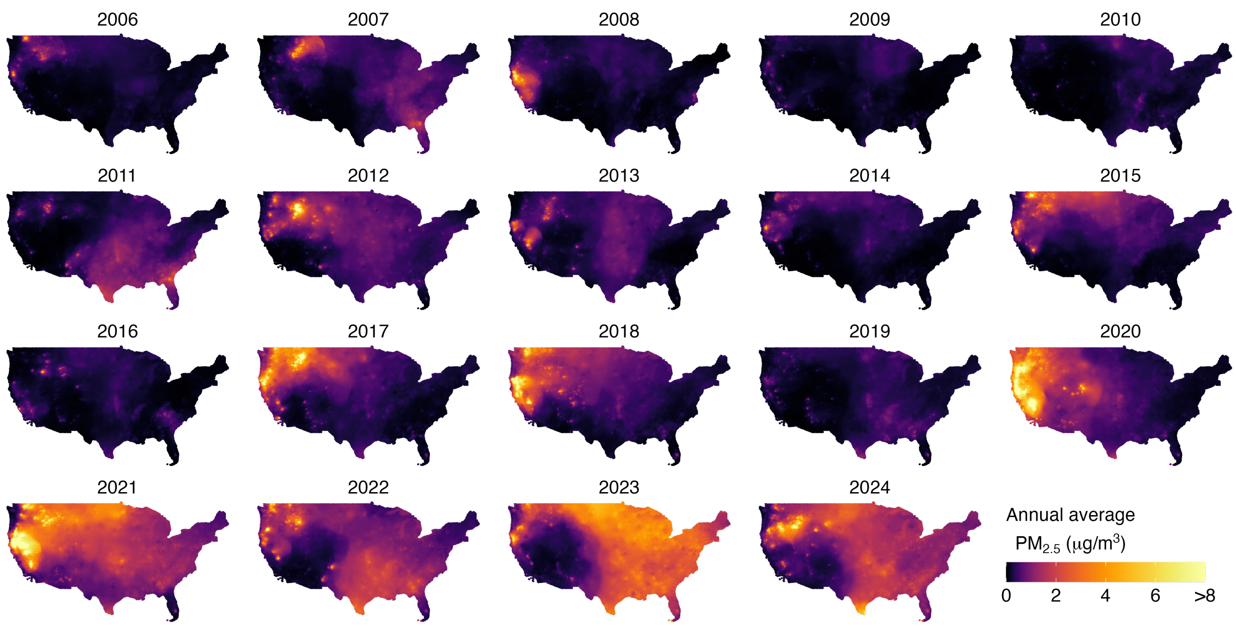

Figure 1: **Average smoke PM$_{2.5}$ for each year in the study period.** Each map shows the annual average of smoke PM$_{2.5}$ for that year and grid cell.

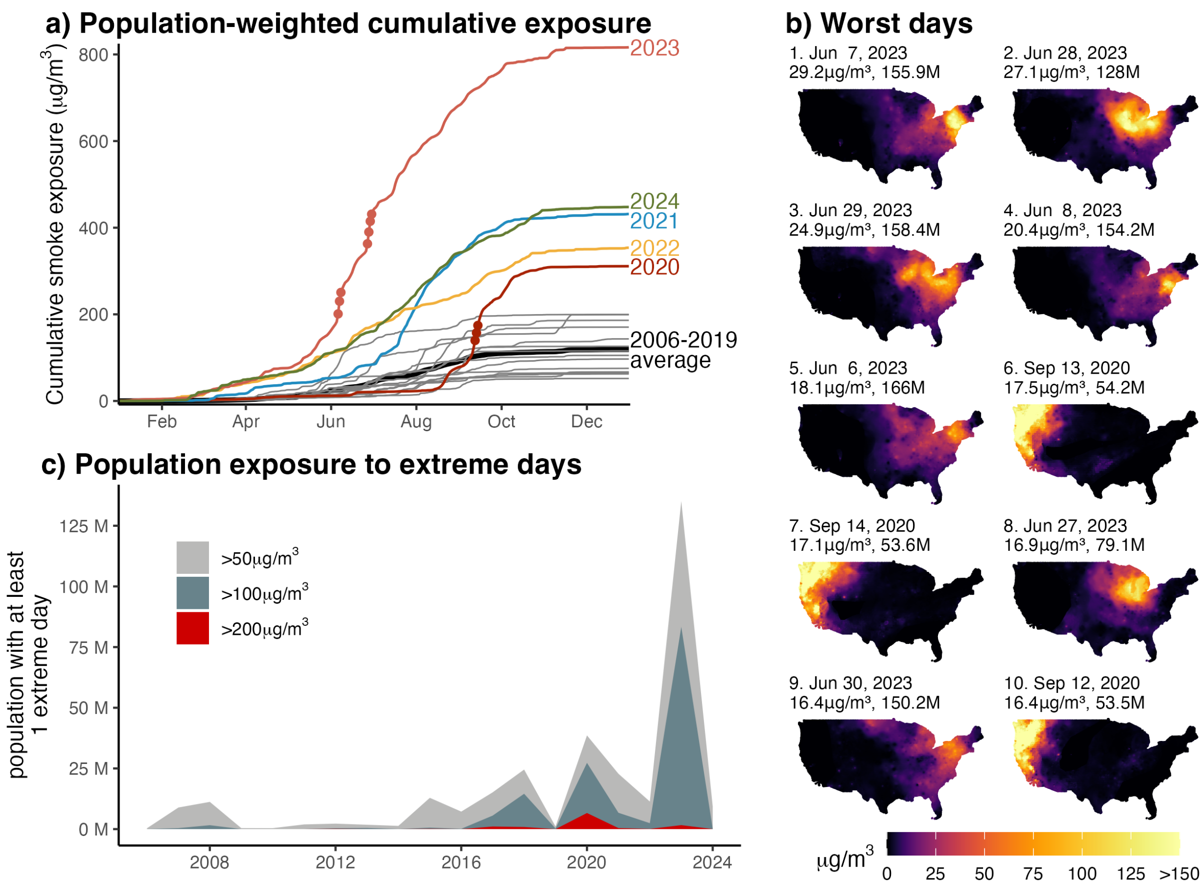

Figure 2: **Population exposure to smoke $PM_{2.5}$ has grown over time, with the years 2020–2024 the worst on record.** a) Cumulative population-weighted exposure (vertical axis) over the year (horizontal axis) shows how extreme 2020—2024 (colored lines) have been relative to the 2006–2019 average (thick black lines). Points show the 10 worst population exposure days corresponding to days in panel b) and grey lines indicate individual years 2006–2019. b) Maps show the spatial distribution of smoke $PM_{2.5}$ estimates on the specified day, and subtitles on each panel show the population average smoke $PM_{2.5}$ in the CONUS and the estimated number of people in the CONUS living in areas where wildfire smoke $PM_{2.5}$ concentrations were greater than 10 μg/m^3 on that day. c) Population living in locations with at least one extreme day (vertical axis) in each year (horizontal axis) for different thresholds of smoke $PM_{2.5}$ (>50 μg/m^3 , light grey;>100 μg/m^3 , blue; >200 μg/m^3 , red). All estimates use fixed 2013 population data to ensure that measured changes in population exposure are due to changes in smoke $PM_{2.5}$ rather than population movements.

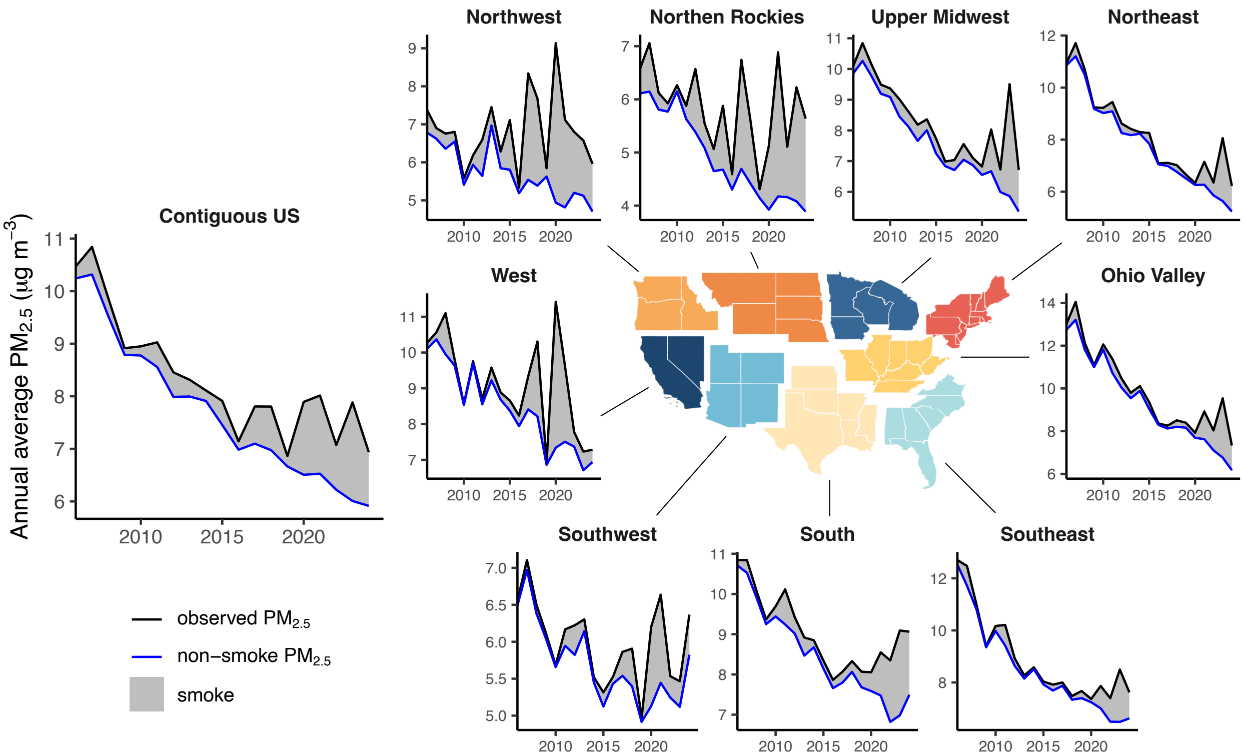

Figure 3: **National and regional patterns in total and non-smoke $PM_{2.5}$ show the growing influence of smoke, and continual declines in non-smoke $PM_{2.5}$.** Black lines show the national or regional annual average observed $PM_{2.5}$, blue lines show the non-smoke $PM_{2.5}$, and grey shaded areas indicate the portion of $PM_{2.5}$ due to smoke. Regional and national annual averages are computed from station annual averages and include only station–years with at least 50 observations. Regions are U.S. climate regions from the EPA (58).

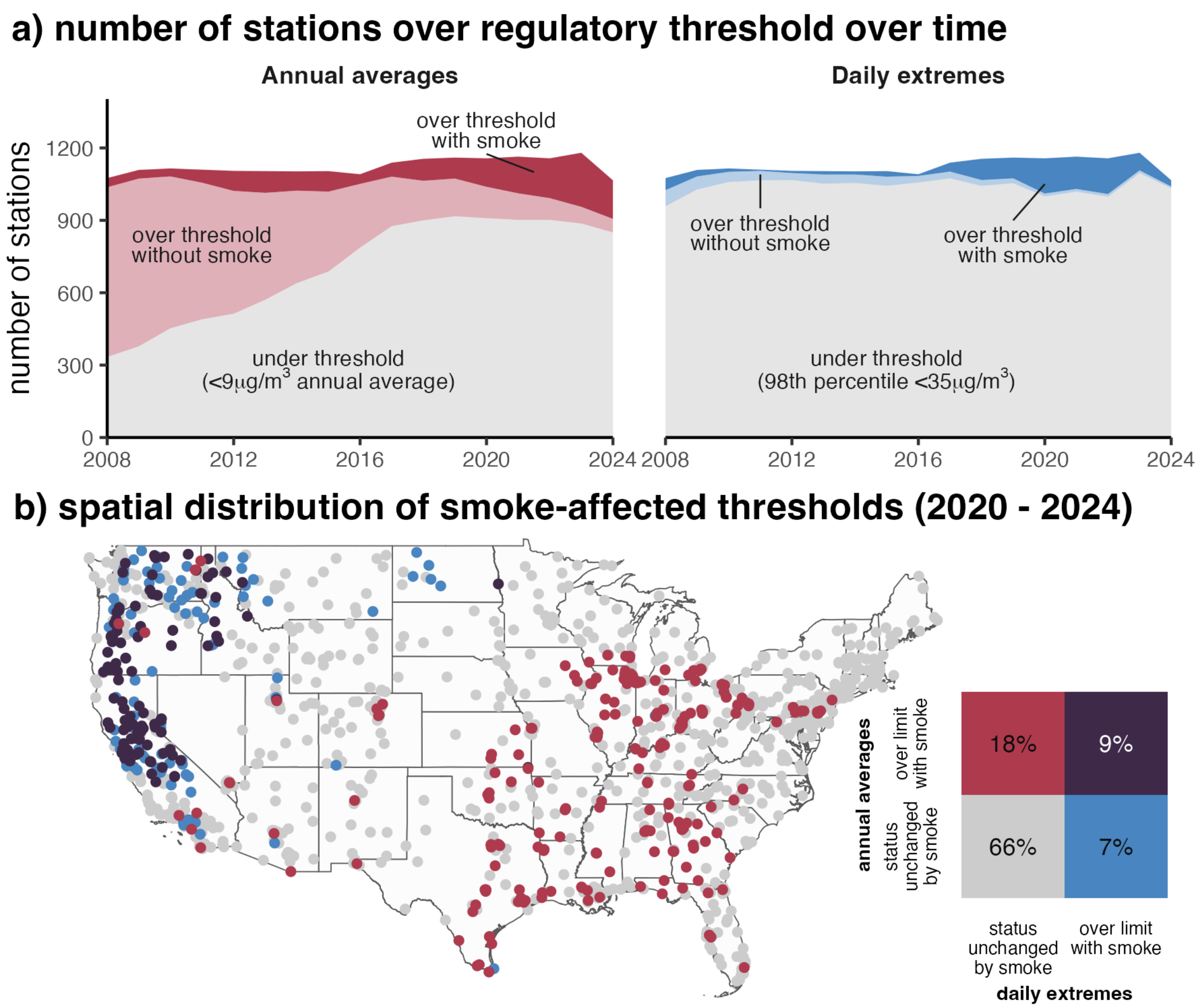

Figure 4: **Smoke is an increasingly important contributor to air quality standard exceedences, for both annual and 24-hour values.** a) A station is classified as under threshold if its trailing 3-year average value is below the updated annual average standard (9 μg/m^3 , left panel) or 24-hour standard (35 μg/m^3 , right panel). A station is classified as over threshold without smoke if the 3-year average value of non-smoke $PM_{2.5}$ is also over the standard, and as over threshold with smoke if the value for total $PM_{2.5}$ is over the standard but the value for non-smoke is under the standard. b) Air quality monitoring stations are colored by their classification over the last 5 years (2020–2024), with red, blue, and purple indicating that at any time in the last 5 years the station was over threshold with smoke for annual average, 24-hour daily extremes, or both, respectively.

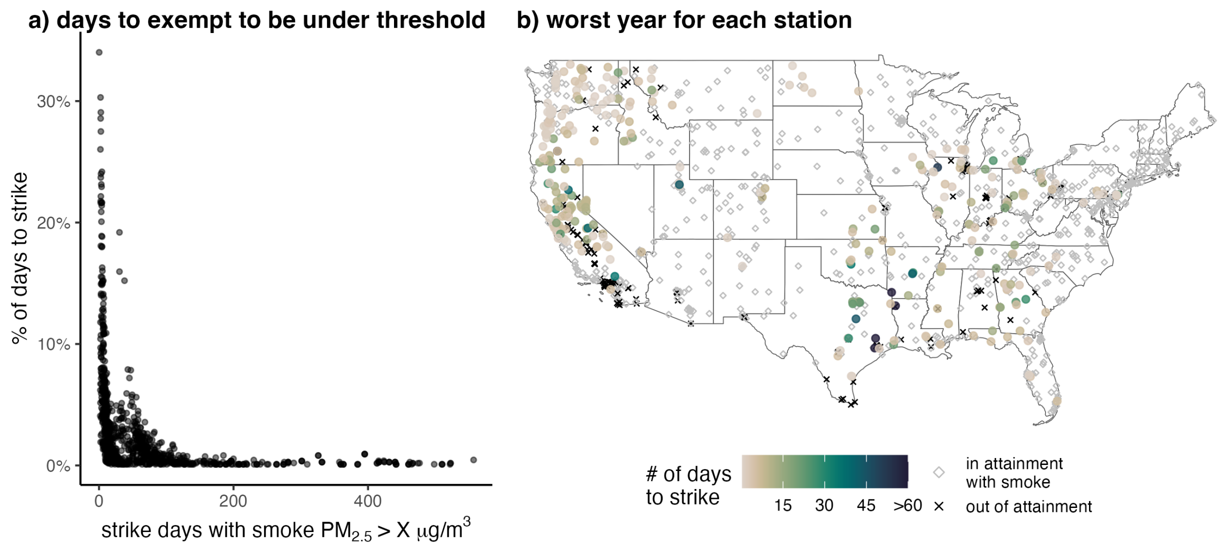

Figure 5: **To meet $PM_{2.5}$ air quality standards, some stations would need to exclude a month or more of smoke days.** a) Each point indicates a station–year where the station did not meet the NAAQS but could meet them by excluding days with smoke $PM_{2.5}$. Points show the smoke $PM_{2.5}$ threshold above which days would have to be excluded (x-axis) and the percent of days that would have to be excluded (y-axis) over the 3-year period used in the 3-year average values in order to be in attainment of both annual and 24-hour NAAQS. b) Map shows the air quality monitoring stations colored by worst year for each station in terms of the number of days that would need to be excluded from the record over the last 5 years (2020–2024). Stations marked by a black "X" were over threshold for at least one year even with all smoke days excluded and stations marked by grey diamonds were under threshold with smoke for all years. The number of days to exclude is the average number needed per year over the 3-year period if the station reported every day.

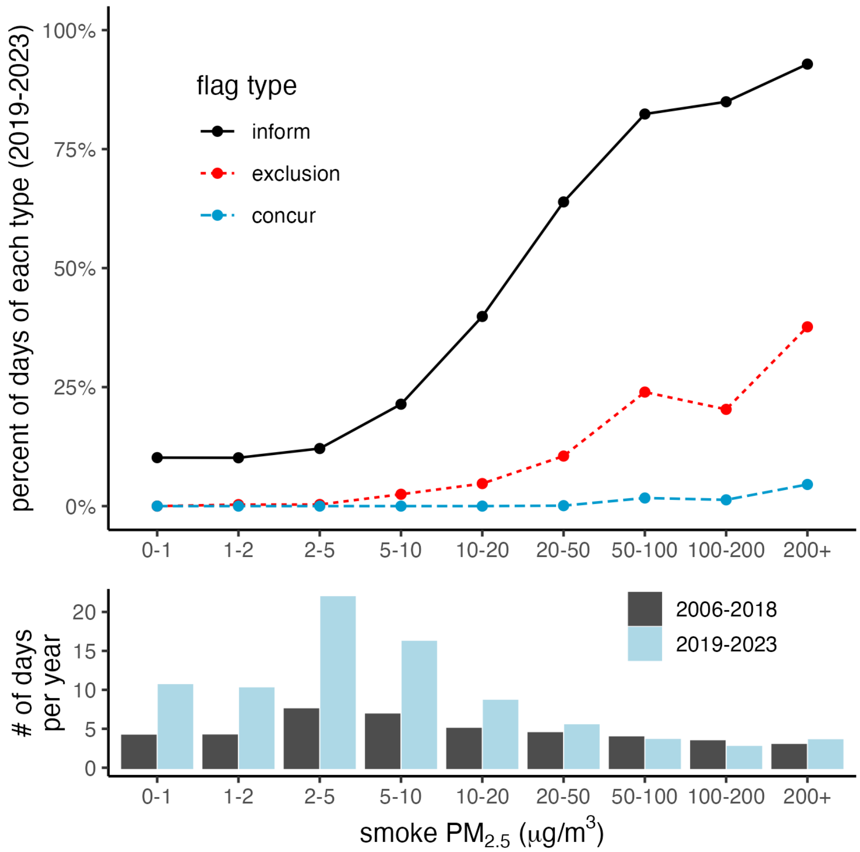

Figure 6: **Local jurisdictions rarely attempt to exclude $PM_{2.5}$ values on increasingly common low-smoke days, even when those days may be relevant for attainment of air quality standards.** We identify monitor-specific smoke days on which the inclusion or exclusion of that day's $PM_{2.5}$ reading could plausibly affect attainment designation for that monitor in a given year (i.e., where daily or annual values for that monitor were very close to NAAQS thresholds). We then calculate, at different levels of smoke $PM_{2.5}$ for the period 2019 to 2023, the percentage of days where the relevant local jurisdiction informed the EPA of potential wildfire influence (black solid line), applied for an exemption for that day's readings (red dotted line), or applied for an exemption that was later approved/concurred by the EPA (blue dashed line). Histograms at bottom show the count of average number of days per year at EPA monitoring stations at different smoke $PM_{2.5}$ concentrations, for the periods 2006 to 2018 (black) and 2019 to 2023 (blue). Efforts to inform or exempt are increasing in smoke $PM_{2.5}$ concentrations, but are rare at increasingly common low-smoke days. The data are from EPA AQS (and thus end in 2023, the last complete year for that data source), except information on concurrences, which were obtained via a Freedom of Information Act request. Note that flags can technically be modified at any time, but are current as of 11 December 2024.

Supplemental Information

Estimates of wildfire-derived $PM_{2.5}$ for the contiguous U.S. and their implication for air quality regulation

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Data access and processing

$PM_{2.5}$ monitoring data Fine particulate matter ($PM_{2.5}$) data was downloaded using the EPA Air Quality System (AQS) API. We download daily ambient air quality observations from state, local, tribal, and federal air pollution control agencies throughout contiguous U.S. using the 'epair' R package (1). Specifically, we download the variables "PM2.5 - Local Conditions" (parameter code 88101, regulatory monitors) and "Acceptable PM2.5 AQI and Speciation Mass" (parameter code 88502, federal reference monitor-like but not used for regulatory compliance) which return 24-hour arithmetic average of $PM_{2.5}$ for each monitor.

Since it can take up to 6 months or more from the time data is collected until it is available through the AQS API, for missing AQS data we call real-time data from EPA AirNow (https://docs.airnowapi.org/), where data originates from the same monitors and stations as AQS but are not fully verified or validated. The AirNow API provides hourly observations for monitors within a given geographic bounding box, so we call the data using the coordinates from the monitors on AQS in the available periods and filter for the same ids. Then we estimate the arithmetic mean of observations within each 24 hour period.

Meteorology Mean sea level pressure and boundary layer height (daily mean, maxm, abd minimum) are retrieved from the ERA5 Global dataset (2), and total precipitation, average wind speed (eastward and northward), average surface pressure, average temperature, and average dew point temperature are retrieved from ERA5 Land dataset (3) using the "Daily statistics calculated from ERA5 data" application https://cds.climate.copernicus.eu/cdsapp#!/software/app-c3s-daily-era5-statistics?tab=app accessed via the CDS Python API. We match ERA5 data with our 10 km grid by using the ERA5 value at the 10 km grid cell centroid and fill grid cell values that do not overlap ERA5 land data products using nearest neighbor matching.

Smoke and fire variables Smoke polygons and fire points are retrieved from NOAA Hazard Mapping System (HMS) (4), which maps the extent of smoke plumes across the U.S. using geostationary satellite imagery and the location of fire hotspots. We define a grid cell–day as a smoke day if any portion of the 10 km grid cell overlaps the a smoke plume from that day.

Similarly, we combine fire point shapefiles into clusters from fire points adjacent to each other and over subsequent days as in (5). Using these fire point clusters, we extract distance from each 10 km grid cell centroid to the nearest fire cluster centroid, as well as the area and number of fire points composing the nearest fire cluster.

Aerosol Optical Thickness Aerosol Optical Thickness (AOT) is extracted from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) data collection (6) by subsetting "total aerosol extinction aot [550 nm]" with the Goddard Earth Sciences Data and Information Services Center (GES DISC) subsetter tool which allows the filtering of geographic coverage and estimation of average daily values. We then calculate AOT anomalies as using deviations from location- and month-specific median as in Eqs. 1 and 2. We match the MERRA-2 AOT anomalies to the 10 km grid based on grid cell centroids.

Aerosol Optical Depth We extract Aerosol Optical Depth (AOD) in the MODIS MAIAC Blue band (0.47 μ m) (7) using Google Earth Engine (8). We calculate daily averages for each 1 km grid cell, as well as calculate the percent of missing observations for 10 km grid cell–day.

Cross sectional variables The land cover classifications come from the USGS National Land Cover Database 2016 (9), and the elevation comes from the USGS National Elevation Dataset (10). Both are accessed using Google Earth Engine (8). We calculate the percent of area in each grid cell belonging to each land cover class, and the mean and standard deviation of elevation in each grid cell.

Population Population was also retrieved through Google Earth Engine (8) from the World-Pop Global Project Population (11), which provides population estimates at a 100 meter grid. The Population estimates used were from the year 2013 which is around halfway between the start and end dates of our predictions. We use population estimates for each grid cell to estimate population-average exposures to wildfire smoke $PM_{2.5}$.

Predicting AOD anomalies While MODIS MAIAC AOD provides higher resolution information on aerosols than MERRA-2 (1 km vs. approximately 50 km), it has a high rate of missingness. As in Childs et al. 2022, we first calculate AOD anomalies as with smoke $PM_{2.5}$ anomalies (Eqs. 1 and 2), train a model to predict 1 km AOD anomalies, predict 1 km AOD anomalies, and finally construct features for the smoke $PM_{2.5}$ model by calculating the mean, minimum, maximum, 25^{th}, 50^{th}, and 75^{th} percentiles of the predicted values for each 10 km grid cell. See Childs et al. 2022 for additional details (5).

Purple Air $PM_{2.5}$ We use data from outdoor PurpleAir sensors from 2016 to 2023, which have a native 10 minute temporal resolution. Following Burke et al. (12), we remove implausible 10 minute observations then aggregate to hourly observations and remove hourly observations that are missing any 10 minute period. We then use the method from Barkjohn et al. to calibrate the hourly concentrations to reference-grade air quality monitors (13). Based on PurpleAir guidance, we drop hourly measurements over 1,000μg/m^3 , and top-code concentrations from 500-1,000μg/m^3 to 500μg/m^3 . We then aggregate to daily total $PM_{2.5}$, keeping daily observations with over 12 hourly observations. Finally, similar to the EPA monitor data, we calculate smoke $PM_{2.5}$ by matching each Purple Air sensor to the 10km grid cell in which it falls, using the gridded smoke-day classifications, and calculating anomalies from the sensor- and month-specific non-smoke median (Eq. 1-2). As with the EPA monitor $PM_{2.5}$, we bottom code PurpleAir smoke $PM_{2.5}$ to zero. Given the shorter observation periods for many PurpleAir sensors, we additionally limit to daily smoke $PM_{2.5}$ observations with at over 10 observations contributing to the non-smoke median.

Requested exclusion and inform flags To estimate the percent of days with exclusion requests and flags we download the hourly sample data from each monitor from the EPA AQS API as well as the monitor metadata that identifies which monitors are used for NAAQS regulatory compliance. We identify the hours flagged following the EPA code table of qualifiers available at https://aqs.epa.gov/aqsweb/documents/codetables/qualifiers.html and classify them as wildfire-related or not, and if wildfire-related, if an exclusion was requested or if an information-only flag was added. Flags can be changed at any time and are current as of 22 April 2025. We then reconstruct daily average $PM_{2.5}$ values and summarize whether any hours in a day are flagged. We then merge that data with the intermediary station-level smoke $PM_{2.5}$ panel to analyze the relationship between flags and smoke $PM_{2.5}$.

Concurred exclusion requests When an air agency submits a request to exclude a monitor reading from the set of readings used to calculate a "design value," which determines compliance or noncompliance with the Clean Air Act, the EPA can later concur with or reject that request after considering available evidence. This information is not among that publicly provided by the EPA. To obtain this information, we submitted a Freedom of Information Act request to the EPA for all exceptional events, as defined by 81 FR 68216, that were excluded from design value calculations per 40 CFR 50.14 for the period 2016 to 2023. This information was provided on 11 December 2024 and is assumed to be current as of that date. Importantly, however, flags can be added or changed at any time, with downstream implications for concurrences of exclusion requests.

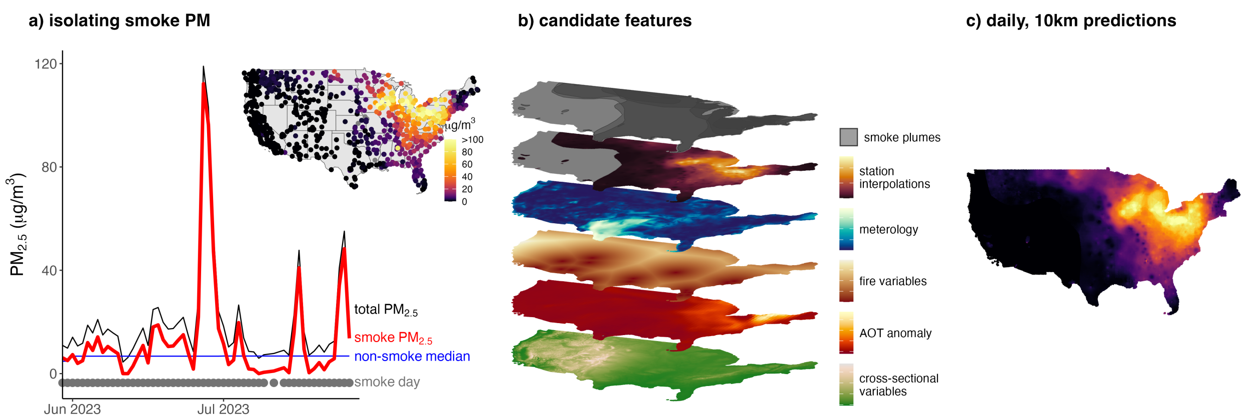

Figure S1: **Model schematic.** a) Model schematic shows approach to isolating smoke $PM_{2.5}$ (red line, left panel) using ground monitoring station $PM_{2.5}$ observations (black line, left panel), and smoke day designation based on smoke plumes (grey points, left panel) to calculate location- and season-specific non-smoke median estimates (blue line, left panel) which is performed at all EPA monitoring stations (inset map, left panel). b) Smoke plumes (top layer, middle panel) are use to identify when smoke might be affecting air quality, and variables including station interpolations of smoke $PM_{2.5}$, meteorological conditions, fire variables, direct aerosol measurements, predicted aerosol optical depth (AOD) anomalies, and cross sectional variables like elevation are all included as candidate features (other layer, middle panel) in a machine learning model to ultimately produce c) daily, 10 km predictions of of smoke $PM_{2.5}$ over the CONUS (right panel). Maps correspond to values on 29 June 2023.

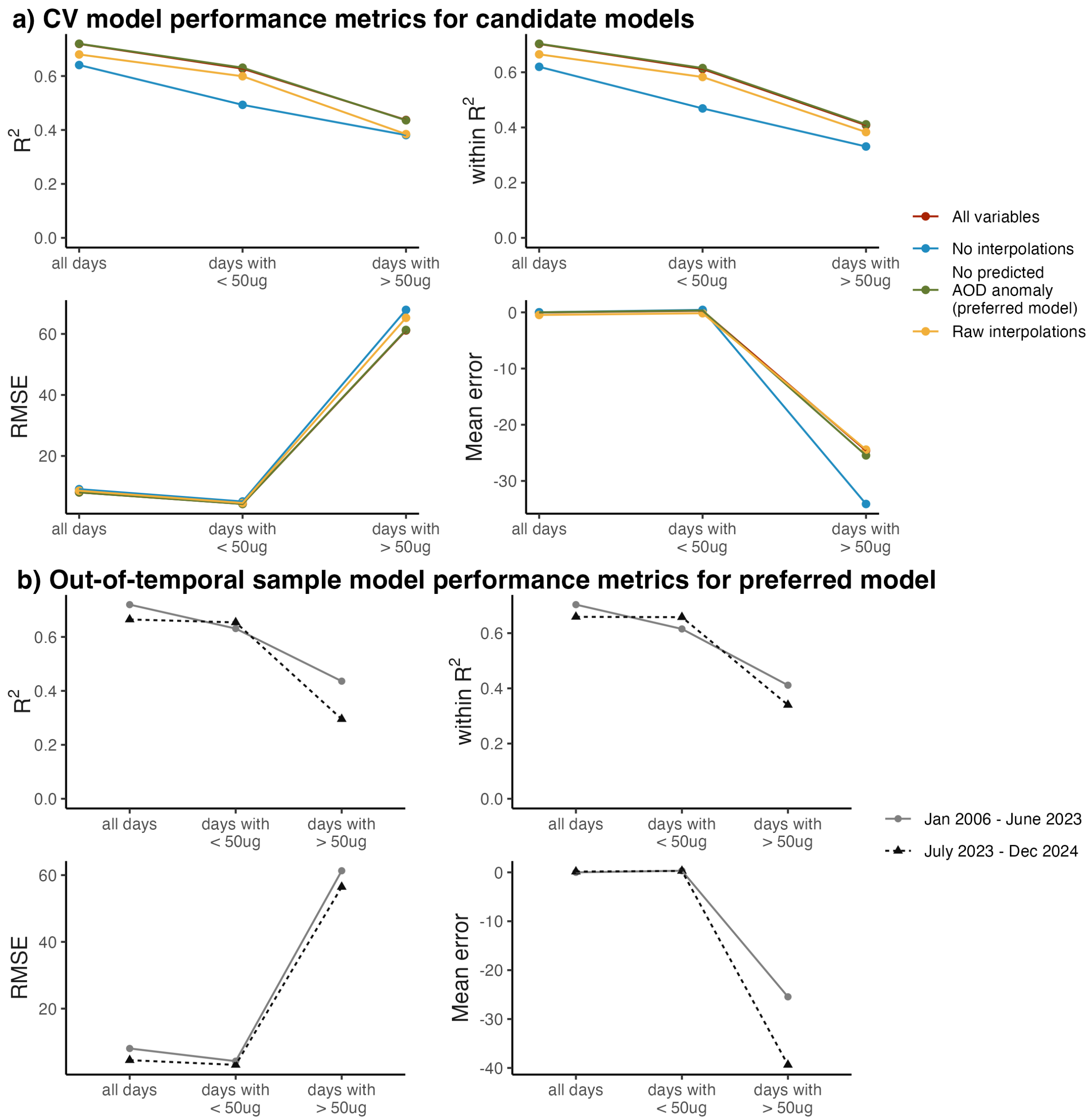

Figure S2: **Out-of-sample model performance from spatial and temporal cross validation.** a) Each color corresponds to a ML model with one of the 3 candidate feature sets or the raw smoke $PM_{2.5}$ interpolations. Panels show four different model performance metrics: R^2 (top left), within R^2 (top right), RMSE (bottom left), and mean error (botton right). For each candidate model, we evaluate model performance over different subsets of the observations (x-axis) including all days, days with observed smoke $PM_{2.5}$ under 50 μg/m^3 , and days with observed smoke $PM_{2.5}$ over 50 μg/m^3 . b) For the preferred model (No predicted AOD anomaly, green points in panel a), out of temporal sample model performance (July 2023 to December 2024, black dashed lines and triangles) is comparable to the predictions that are only spatially out of sample (grey circles and solid lines). Panels show same model performance metrics as in (a).

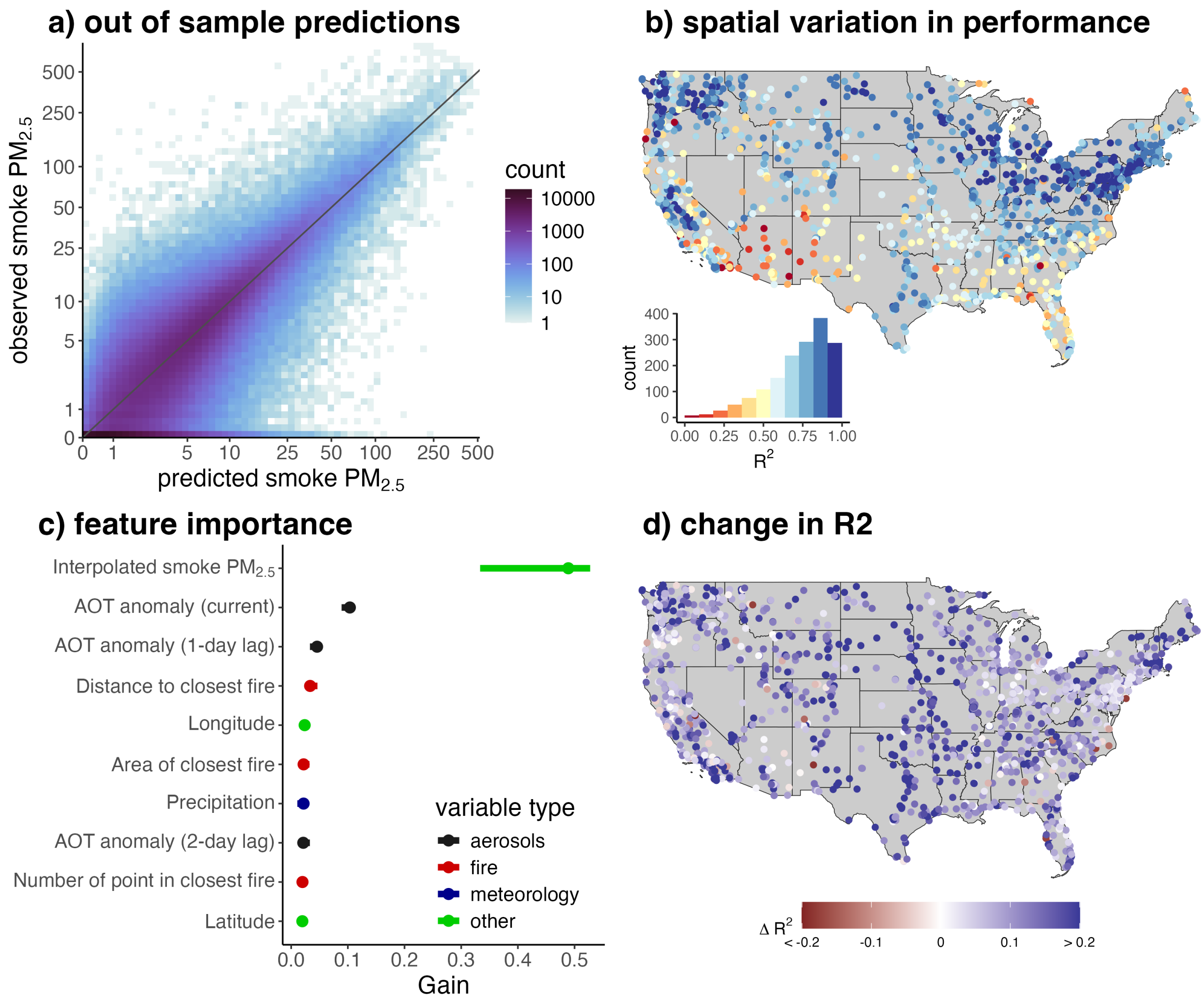

Figure S3: **Model performance.** a) Comparison of out-of-sample predicted smoke $PM_{2.5}$ from spatial cross validation (horizontal axis) and observed smoke $PM_{2.5}$ (vertical axis). Colors indicate the number of monitor–days for a given predicted and observed value. Both axes and color scale are psuedo-log transformed for visibility. Grey 1-1 line shows where predictions and observations perfectly match. b) Model performance is measured at each station as the station-specific R^2 for all stations with at least 50 smoke-day observations. Dark blue indicates stations where model performance is best while red indicates stations with worst model performance. Inset histogram shows distribution of R^2 values over ground monitors. c) Feature importance is measured by gain (horizontal axis) for the ten features (vertical axis) with the highest gain in the full model, with points showing the gain in the full model and line segments showing the range of gain values from the spatial CV models. d) Change in station model performance (measured as change in location-specific R^2) from model with AOD predictions and no smoke $PM_{2.5}$ interpolations (most closely resembling the features used in Childs et al. (5)) to new preferred model which uses smoke $PM_{2.5}$ interpolations and no AOD predictions.

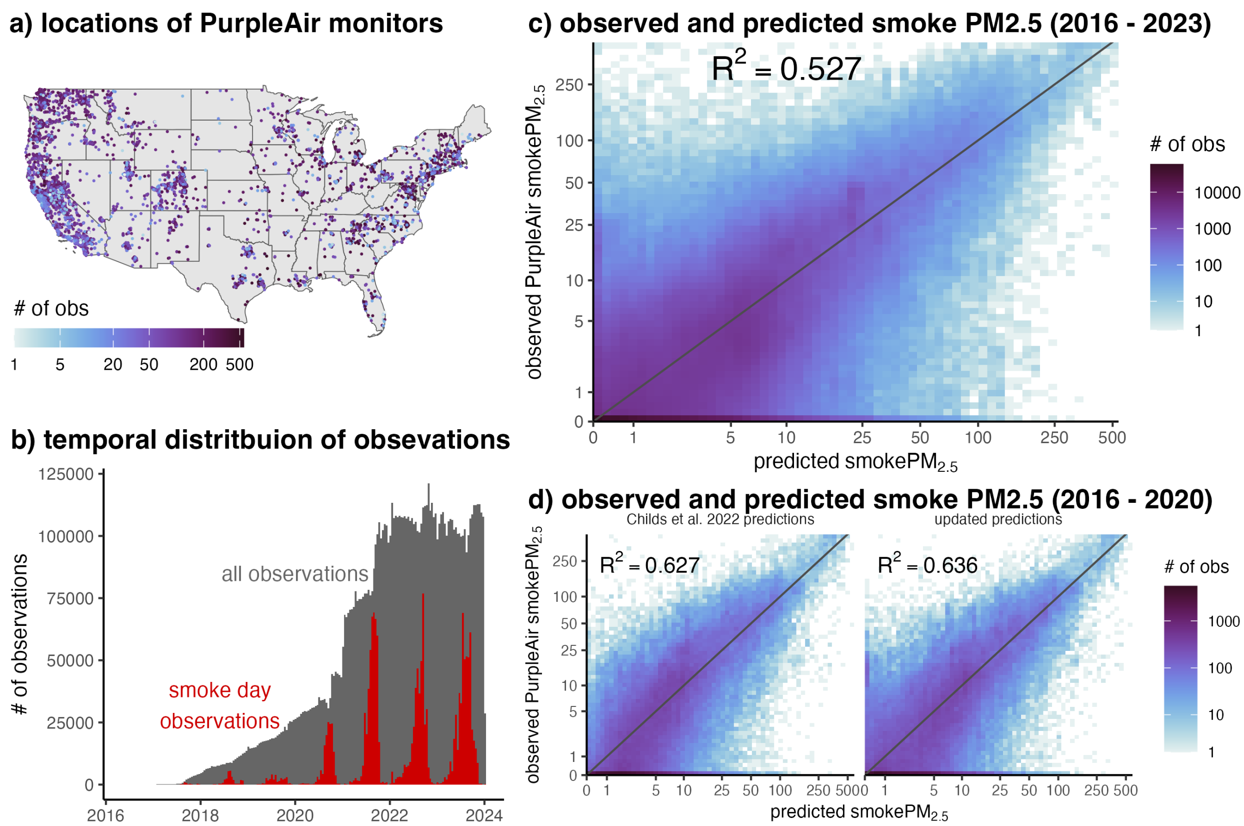

Figure S4: **Comparison of predicted smoke $PM_{2.5}$ with estimates from low-cost Purple Air monitors.** a) Locations of Purple Air monitors, colored by the number of smoke-day observations each monitor contributes. b) Number of monitor-day observations over time for all days (grey) and smoke days (red). c) Predicted smoke $PM_{2.5}$ from this paper (horizontal axis) and observed smoke $PM_{2.5}$ at Purple Air monitors (vertical axis) for 2016-2023, with R^2 shown on the plot. Axes are pseudo-log transformed and color scale is log transformed for visibility. Black line indicate 1-1 line. d) Updated smoke $PM_{2.5}$ predictions from this paper (right panel) and Childs et al. 2022 (left panel) compared to observed Purple Air smoke $PM_{2.5}$. Comparison is limited to 2016-2020 given the time frame of estimates from Childs et al. 2022 (5). Colors, axes, and annotations are as in c).

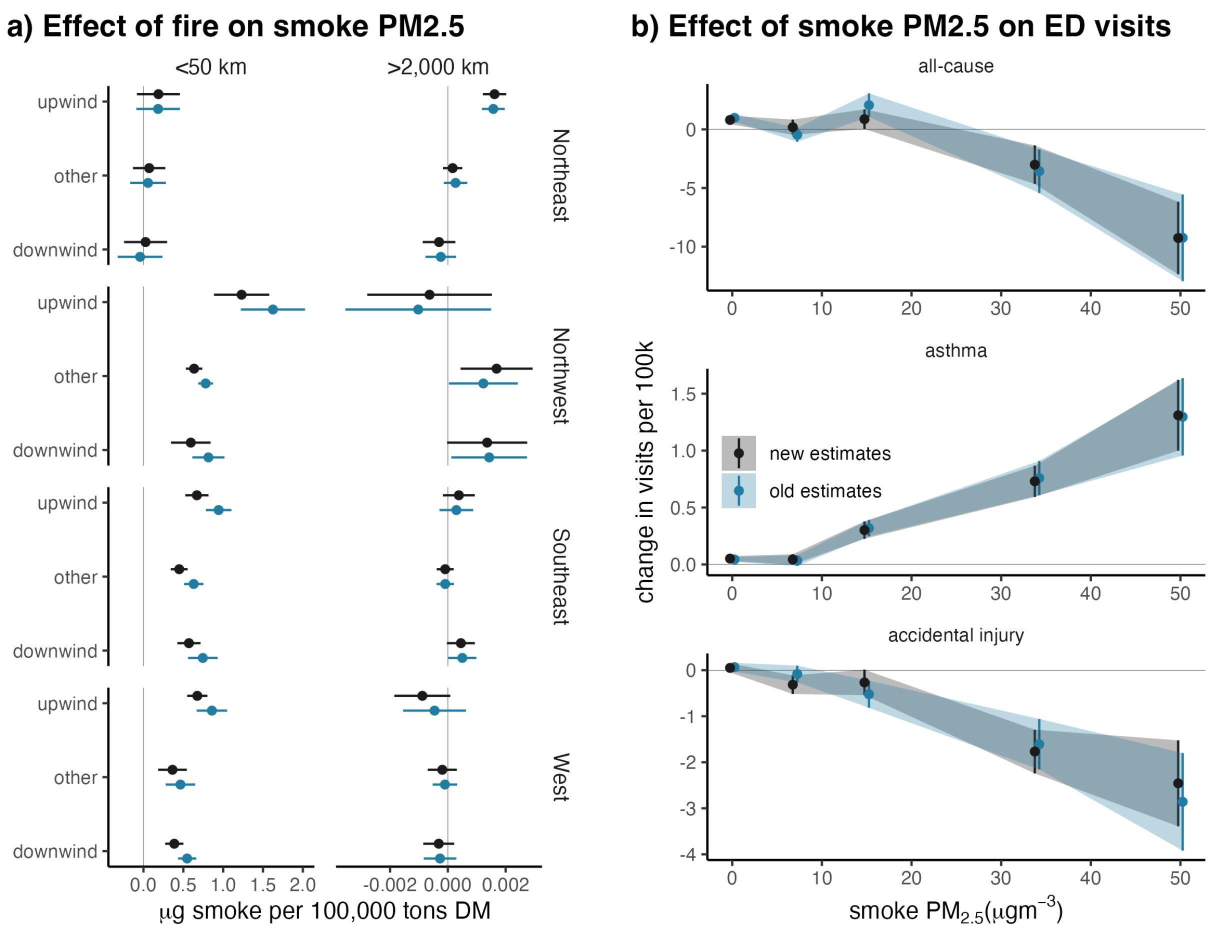

Figure S5: **Estimated relationships between fire and smoke $PM_{2.5}$ and smoke $PM_{2.5}$ and emergency department (ED) visits are consistent between smoke $PM_{2.5}$ estimates.** a) The impact of upwind, downwind, and other fires (vertical axis) per 100,000 tons of dry matter (DM) on smoke $PM_{2.5}$ concentrations for three four regions (vertical panels) when the burned dry matter is less than 50 km (left panel) or over 2,000 km (right panel). Previous estimates (from (14)) closely match to new estimates using new smoke $PM_{2.5}$ product with new preferred model. b) The impact of smoke $PM_{2.5}$ on ED visits for all cause (top), asthma-related (middle), and accidental injury visits (bottom). Impacts are measured in change in visits per 100,000 population (vertical axis) for different daily smoke $PM_{2.5}$ concentration bins (horizontal axis). Previous estimates are from (15).

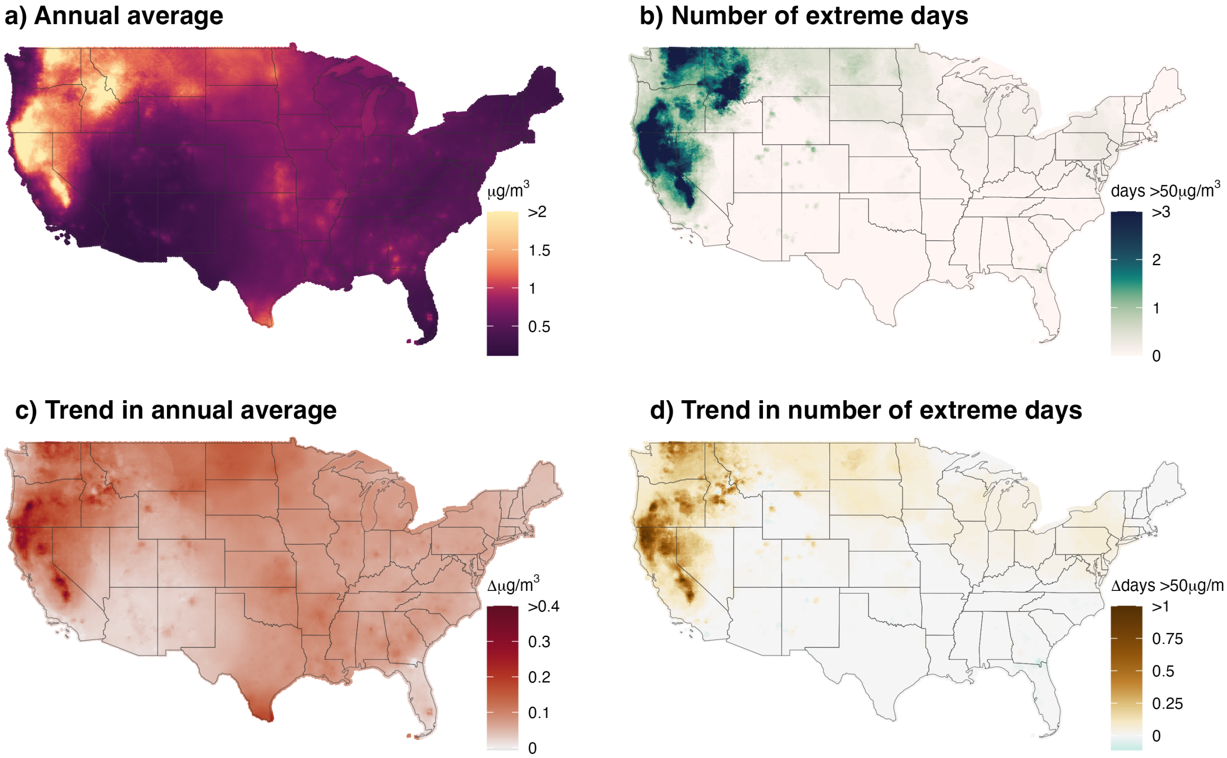

Figure S6: **Annual average smoke $PM_{2.5}$ and number of days with extreme smoke $PM_{2.5}$ concentrations over the study period, and yearly trend in those values.** a) Average annual smoke $PM_{2.5}$ and b) average number of extreme days (smoke $PM_{2.5}$ >50 $\mu g/m^3$) per year over the study period (2006–2024). c) Trend in annual smoke $PM_{2.5}$ and d) trend in number of extreme days per year are estimated as a location-specific time trends over the 18-year study period. Some panels are top coded for visibility, as noted by the legends in each panel.

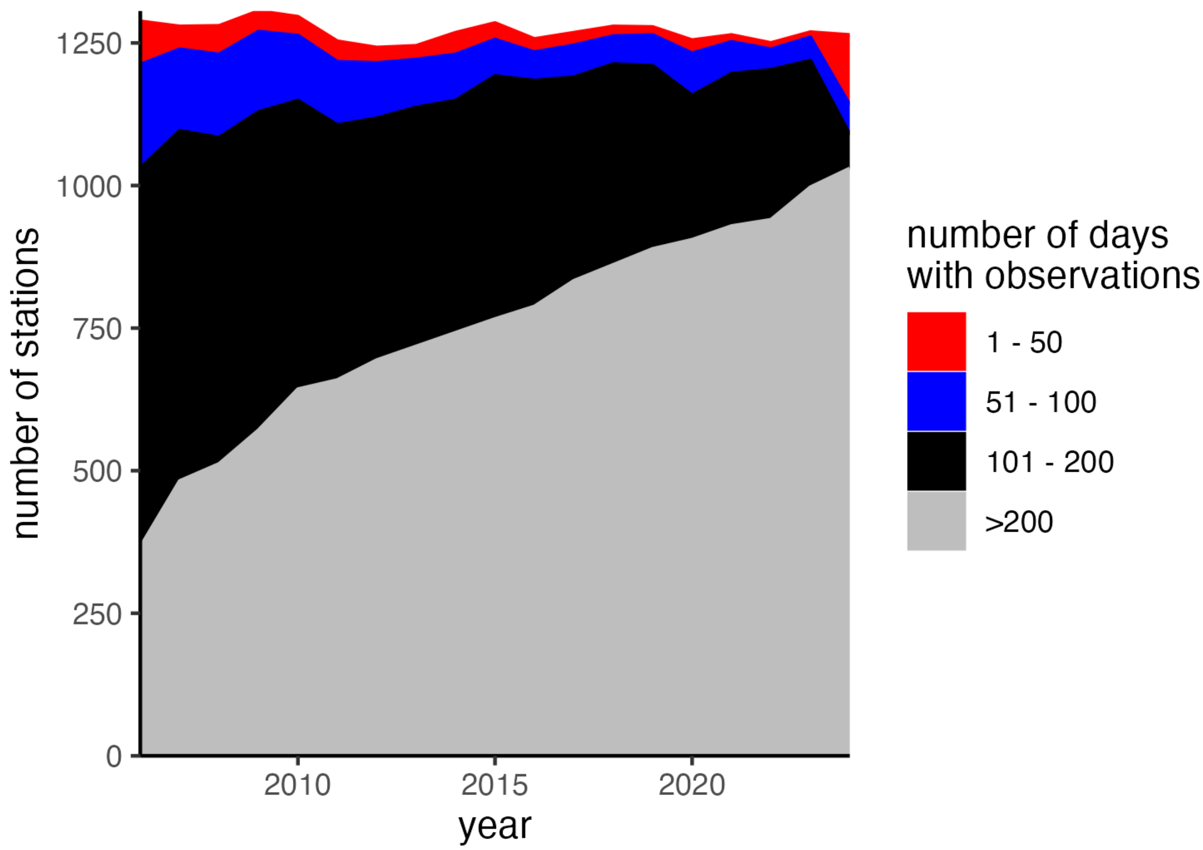

Figure S7: **Changes in number of stations and observations per year** While the number of stations reporting data each year remains roughly constant, over the time period (2006–2024) an increasing number of stations are reporting over 200 and over 100 observations per year, consistent with a transition from every sixth day (~60 observations per year) and every third day (~120 observations per year) reporting to daily reporting.

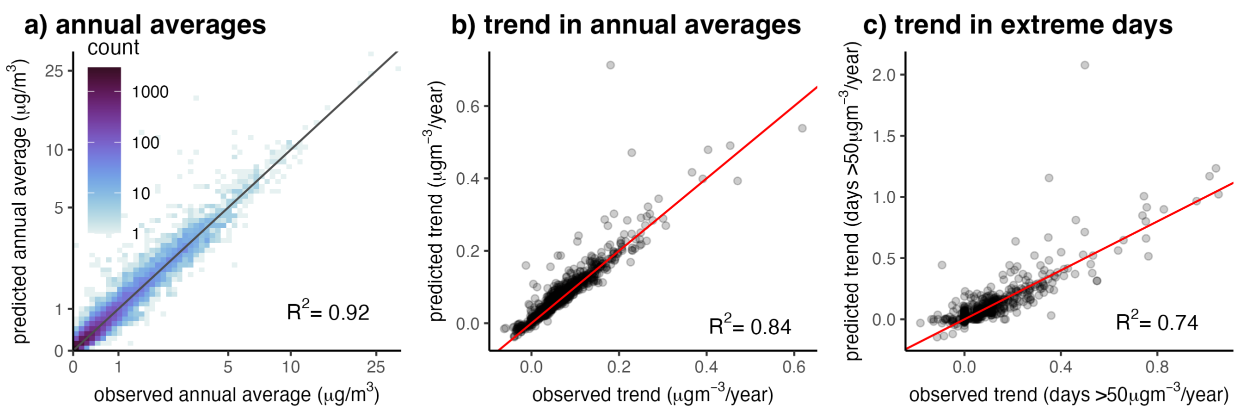

Figure S8: **Patterns and trends in smoke are consistent when controlling for station reporting.** To understand whether estimated trends in smoke $PM_{2.5}$ could be driven by changes in station reporting that affects the predicted smoke $PM_{2.5}$ as stations shift from reporting every third day to every day (Fig. S7), we use a consistent every-third-day sample of observed smoke $PM_{2.5}$ from station locations (horizontal axis) to calculate annual averages in smoke $PM_{2.5}$, as well as trends in annual averages and extreme days. We then compare the consistent-reporting station-based estimates with our prediction-based estimates (vertical axis). The estimates are highly consistent between the two approaches, suggesting that increasing trends in smoke $PM_{2.5}$ averages and extremes are not an artifact of changes to the data, but rather driven by real changes in smoke $PM_{2.5}$ concentrations. The every third day reporting schedule is identified as the 1 in 3 day schedule that has the largest number of stations reporting data each year. Axes are pseudo-log transformed for visibility.

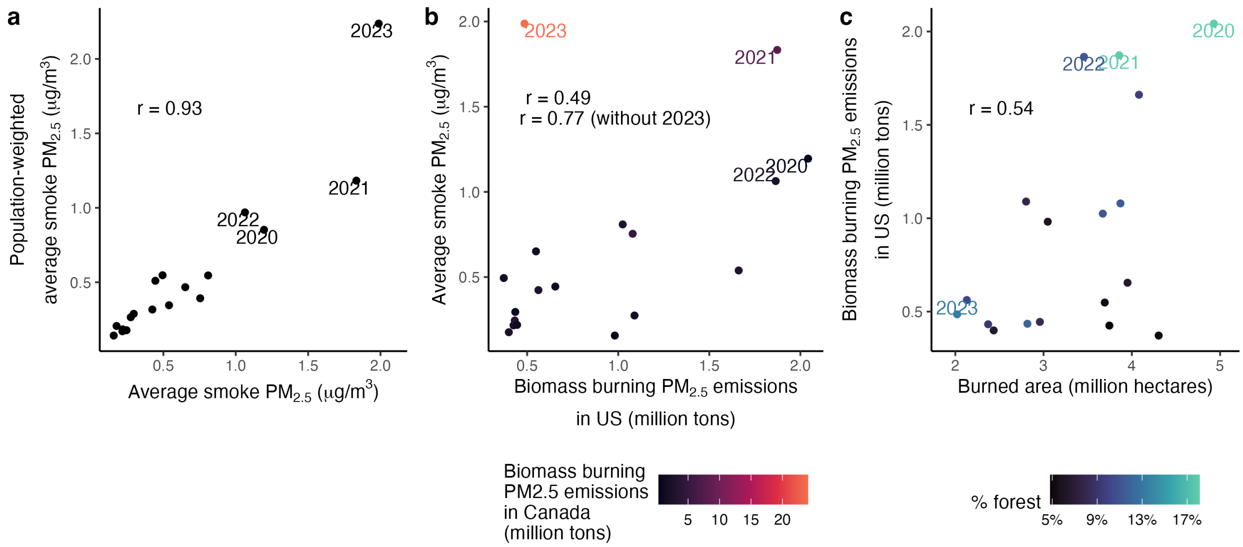

Figure S9: **Higher recent population-average smoke $PM_{2.5}$ is consistent with higher biomass burning emissions and burned area.** a) Annual population-average smoke $PM_{2.5}$ (vertical axis) is strongly correlated with geographic average smoke $PM_{2.5}$ (horizontal axis) with differences driven by smoke occuring in locations with differing population density. Points corresponding to recent years (2020-2023) are labeled and text indicates Pearson's correlation. b) Geographic average smoke $PM_{2.5}$ (vertical axis) is similarly positively correlated with annual biomass burning $PM_{2.5}$ emissions in the US (vertical). Points are colored by annual emissions in Canada. Labels are as in (a). Biomass burning $PM_{2.5}$ emissions in the US and Canada are monthly biomass burning emissions of $PM_{2.5}$ by administrative unit from the Global Wildfire Information System (16) derived from the Global Fire Emission Database (GFED). c) Biomass burning emissions (vertical axis) are associated with total annual burned area in the US (horizontal axis). Points are colored by percent of annual burned area in forest. Labels are as in (c). Burned area by landcover class for administrative units is from the Global Wildfire Information System (16) derived from MODIS MCD64A1 burned area product.

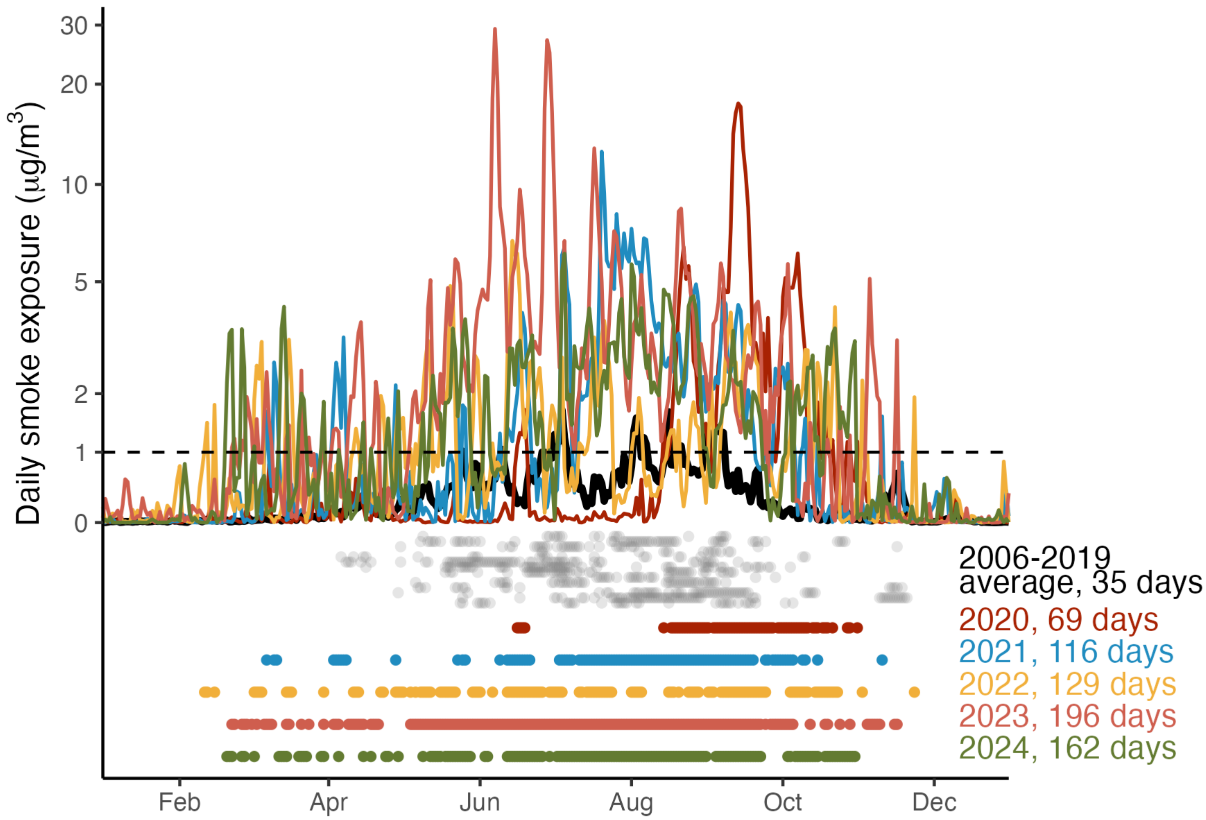

Figure S10: **Since 2021, the length of the "smoke season" has more than doubled compared to 2006–2019 average.** We define the "smoke season" as the days of the year when the daily population-average smoke $PM_{2.5}$ exposure exceeds 1 $\mu g/m^3$. Lines show the daily population-average smoke $PM_{2.5}$ exposure (vertical axis) throughout the year (horizontal axis), for 2021–2024 (colored lines) and the 2006–2019 average (black line). The 2006–2019 average is calculated as the day-of-year average over the relevant years. The "smoke season" days are shown by points at the bottom of the figure, labeled with the year and the length of the smoke season. Days for each year 2006-2019 are shown in grey with higher transparency for visibility. The 2006-2019 average season length is calculated as the average of the season length for each of those years. Vertical axis is pseudo-log scaled for visibility.

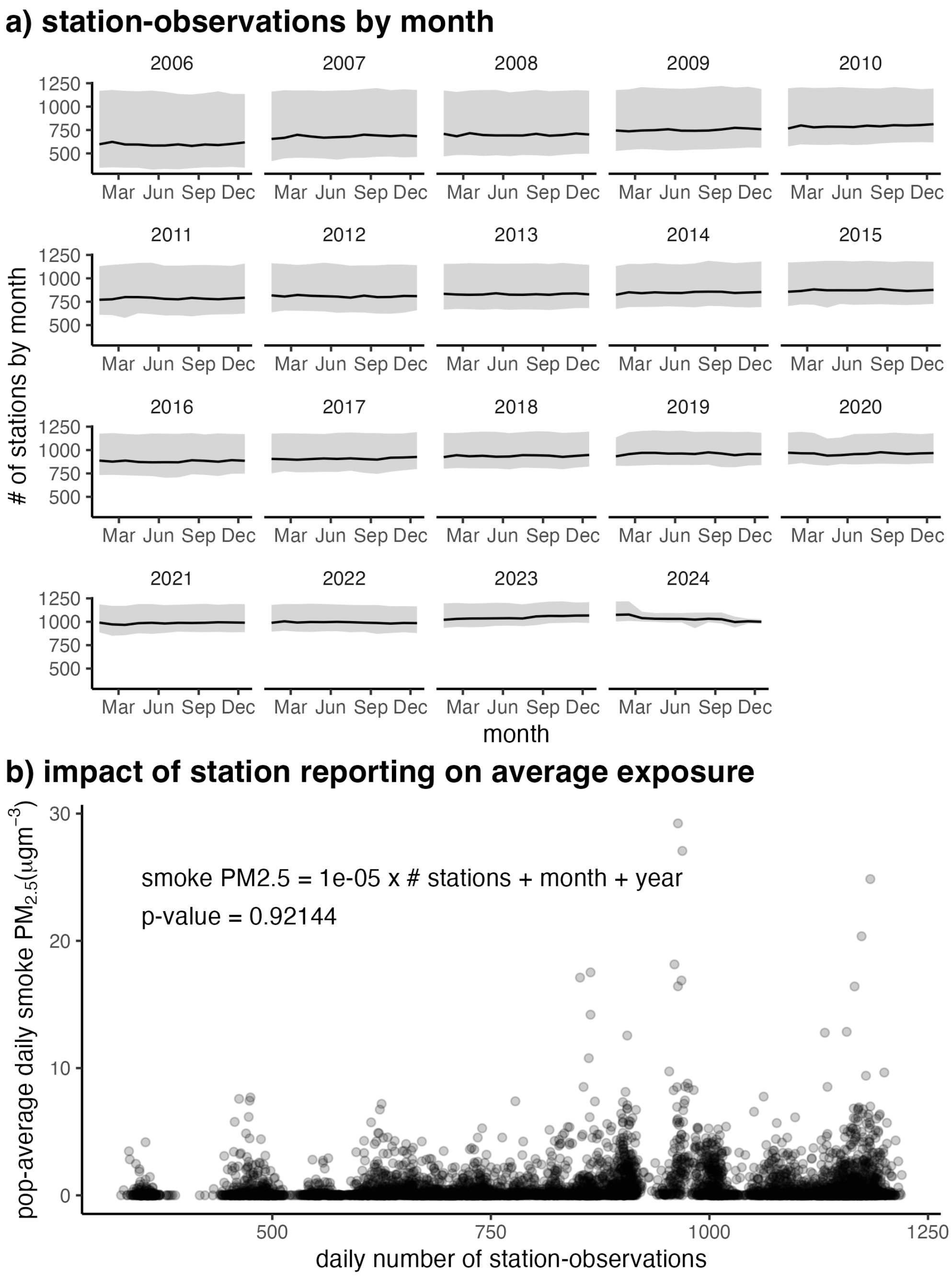

Figure S11: **Changes in station reporting do not explain increases in estimated population exposure.** a) The mean (solid line) and range (shaded area) in the number of stations reporting $PM_{2.5}$ each month over different years. When many stations reported on a 1-in-3 day schedule, there was large variation within a month of how many stations reported each day. As stations have transitioned to a daily reporting schedule, this variation has declined. Number of stations reporting data is largely consistent throughout a year, and shows little seasonal variation. b) The number of stations reporting on a given day (horizontal axis) is not associated with changes in estimated population-average smoke $PM_{2.5}$ (vertical axis) after controlling for year and month-of-year, suggesting that station reporting does not drive long-term increases in wildfire smoke $PM_{2.5}$ exposure. Equation show the estimated coefficient for number of station-observations and its p-value.

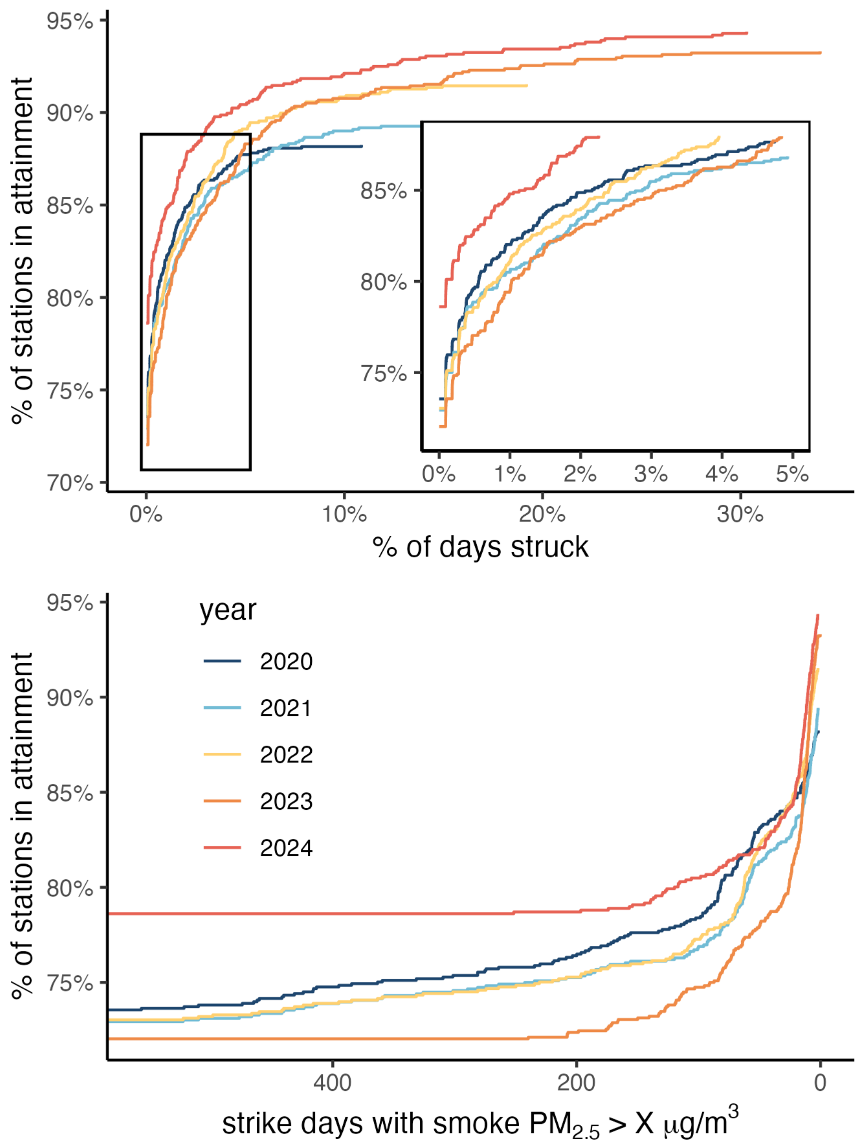

Figure S12: **Cumulative percent of stations that come under the annual and daily regulatory limits as additional smoke days are struck from the record.** As additional days (top panel, horizontal axis) with lower smoke $PM_{2.5}$ levels (bottom panel, horizontal axis) are struck from the record, more monitoring stations (vertical axis) can meet the regulatory limits. Lines show individual years from 2019–2024, with colors matching between top and bottom panels. Inset in top panel corresponds to the black rectangle marked on the plot.

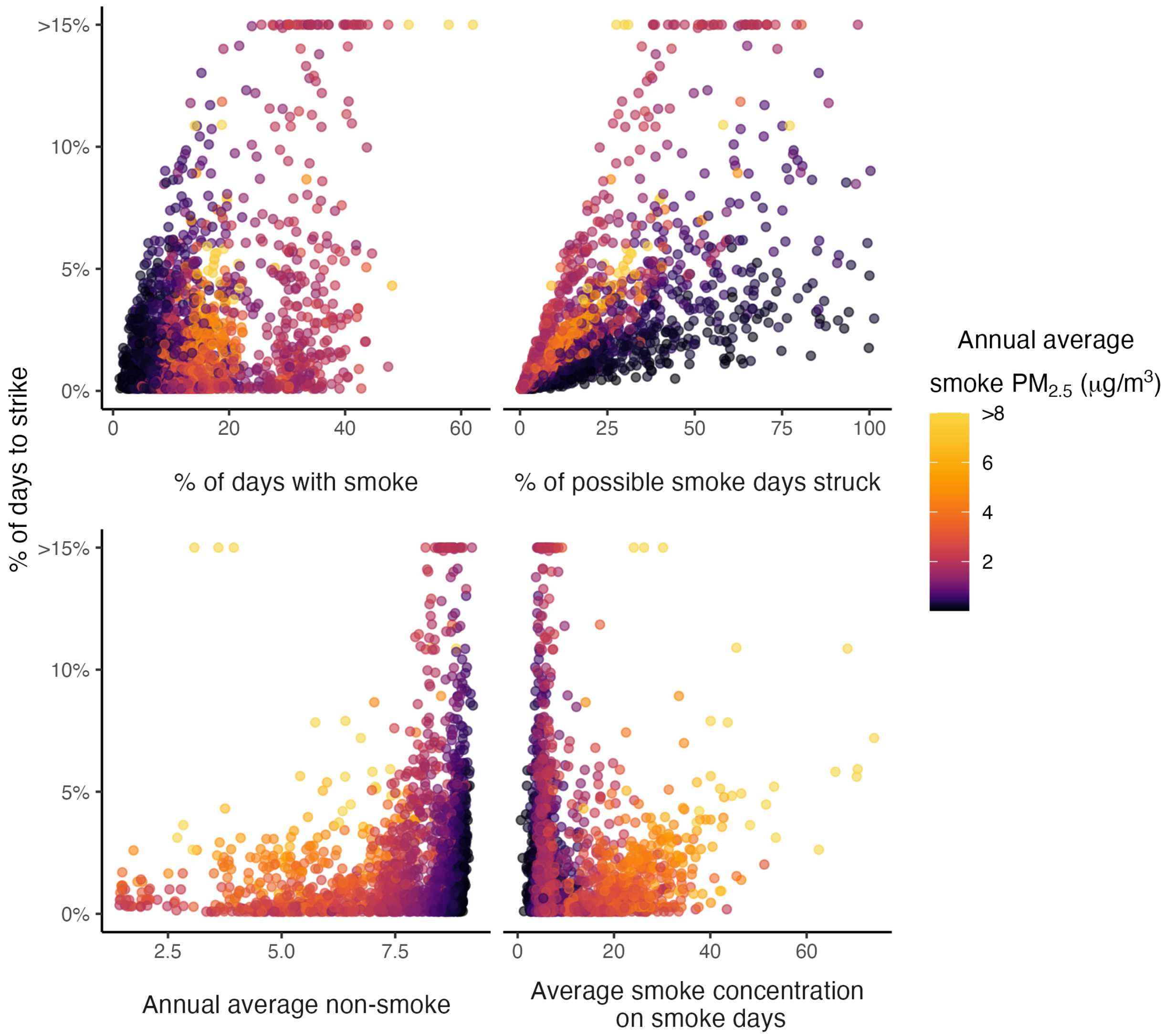

Figure S13: **Stations needing to strike many days from the record to be within regulatory limits tend to have a large number of days with smoke, low average smoke $PM_{2.5}$ concentrations on smoke days, and high non-smoke $PM_{2.5}$ averages.** The percentage of days over the 3-year period with positive smoke $PM_{2.5}$ (top left), the percentage of possible positive smoke $PM_{2.5}$ days that were struck (top right), the 3-year annual average design value calculated with non-smoke $PM_{2.5}$ (bottom left), and the average smoke $PM_{2.5}$ concentration on days with positive smoke $PM_{2.5}$ (bottom right). Each point is a station–year that can come under regulatory limits by striking smoke days from the record, and is colored by the 3-year annual average smoke $PM_{2.5}$ concentration.

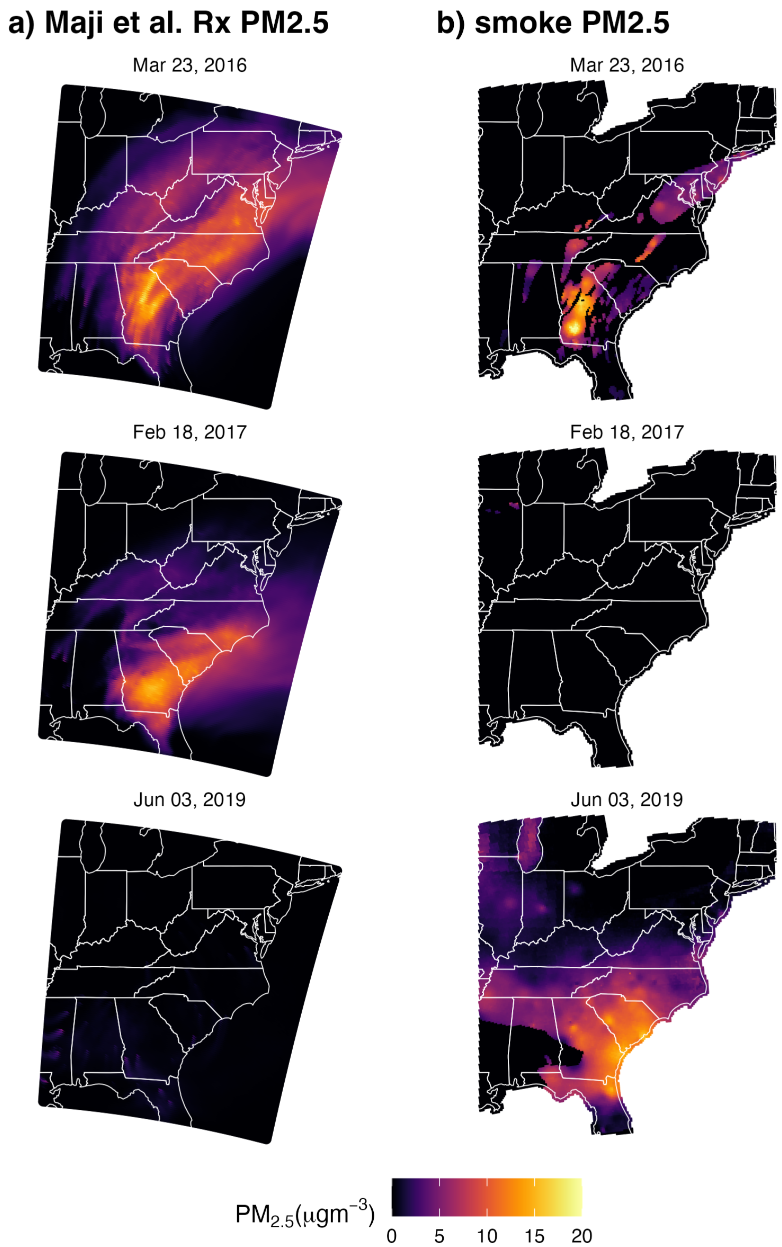

Figure S14: **Comparison of smoke $PM_{2.5}$ estimates with prescribed burn $PM_{2.5}$ in the Southeastern US on select days.** a) $PM_{2.5}$ from prescribed burns (17) and b) estimated smoke $PM_{2.5}$ from this paper on the same three days over the Southeastern US. While smoke $PM_{2.5}$ estimates capture prescribed fire $PM_{2.5}$ on some days (e.g., March 23, 2016), on other days smoke $PM_{2.5}$ estimates not increase in ground concentrations in contrast to presribed fire $PM_{2.5}$ (e.g., Feb 18, 2017). Finally, smoke $PM_{2.5}$ estimates increases on some days when no prescribed fire $PM_{2.5}$ has occurred due to wildfires that may be occurring locally or in more distant areas.

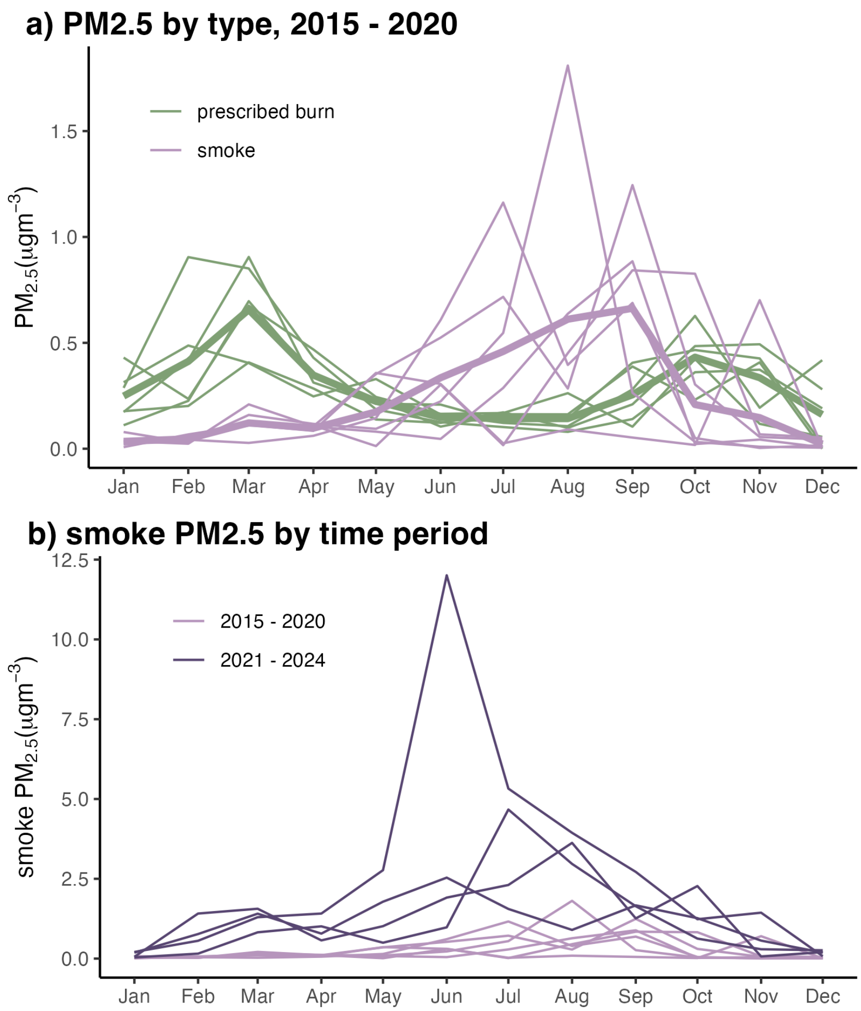

Figure S15: **Average $PM_{2.5}$ from prescribed fire and smoke shows differing seasonal patterns and higher smoke $PM_{2.5}$ in recent years, particularly in summer months.** a) Average smoke (light purple) and prescribed burn (green) $PM_{2.5}$ over the geographic extent shown in Fig. S14; smoke estimates are from this paper, prescribed burn $PM_{2.5}$ estimates are from Maji et al. (17). Each line indicates a year (2015-2020) with the average over the period shown in the thicker line. Prescribed fire $PM_{2.5}$ peaks in March and October while smoke $PM_{2.5}$ peaks in August and September. b) Average monthly smoke $PM_{2.5}$ in the same region for 2015 - 2020 (light purple) and 2021-2024 (dark purple). Scales on vertical axes differ for visibility.

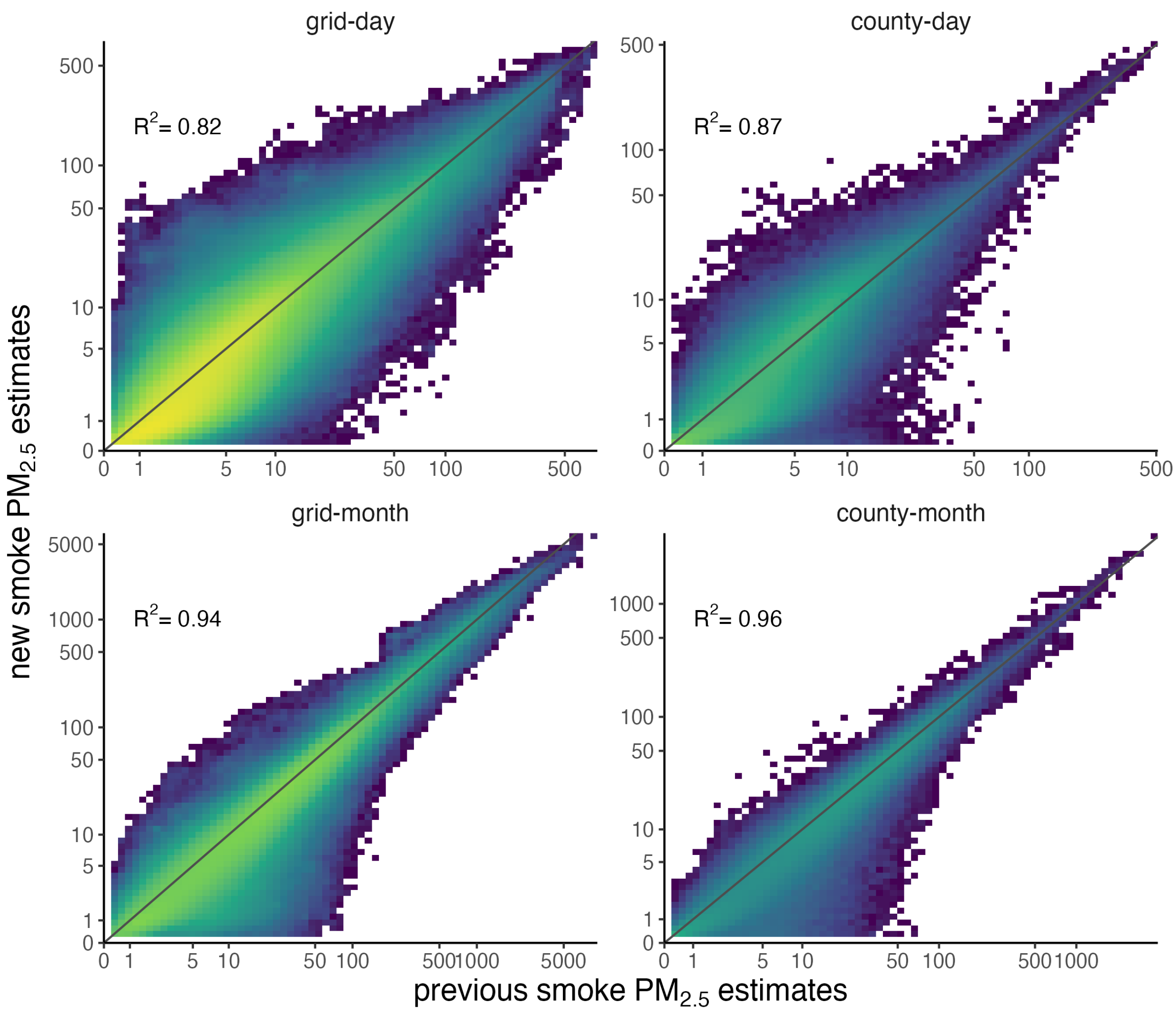

Figure S16: **Comparison with previous predictions from Childs et al. (5)** New smoke $PM_{2.5}$ estimates (vertical axis) are highly correlated with existing estimates (horizontal axis) at the native grid–day predictions (top left) and correlations increase with temporal aggregation (grid-month, bottom left), spatial aggregation (county–day, top right), and both spatial and temporal aggregation (county-month, bottom right). Comparison is run over the time period where estimates are available for both products (2006–2020) and includes days that were previously identified as smoke-affected based in HYSPLIT trajectories (5) in the previous estimates and are coded as having zero smoke $PM_{2.5}$ in the new estimates. Axes are pseudo-log transformed for visibility.

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