Competing Health Impacts of Smoke from Wildfires, Agricultural Burning, and Prescribed Fires in California

Authors: Makoto Kelp[1, 2, ^*], Minghao Qiu[3,4, ^*], Sam Heft-Neal[1], Rebecca Sandoval[5], Claire Schollaert[6], Miriam E. Marlier[6], Marshall Burke[1], and Noah S. Diffenbaugh[1]

[1] Doerr School of Sustainability, Stanford University, Stanford, CA, USA
[2] Department of Atmospheric Sciences, University of Utah, Salt Lake City, UT, USA
[3] School of Marine and Atmospheric Sciences, Stony Brook University, Stony Brook, NY, USA
[4] Program in Public Health, Stony Brook University, Stony Brook, NY, USA
[5] Environmental Studies Program, University of California, Santa Barbara, Santa Barbara, CA, USA
[6] Department of Environmental Health Sciences, UCLA Fielding School of Public Health, Los Angeles, CA, USA

^ These authors contributed equally.
*Corresponding authors: Makoto Kelp (makoto.kelp@utah.edu), Minghao Qiu (minghao.qiu@stonybrook.edu)

Key Points:

- Wildfire and agricultural smoke have similar asthma ED impacts per μg/m^3 while prescribed fire impacts are smaller and more uncertain.
- Weather conditions rather than area burned drive higher agricultural smoke impacts with 7% of agricultural burn days causing 25% of ED visits.
- Many agricultural nonburn days had weather patterns linked to lower ED impacts, suggesting additional lower impact burn windows may have existed.

Abstract:
Wildfire smoke is a dominant threat to air quality and public health in North America, but smoke from other fire sources can also affect health during wildfire seasons. In California, smoke from agricultural burning and prescribed fire co-occurs with wildfire smoke, yet the competing health impacts of these sources remain poorly quantified. To investigate these differential impacts, we estimate daily source-specific fine particulate matter ($PM_{2.5}$) from wildfires, agricultural burning, and prescribed fires across California from 2014 to 2020 by combining empirical smoke estimates with emissions-based source attribution; and link these concentrations to statewide emergency department (ED) records of asthma-related visits. A 10 $\mu g/m^3$ increase in smoke $PM_{2.5}$ is associated with similar increases in asthma-related visits for wildfire (3.0% [95% CI: 2.6%, 3.5%]) and agricultural burning (2.7% [1.2%, 4.3%]), while the estimate for prescribed fire smoke is smaller and more uncertain (1.5% [-0.1%, 3.1%]). Although wildfire dominates the statewide burden, agricultural burning and prescribed fire account for 24% and 11% of smoke-attributable asthma ED visits during 2014-2020. Using the historical agricultural burning record to evaluate how planned burns relate to health impacts, we find that 5-7% of burn days accounting for 20-25% of ED visits across the Central Valley, indicating that impacts are concentrated on a few meteorologically unfavorable days rather than scaling directly with emissions or burned area. We also find that 24% of nonburn days have atmospheric conditions associated with lower ED impacts, suggesting that additional lower impact burn windows may have existed.

Plain Language Summary:
Smoke from wildfires is a major public health concern, but wildfires are not the only fire source that affects air quality during fire seasons. Agricultural burning and prescribed fire also produce smoke, with potentially different health impacts. In this study, we separate smoke from wildfires, agricultural burning, and prescribed fire across California from 2014-2020 and estimate how each source affects asthma emergency department (ED) visits. We find that wildfire and agricultural burning smoke are associated with increased ED visits, while the health impact of prescribed fire smoke is smaller (but more uncertain). California has a longer recent record of frequent agricultural burning than prescribed fire with both fire types conducted through similar burn permitting systems. We use agricultural burning as an analog for understanding which environmental conditions lead to the largest health impacts from planned burning. We find that 6.7% of burn days account for almost one-quarter of ED visits in the Sacramento Valley and that the highest-impact days depend more on weather conditions than on area burned. These results suggest that as prescribed fire expands, smoke management should increasingly account for the conditions under which burning occurs.

Keywords: wildfires**,** prescribed fires, agricultural fires, $PM_{2.5}$, smoke pollution, environmental health

INTRODUCTION

Smoke from wildfires is one of the greatest environmental threats to air quality and public health in the United States (Burke et al., 2023; Feng et al., 2025; Qiu et al., 2025). Because smoke consists of fine particulate matter ($PM_{2.5}$) that can penetrate deep into the lungs, exposure contributes to a broad range of adverse health outcomes, including pulmonary disease, respiratory disease, mental health outcomes, and premature death (e.g., Landguth et al., 2020; Liu et al., 2017). Emerging evidence suggests that smoke-derived $PM_{2.5}$ may pose greater respiratory health risks than the same mass concentration of ambient $PM_{2.5}$ from other sources (Aguilera et al., 2021; Williams et al., 2013). Although wildfires are a dominant source of smoke $PM_{2.5}$ in the western US, land management practices such as agricultural ("Ag") burning, which uses fire to remove crop residue after harvest, and prescribed ("Rx") fire, which is used to manage wildland vegetation and reduce wildfire risk, also contribute to smoke exposure. Smoke from different fire sources may carry distinct health risks due to their different chemical composition, affected populations, and resulting behavioral response. However, no study has quantified and compared the health impacts of smoke from these three different fire sources in a consistent framework.

California is experiencing increasing wildfire activity while also expanding the use of Rx fire as a mitigation strategy to reduce the risk and intensity of future wildfires. During California's fire seasons, all three sources can contribute to smoke exposure, making their health effects difficult to disentangle without source-specific exposure estimates. As the state's fire management practices continue to evolve, the distribution and health impacts of smoke from different fire sources are also likely to change. Numerous studies have investigated the health impacts and behavioral responses to wildfire smoke $PM_{2.5}$ exposure in the state (e.g., Heft-Neal et al., 2023; Magzamen et al., 2021; Reid et al., 2016). However, because most exposure metrics do not explicitly separate wildfire, Ag burning, and Rx fire smoke, these estimates often reflect broader landscape-fire smoke exposure, even when wildfire smoke is the dominant contributor. In contrast, there are few empirical studies of the health impacts of Rx fire smoke in California (Rosenberg et al., 2024), and most existing work has focused on the southeastern US where Rx burning is more prevalent (Afrin and Garcia-Menendez, 2021; Stowell et al., 2025). Given California's goal of treating one million acres annually, largely through Rx fire (California's Wildfire and Forest Resilience Action Plan, 2021), this limited evidence base restricts efforts to evaluate the public health tradeoffs of expanded Rx burning and to identify the conditions under which intentional burning may impose lower or higher smoke-related health burdens (Kelp et al., 2025; Kreider et al., 2026).

Health impact studies of smoke $PM_{2.5}$ from Ag fires in California are similarly limited. Approximately 40% of the state's area is dedicated to agriculture, primarily in the Central Valley, where an estimated 7 million people live. Historically, around one million tons of agricultural biomass (largely prunings and orchard removals) were burned annually in the San Joaquin Valley (California Air Resources Board, 2021). Several studies have examined wildfires affecting Ag productivity (Dillis et al., 2022; Kabeshita et al., 2023; Mann et al., 2014), Ag worker exposure to wildfire smoke (Marlier et al., 2022), and emissions from Ag burns (Harnly et al., 2012; Pinakana et al., 2024), but few have assessed the health impacts of smoke $PM_{2.5}$ from Ag burning itself (Kamai et al., 2023). Legislation enacted in California began phasing out Ag burning in the Central Valley in 2021 (Florez, 2003) with a near-total ban as of January 1, 2025 (Wigglesworth, 2025). However, during our study period (2014-2020), an average of 600,000 tons of agricultural material were still burned each year in the San Joaquin Valley (California Air Resources Board, 2021). This recent history provides a valuable empirical basis for quantifying the health burden of Ag burning smoke before the practice was phased out. Ag burning and Rx fire are both planned fire uses conducted through similar permitting systems that consider meteorology and smoke dispersion (Bay Area Air District, 2025). Because Ag burning provides a much larger recent record of permitted burn events than Rx fire in California, it offers a useful empirical analog for studying how burn timing influences smoke-related health burdens.

Estimating spatially and temporally resolved smoke $PM_{2.5}$ from different fire sources remains challenging. Statistical and machine learning (ML) approaches are increasingly used to estimate smoke $PM_{2.5}$ by linking remotely sensed atmospheric observations, meteorological conditions, and other predictors to surface $PM_{2.5}$ measurements during fire episodes. Prior studies have used these methods to estimate wildfire smoke concentrations (Aguilera et al., 2023; Childs et al., 2024, 2022; Zhang et al., 2023) and to assess the health impacts of wildfire smoke (Heft-Neal et al., 2023; Qiu et al., 2025; Zhu et al., 2024). However, these empirical approaches depend on satellite smoke-plume products and related observations that often miss the smaller and shorter-duration Ag and Rx burns performed in California. In addition, in the US these satellite plume products correlate imprecisely with surface $PM_{2.5}$, especially outside the western US and under light smoke conditions (Liu et al., 2024). Chemical transport models (CTMs) provide a complementary approach to estimate smoke impacts on surface pollution levels by simulating fire emissions, transport, and chemical transformation. These models typically estimate smoke contributions as the difference between simulations with and without fire emissions (Kelp et al., 2023; Schollaert et al., 2024b), but the resulting estimates remain sensitive to uncertainties in emissions inventories (Carter et al., 2020; Liu et al., 2020) and plume rise (Li et al., 2023), which often lead to differences in smoke concentrations when compared to surface observations (Feng et al., 2024; Qiu et al., 2024). Recent work suggests that ML models can better capture observed spatiotemporal variability in smoke $PM_{2.5}$ on heavy smoke days because they are trained directly on surface observations, yet CTM-based methods can show better performance under low-smoke conditions (Qiu et al., 2024).

To our knowledge, no previous study has estimated source-specific smoke $PM_{2.5}$ from wildfire, Ag burning, and Rx fire and compared their health impacts within a unified statewide framework in California. To that end, we estimate daily $PM_{2.5}$ concentrations (10-km resolution) and population exposure from wildfires, Ag burns, and Rx fires across California during 2014-2020. We combine an ML model designed to predict wildfire smoke concentrations with a CTM that uses biomass burning emissions to explicitly attribute smoke $PM_{2.5}$ to specific fire sources. We then link these spatially resolved exposure estimates with geolocated records of all ED visits to nonfederal hospitals in California from 2014-2017 to quantify the distinct impacts of overlapping smoke exposures from different fire sources on ED visits due to asthma. To examine how atmospheric conditions influence the health impacts of planned fires, we use California’s larger recent record of Ag burning as an empirical analog and train convolutional neural networks (CNNs) on Ag-burning-related ED visits and large-scale meteorological fields to identify conditions associated with lower- and higher-impact smoke days.

METHODS

2.1 Machine Learning-Based Estimates of Wildfire Smoke $PM_{2.5}$

We use gridded daily wildfire smoke $PM_{2.5}$ estimates for California at 10 km resolution from 2014 to 2020 from Childs et al. (2024). They construct an eXtreme Gradient Boosting (XGBoost) ML model to predict increases in surface $PM_{2.5}$ concentrations during smoke episodes using satellite-derived smoke plume data, reanalysis products of aerosol optical thickness and surface meteorological variables, and fire activity indicators. Specifically, Childs et al. apply an XGBoost algorithm to estimate $PM_{2.5}$ enhancement on smoke days, defined using NOAA's Hazard Mapping System (HMS) smoke plumes, relative to baseline concentrations on non-smoke days. The model achieves an out-of-sample R^2 of 0.72 when evaluated against US Environmental Protection Agency (EPA) surface observations of all source $PM_{2.5}$.

While the Childs et al. dataset (hereafter referred to as the ML model) is widely used in research on wildfire smoke impacts on air quality and health, the data do not distinguish wildfire smoke from smoke produced by Ag burns or Rx fires. In California, all three fire sources can contribute to smoke exposure during the fire season. Because Rx fires and Ag burns are generally smaller in spatial extent than wildfires, the HMS smoke plume product underlying the ML model is unlikely to consistently detect these events. Furthermore, the spatial distribution of surface monitoring sites may be insufficient to characterize emissions from Rx and Ag fires, limiting the ML model's ability to capture their contributions. Nonetheless, the ML model may still capture some of their resulting smoke when these fires are detectable in satellite data and surface observations, or when these burns co-occur with larger wildfire smoke episodes.

2.2 Chemical Transport Model-Based Estimates of Wildfire, Ag Burning, and Rx Fire Smoke $PM_{2.5}$

We use gridded daily $PM_{2.5}$ estimates for California from 2014 to 2020 from Schollaert et al. (Schollaert et al., 2024b, 2024a) using the GEOS-Chem CTM (v13.1). These estimates incorporate biomass burning emissions from a reclassified version of the "Fire INventory from NCAR" (FINN v2), a 1 km inventory that provides daily aerosol and gas-phase emissions, including $PM_{2.5}$ (van der Werf et al., 2017; Wiedinmyer et al., 2011). FINN is based on fire radiative power detections from Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) satellite observations. Compared to coarser emission inventories, which typically have grid resolutions up to about 10 km at their finest scale (e.g., GFED, QFED), FINN improves the detection of smaller fires including Rx and Ag burns (Oliva and Schroeder, 2015). Although transient and small fires may still be missed because of the once- or twice-daily overpasses of low Earth orbit satellites, FINN offers improved spatial attribution of emissions from these sources. To classify fire emissions by source, Schollaert et al. overlay FINN fire detections with multiple administrative datasets, including the Monitoring Trends in Burn Severity (MTBS), the Forest Service Activity Tracking System (FACTS), and state-level fuel treatment records. Fires are matched to these datasets by location and date to identify wildfires and Rx fires, while unmatched FINN detections occurring on agricultural land (National Land Cover Dataset pasture/hay or cultivated cropland) are classified as Ag burns. Remaining unmatched detections are classified as wildfires, allowing emissions to be attributed to wildfires, Rx fires, or Ag burns.

The GEOS-Chem simulations are run at 0.25° × 0.3125° spatial resolution and are driven by assimilated meteorological fields from the GEOS Forward Processing system. Total $PM_{2.5}$ is simulated as the sum of organic carbon, black carbon, nitrate, ammonium, and sulfate (Palm et al., 2020; Tsigaridis et al., 2014). To isolate the contribution of each fire source to $PM_{2.5}$ concentrations, four scenarios are simulated: (a) a background simulation with no biomass burning emissions, (b) background plus wildfire emissions, (c) background plus Rx fire emissions, and (d) background plus Ag burning emissions. The difference between each fire-source simulation and the background simulation provides an estimate of source-specific $PM_{2.5}$ enhancement.

Although these GEOS-Chem estimates provide daily smoke $PM_{2.5}$ by fire source, the dataset (hereafter referred to as the CTM model) is not directly constrained by surface observations. Schollaert et al. report that modeled total $PM_{2.5}$ can exceed EPA surface monitor observations by as much as 76% during wildfire seasons, consistent with known CTM biases during extreme smoke events in 2020 (Connolly et al., 2026; Qiu et al., 2024). We also find that the CTM tends to produce persistent low, nonzero smoke concentrations (e.g., <0.01 $\mu g/m^3$) even on days and in locations where smoke is not observed. For example, during the 2017 fire season, the ML model identifies approximately 2 million grid-days with zero wildfire smoke concentrations, compared with fewer than 200,000 in the CTM model. Despite this tendency to overestimate diffuse background smoke, the CTM model has the advantages of attributing $PM_{2.5}$ to specific fire sources and identifying the observational records of emissions from smaller fires.

2.3 Hybrid Estimation of Source-Specific Smoke $PM_{2.5}$

Here, we develop a hybrid framework to estimate source-specific smoke $PM_{2.5}$ for the three fire types by combining the empirically constrained smoke product from Childs et al. with fire-type emissions attribution from Schollaert et al. This approach produces two derived datasets for Ag burning and Rx fire: a 'partitioned' product and a 'blended' product.

For the partitioned product, first we regrid the CTM model outputs to the same 10 km grid as the ML model. For each grid-day, we use the CTM model to estimate the relative contribution of wildfire, Ag burning, and Rx fire to total smoke $PM_{2.5}$. We then apply these source-specific fractions to the ML model smoke field to construct a partitioned smoke dataset. In this partitioned product, the total smoke $PM_{2.5}$ from the ML model is apportioned across wildfire, Ag burning, and Rx fire according to the CTM model source fractions. This step preserves the magnitude of the ML model smoke estimates while introducing source attribution from the CTM model. The tradeoff is that the partitioned product assumes the ML model provides a reasonable estimate of total smoke $PM_{2.5}$ on each grid-day, even though smaller and shorter-duration Ag and Rx smoke events may be under-detected in the empirical smoke field.

For the blended product, wildfire smoke $PM_{2.5}$ was taken directly from the ML model and was not further altered because that product has been previously validated against surface observations and is designed to detect the large smoke events that dominate California fire seasons. For Ag burning and Rx fire, we combine the CTM model's source-specific estimates with the corresponding partitioned ML model's estimates using a concentration-weighted averaging approach. The blending weight, w, is defined as

$$w = \frac{C_{CTM}}{C_{CTM} + C_{ML} + \varepsilon} \qquad \text{Eq 1.}$$

and the blended concentration is calculated as

$$C_{hybrid} = w \cdot C_{CTM} + (1 - w) \cdot C_{ML} \qquad \text{Eq 2.}$$

where C_{CTM} is the CTM model-derived smoke $PM_{2.5}$ concentration and C_{ML} is the corresponding source-specific value from the partitioned product. A small constant $\varepsilon = 1e^{-10}$ is added for numerical stability. Under this formulation, grid-days for which the CTM model predicts relatively larger source-specific concentrations receive greater weight on the CTM model value, whereas cases in which the partitioned product is larger receive greater weight on the ML model value.

Prior to blending, both Rx fire and Ag burn estimates are confined to physically plausible ranges, with partitioned estimates bounded between 0 and 50 $\mu g/m^3$ and CTM model-based estimates bounded between 0.5 and 5 $\mu g/m^3$. Additionally, on grid-days where both the estimated CTM model Ag burning and Rx fire concentrations fall below 0.5 $\mu g/m^3$, the blended estimates for both fire types are set to zero. This step uses emissions information from the CTM model to remove spurious smoke attribution from the ML model on days with no detectable fire signal from either source. These thresholds are selected considering the best agreement with the surface observation data from EPA monitors among the blended estimates. Specifically, we evaluate the resulting source-specific estimates against daily total $PM_{2.5}$ measurements from EPA monitors across California using a fixed-effects regression model to quantify the association between smoke $PM_{2.5}$ estimates and $PM_{2.5}$ data from the EPA sites. This step allows us to assess whether the variation in estimated smoke concentrations is likely to be associated with variations in the EPA $PM_{2.5}$ measurements (Table S1).

We conduct two sets of sensitivity analyses to evaluate how the results may change across alternative smoke estimates. First, we adopt different thresholds for the blending process to generate alternative sets of Ag and Rx smoke estimates (referred to as "blended 1," …, "blended 4"); the different thresholds and ranges are reported in Table S1. Second, to address the potential concern of misattributing smoke to the wrong fire types, we retain a blended Ag or Rx contribution only on grid-cell days where that single source accounts for at least X% of total smoke $PM_{2.5}$ from all three fire types combined. Otherwise, the contribution is set to zero. These smoke estimates are referred to as “filter-99%”, “filter-90%”, “filter-80%”, and “filter-50%”, corresponding to different values of X. This sensitivity test therefore uses only the estimated smoke concentrations with very low misattribution risk. Overall, we find that using these alternative smoke estimates yields highly similar smoke-ED patterns (see Results) and generally similar population-weighted smoke concentrations (Figure S1-2).

2.4 Emergency Department Visits Data

ED visit data are obtained from the California Department of Health Care Access and Information, known prior to 2021 as the Office of Statewide Health Planning and Development. Our sample of the ED patient visit-level dataset covers ED visits that occur in the 353 nonfederal EDs in California, which serve more than 95% of the state’s population. Our data include 47.9 million ED visits in total between January 1, 2014 and December 31, 2017. Additional details of the ED data are described in Heft-Neal et al. (2023).

We aggregate visits to daily rates by zip code of residence. For each zip code and day, we divide the total number of visits by the annual zip code population from the American Community Survey

(ACS) and express the result as a daily visit rate. Our analysis focuses on ED visits due to asthma, given that asthma is consistently identified as a health outcome associated with smoke pollution exposure. Each ED visit record includes one primary diagnosis code and up to 20 secondary diagnosis codes and we classify visits using the primary diagnosis only.

Because California hospitals transitioned from ICD-9 to ICD-10 coding during the study period, we define outcome groups using ICD-9 categories mapped to ICD-10 codes, relying on the Centers for Medicare & Medicaid Services General Equivalence Mappings (Centers for Medicare & Medicaid Services, 2010). The corresponding ICD-9 and ICD-10 codes used in our analysis are listed in Heft-Neal et al. (2023). Our sample includes 4.95 million respiratory disease visits, including 743,000 asthma visits, and 2.55 million visits for respiratory symptoms.

2.5 Estimating Smoke Impacts on ED visits

We estimate the impacts of smoke concentrations from wildfire, Ag burning, and Rx fire on ED visits at the zip code-day level using a distributed lag model. Following prior work (Heft-Neal et al., 2023; Jung et al., 2025), we model ED visits as a function of same-day smoke exposure and exposure during the preceding L days:

$$y_{zd} = \sum_{l=0}^{L} \beta_l^{WF} \times WF_{z,d-l} + \sum_{l=0}^{L} \beta_l^{AG} \times AG_{z,d-l} + \sum_{l=0}^{L} \beta_l^{RX} \times RX_{z,d-l} + \gamma W_{zd}$$

$$+\delta_z + \eta_{cm} + \theta_{ym} + dow_d + \varepsilon_{zd} \qquad \text{Eq. 3}$$

y_{zd} denotes the ED rates in zip code z and date d; WF, AG, and RX denote population-weighted zip code smoke $PM_{2.5}$ concentrations attributable to wildfire (WF), Ag burning (AG), and Rx fires (RX), respectively. The distributed lag specification includes smoke exposure on the day of visit and over the previous L days. We use $L = 7$ in our main specification, although we also examine alternative lag lengths. W_{zd} includes time-varying covariates, specifically ambient temperature, precipitation, and distance to the nearest fire to account for the effects of fires on mobility patterns. The model also includes a rich set of fixed effects, including zip code fixed effects (δ_z) to account for time-invariant differences across different zip codes, county-month fixed effects (η_{cm}) to account for underlying seasonality in ED visits as well as smoke concentrations, year-month fixed effects (θ_{ym}) to account for the overall long-term trend and common shocks for California, and day-of-week (*dow*) to capture variability across different days of the week. In essence, our analysis establishes the associations between smoke and ED visits by exploiting within zip code variation in smoke concentrations after accounting for time trends, seasonality, and daily patterns. Because short-run smoke concentrations are driven largely by fire ignition and atmospheric transport, these daily fluctuations are plausibly exogenous to other short-run factors affecting local health conditions. The coefficients are estimated using the weighted ordinary least squares method (OLS) using zip-level population as regression weights. While our main specification only uses linear models, we also estimate the health effects using typical non-linear models (including polynomial and bin models).

The coefficients β_l^{WF}, β_l^{AG}, and β_l^{RX} represent the changes in ED visit rate associated with a 1 $\mu g/m^3$ increase in smoke $PM_{2.5}$ from each fire source L days before the visit. We report cumulative effects by summing the coefficients across all lags for each fire source. These cumulative estimates represent the increase in ED visits associated with one day of smoke exposure after accounting for delayed effects over the following week. Because the model includes smoke concentrations from all three fire sources simultaneously, each estimate reflects the association for a given source conditional on exposure to the other two sources. Our primary analysis focuses on California's fire season, defined here as April-October, when all three smoke sources overlap most strongly. Our sensitivity analysis employing data across all months finds similar smoke impacts from wildfire and Rx sources on asthma ED visits, while the impacts of Ag smoke become not statistically significant.

2.6 Estimating ED visits attributable to smoke from three fire sources

We estimate the number of ED visits attributable to the smoke $PM_{2.5}$ from each fire source by combining the cumulative exposure-response coefficients from Section 2.5 (sum of all βs for each fire source) with historical smoke concentrations for each zip code-day. Although the empirical exposure-response functions are estimated using ED data from 2014 to 2017, we apply those coefficients to the full smoke record from 2014 to 2020 to estimate attributable ED visits across the entire study period. We calculate the change in ED visit rates (per 100,000 residents) for each zip code and day and then calculate the changes in ED visits using the population in each zip.

To evaluate the distribution of the health burden associated with smoke pollution, we further estimate the ED burden for each race/ethnicity and income group. For this analysis we use population estimates by race/ethnicity group and income deciles derived from the Gridded Environmental Impacts Frame (Gridded EIF) from the US Census Bureau. EIF data include population estimates at a resolution of 0.01 degree in different race/ethnicity groups and income deciles. We first aggregate the data into 10 km (consistent with the resolution of our smoke data) to estimate the population counts from each race/ethnicity and income group in each 10 km grid. We then separately apply our exposure-response function to the population counts to calculate the ED burden of different population subgroups. We use the same exposure-response function across different population groups and thus the attributable ED burden reflects the different exposure and baseline ED visit rates.

2.7 Identifying Atmospheric Drivers of High- and Low-Burden Burning Days

Ag burning and Rx fire smoke show recurrent seasonal overlap with both sources co-occurring most frequently in fall (Figure S3). Ag burning also occurs in winter, when Rx fire is rare, but our health impact estimates already treat the smoke-ED relationship as consistent across seasons (Section 2.6). As such, the full annual Ag burn-day record remains informative for characterizing atmospheric conditions relevant to intentional burning generally, including as Rx fire expands into a wider range of seasonal conditions (Swain et al., 2023). To characterize the large-scale atmospheric conditions associated with elevated Ag-burning smoke health impacts, we train CNNs following Davenport and Diffenbaugh (2021). Analyses are performed separately for the San Joaquin Valley and Sacramento Valley air basins using Ag burn days identified from the reclassified FINN fire inventory (Schollaert et al., 2024a). Burn days are defined as days on which total black carbon emissions from Ag fires within each valley exceed zero using the full 2014 to 2020 record. Days on which total wildfire smoke $PM_{2.5}$ from the ML model exceeds twice the blended Ag burning estimate across the region are additionally excluded to reduce confounding from wildfire-dominated smoke episodes. Sensitivity analyses across thresholds ranging from 1 to 5 times yielded burn day counts within 5–6% of this value. This grouping yields 545 burn days for the San Joaquin Valley and 356 burn days for the Sacramento Valley during 2014 to 2020.

Daily meteorological fields from the North American Regional Reanalysis (NARR) over the western US, represented on a 139 × 141 grid at approximately 32 km resolution, serve as inputs to the CNN. Four variables are used as input channels: surface air temperature, relative humidity, sea level pressure, and 500 hPa geopotential height. Each variable is normalized by subtracting the grid cell temporal mean and dividing by the grid cell temporal standard deviation. Temporal encodings for day of year, day of week, and month, expressed as sine and cosine cyclical pairs, are appended as additional input channels.

We train two complementary CNNs that are restricted to Ag burn days. The first is a regression CNN that predicts daily regional ED visit counts after applying a log(1+x) transformation, which reduces the influence of extreme values while preserving the ordering of days by burden. The model uses three stride-2 convolutional layers with 64, 128, and 128 filters and 3 × 3 kernels followed by a 1 × 1 bottleneck convolution and two fully connected layers. Group normalization and dropout with p = 0.25 are used for regularization. The second is a classification CNN that predicts (among Ag burn days) whether a given day is a low-ED impact day. Days are labeled as low-ED impact if two conditions are jointly satisfied: (1) the true regional ED visit count falls below a region-specific threshold (0.5 visits per day for the Sacramento Valley and 1.0 for the San Joaquin Valley), and (2) the first-stage CNN regression model predicts that count to within 0.05 visits. This second condition ensures that the classification model learns from days when meteorological conditions are predictive of low health burden rather than from days with low counts driven by factors not captured in the atmospheric inputs. Thresholds are selected separately for each region to account for differences in the underlying ED visit distributions between the two valleys. This model uses two convolutional layers with 64 and 128 filters, max pooling, and a 256-unit fully connected layer with dropout ranging from p = 0.30 to 0.55. The classification CNN also ingests the regression model's predicted mean and Monte Carlo dropout uncertainty as additional spatial input channels, enabling a two-stage prediction pipeline that uses both expected ED burden and predictive uncertainty to improve identification of high-impact burn days.

We train 30-model ensembles per region using different random seeds (e.g., Trok et al., 2024) and apply early stopping with a patience of six epochs. To assess whether the highest-impact days simply reflect the largest burn events, we also compare meteorologically defined high-impact days with the top 10% of burn days ranked by Ag emissions and burned area in each valley. We then apply Layerwise Relevance Propagation to identify the spatial meteorological features most strongly driving model predictions and to improve interpretability of the learned atmospheric patterns (e.g., Davenport and Diffenbaugh, (2021)).

RESULTS

3.1 Spatial and Temporal Characteristics of Smoke

Smoke from the three fire sources exhibits distinct spatial patterns and temporal profiles across California, with wildfire smoke accounting for the most extreme daily concentrations and Rx fire and Ag burning producing lower but recurring concentrations that overlap with wildfire smoke (Figure 1, Figure S3). From 2014 to 2020, annual average wildfire smoke concentrations across California are 1.33 $\mu g/m^3$ (population-weighted mean of 0.63 $\mu g/m^3$). The largest wildfire smoke concentrations occur in the state's northwestern forests and in the Sierra Nevada and are concentrated primarily between June and October. In comparison, annual average Rx fire smoke concentrations are 0.20 μg/m^3 (population-weighted mean of 0.22 μg/m^3). Most Rx burning occurs in the Sierra Nevada foothills with smoke often settling into the Sacramento Valley. These spatiotemporal patterns are consistent with the seasonal timing of prescribed burning outside peak summer wildfire conditions. Annual average Ag burning concentrations are 0.21 μg/m^3 (population-weighted mean of 0.27 μg/m^3) and are concentrated almost entirely in the Central Valley with most burning occurring in fall and winter.

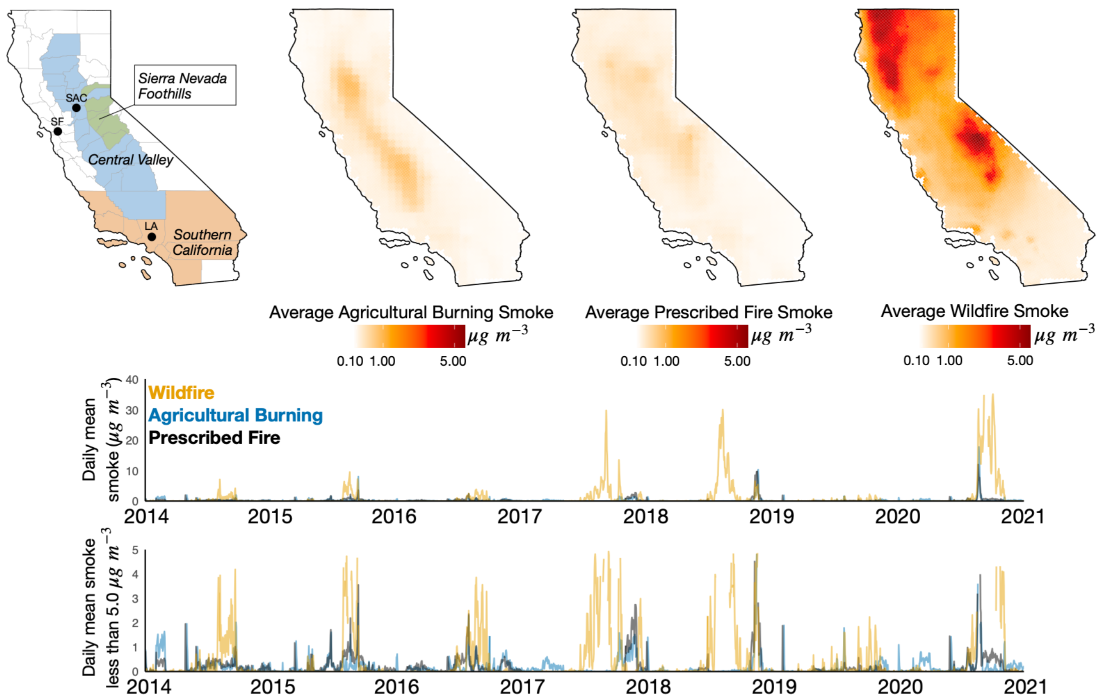

Figure 1. Spatial and temporal patterns of wildfire, Ag burning, and Rx fire smoke $PM_{2.5}$ across California from 2014 to 2020. Maps show average smoke $PM_{2.5}$ for the three fire types for the study period using the blended dataset. Time series show the corresponding statewide daily mean concentrations from 2014 to 2020, with a second panel displaying days with daily mean smoke $PM_{2.5}$ below 5.0 μg/m^3.

We conduct several sensitivity analyses of the smoke datasets to characterize uncertainty in the Ag and Rx smoke estimates used in the subsequent health analyses (Figure S1-2, Table S1). Directly using the CTM model estimates increases mean population-weighted Ag burning smoke across 2014 to 2020 by 8% compared to the blended product. For Rx fire, the CTM model increases population-weighted smoke by 18%. To further isolate days and locations where smoke exposure could be attributed with greater confidence to a single fire source, we apply an additional source filter. For each grid-day, we calculate each source's fractional contribution to total estimated smoke $PM_{2.5}$ and set sources contributing less than a percentage threshold of the total to zero, retaining only observations for which one source is dominant. We evaluate thresholds of 50%, 80%, 90%, and 99% in a sensitivity analysis. The 50% threshold reduces average Ag and Rx smoke concentrations by about one third. We evaluate how the estimated exposure-response function and estimated ED visits (see below) differ by these alternative assumptions for smoke modeling.

3.2 Health impacts of Wildfire, Ag, and Rx Smoke

We find that asthma-related ED visit rates increase in response to smoke from all three fire sources, although the effect of Rx fire smoke is smaller and more uncertain (Figure 2). We find exposure to wildfire smoke $PM_{2.5}$ is associated with an increase of 3.04% [95% CI: 2.58%, 3.49%] per 10 $\mu g/m^3$ smoke. Ag burning also has a positive relationship across all smoke datasets with a main estimate of 2.73% [95% CI: 1.21%, 4.25%], although the confidence intervals are wider than for wildfires. Rx fire estimates are the most sensitive to the attribution method with a main estimate of 1.50% [95% CI: -0.14%, 3.13%]. Uncertainty intervals for Rx fire are wider and, in some cases, cross zero, with the partitioned dataset producing a negative point estimate. We attribute this greater sensitivity to the smaller magnitude, shorter duration, and more localized spatial footprint of Rx fire smoke, which make source attribution and health effect estimation more uncertain (Schollaert et al., 2024b). Results for analyses using year-round ED visit rates are reported in the Supporting Information (Figure S4). The response patterns were similar to our main results for wildfire and Rx fire smoke. Exposure to Ag smoke is also associated with increased ED asthma visits, but the magnitude is smaller and not statistically significant possibly due to the underlying seasonal patterns in asthma. Furthermore, we do not find statistically significant differences in health burden across race or income groups between the three fire types (Figure S5).

Differences across attribution methods are largest for the CTM model and partitioned product. For wildfire smoke, the CTM estimate is near zero relative to the consistently positive blended and partitioned estimates. For Ag burning, the CTM model remains positive and is similar in magnitude to the blended estimates, although uncertainty is larger. For Rx fire, the CTM model is also positive, but the partitioned product is negative and more uncertain, in contrast to the positive central estimates from the blended products.

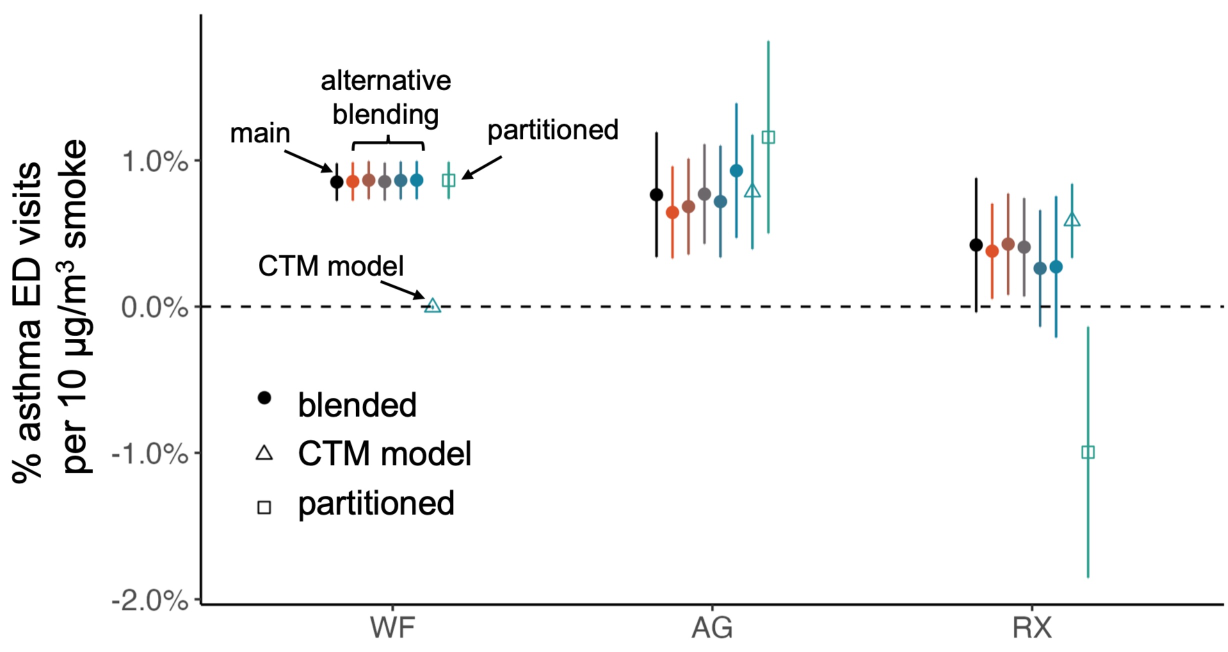

Figure 2. Asthma ED visit rates increase with additional exposure to wildfire and Ag smoke, whereas responses to Rx fire smoke are smaller and more uncertain. ED and smoke data are shown for 2014 to 2017 (April-October). Points show the estimated percent change in asthma ED visits per 10 $\mu g/m^3$ smoke for wildfire (WF), Ag burning (AG), and Rx fire (RX), with vertical

bars indicating 95% confidence intervals. Filled circles denote blended estimates, open triangles denote CTM model estimates, and open squares denote partitioned estimates. Multiple colored points within the blended group indicate the main and alternative blending specifications ranging from 50% (orange) to 99% (blue). Description of alternate blending specifications can be found Table S1.

Wildfire smoke imposes the largest asthma-related ED burden in California, but Ag burning also contributes substantially and in a more geographically concentrated manner (Figure 3). We estimate that wildfire smoke accounts for 2,455 attributable ED visits per year [95% CI: 2,087, 2,823] from 2014 to 2020, and Ag burning accounts for 922 visits per year [95% CI: 408, 1,436], consistent with the roughly 3:1 ratio of pop-weighted smoke exposure from the two sources. We estimate that Rx fire smoke accounts for an average of 420 visits per year [95% CI: -38, 877], with a confidence interval that contains zero. Wildfire smoke also drives the greatest year-to-year variability with the largest burdens occurring in 2017, 2018, and 2020, consistent with the most severe wildfire smoke years in the study period. In contrast, Ag burning and Rx fire produce smaller annual burdens. Ag burning is relatively stable over time. Rx fire is more variable from year to year than Ag burning but less variable than wildfire smoke, likely reflecting land management priorities and implementation constraints (CAL FIRE, 2025).

The geography of attributable asthma burden differs sharply across smoke sources (Figure 3). Ag burning-related asthma impacts are concentrated in the Central Valley, especially in major agricultural regions. Rx fire-related impacts are smaller in magnitude and more spatially diffuse with localized burdens in parts of inland northern and central California. Wildfire smoke-related asthma burden is both larger and more widespread with the highest rates occurring across northern California, the Sierra Nevada foothills, and other regions repeatedly affected during major wildfire years. These results show that wildfire smoke dominates the statewide asthma burden, but Ag burning contributes 25% of the total average annual burden and produces a concentrated regional health burden that would likely be obscured in analyses that do not distinguish among fire sources. ED burden estimates using alternative smoke estimates for Ag and Rx are reported in the Supporting Information (Figure S6).

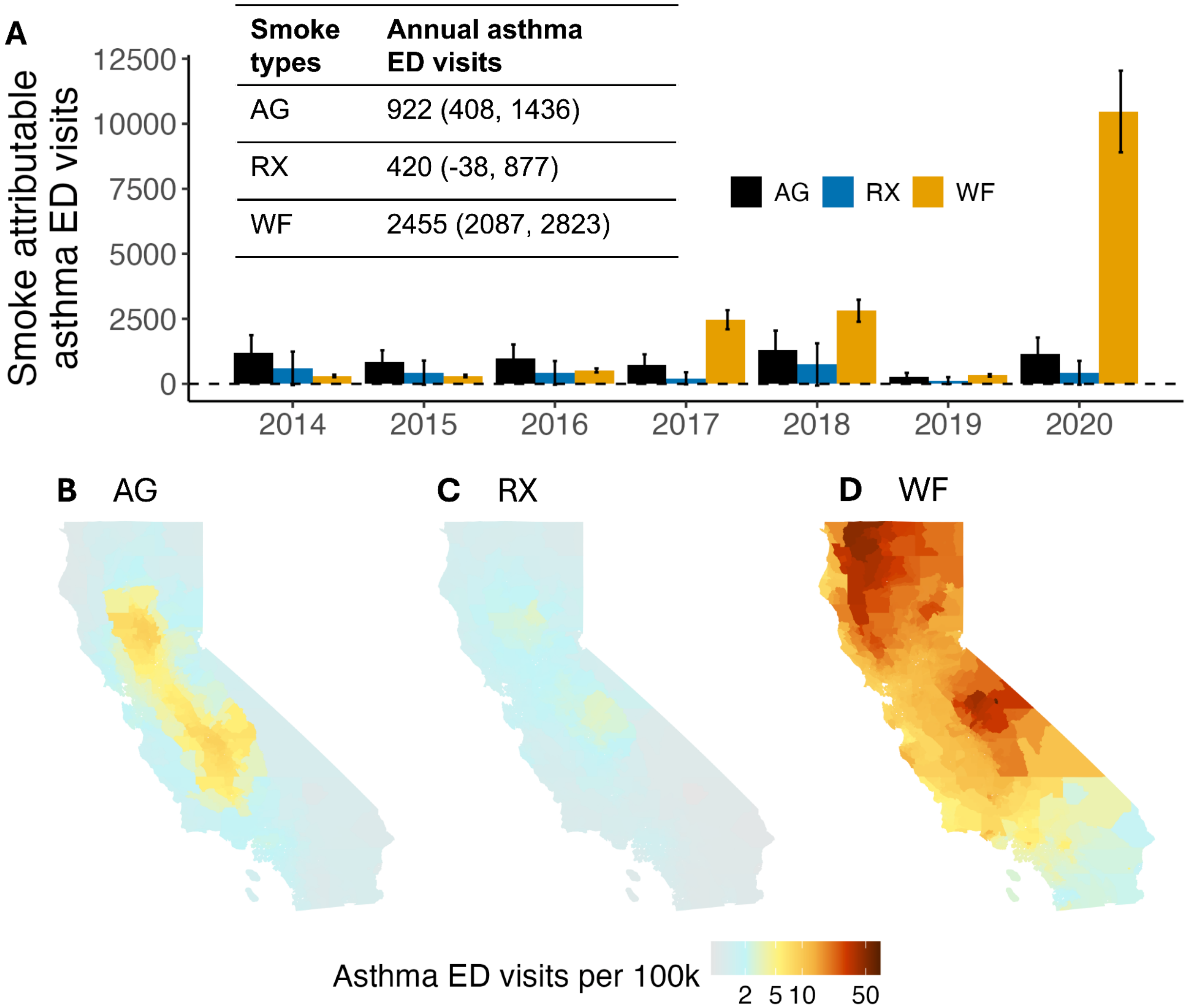

Figure 3. Wildfire smoke accounts for the largest asthma ED burden in California, while Ag burning impacts the Central Valley and Rx fire contributes more localized burdens. Panel A shows annual attributable asthma ED visits by fire source calculated by applying the main source-specific exposure-response coefficients from Figure 2 to the full 2014-2020 estimated smoke $PM_{2.5}$ concentrations. Error bars indicate 95% confidence intervals, and the inset table reports annual average attributable visits across the study period. Panels B-D show the spatial distribution of attributable asthma ED visits per 100,000 people.

3.3 Atmospheric Patterns Associated with High- and Low-Impact Ag Burning Days

Because Ag burning is only permitted on approved burn days when agencies consider forecasted meteorology and expected air quality impacts (California Air Resources Board, 2023), historical burn and nonburn days provide an opportunity to evaluate how atmospheric conditions relate to realized health impacts. Rx fire permitting uses similar smoke management considerations, including weather and dispersion forecasts, although the specific criteria and operations may differ by burn type, location, fuel conditions, and management objective (Bay Area Air District, 2025). A small fraction of Ag burning days accounts for a disproportionate share of asthma-related ED impacts in both valleys as identified by the classification CNN (Figure 4). The cumulative burden is larger in the San Joaquin Valley than in the Sacramento Valley with 578 ED visits over 545 burn days in the San Joaquin Valley compared with 199 ED visits over 356 burn days in the Sacramento Valley (Figure 4A). In the Sacramento Valley, the CNN model classifies 24 of 356 burn days (6.7%) as high ED-impact days (Figure S7), which account for 24.6% of total Ag burning-related ED visits with a mean burden of 2.04 ED visits per day (Table S2, Figure S7). In the San Joaquin Valley, the CNN model classifies 28 of 545 burn days (5.1%) as high ED-impact days (Figure 4C), which account for 20.4% of total Ag burning-related ED visits with a mean burden of 4.20 ED visits per day (Table S2, Figure 4C). Low ED-impact days account for a larger share of burn days, including 151 of 356 burn days (42.4%) in the Sacramento Valley (Figure S7) and 220 of 545 burn days (40.4%) in the San Joaquin Valley (Figure 4C). The remaining burn days fall between these two categories and are not classified as either high- or low-impact.

We find that the burn days with the largest Ag emissions or burned area are not the days that cause the greatest health impacts. The top 10% of Ag emission days account for only about ~14%-15% of total ED visits in both valleys (Table S2). On the other hand, CNN-defined high-impact days account for 20.4% of total ED visits in the San Joaquin Valley despite representing only 5.1% of burn days, and 24.6% of total ED visits in the Sacramento Valley despite representing only 6.7% of burn days. This contrast suggests that a relatively small number of burn days with unfavorable atmospheric conditions contribute disproportionately to health impacts. Along with the identification of lower-impact conditions on many historical nonburn days, this pattern points to opportunities for better targeting burn windows rather than simply restricting the number of burn days. In the San Joaquin Valley, these high-impact days are characterized by warmer surface temperatures, lower relative humidity, higher geopotential heights, and sea level pressure patterns consistent with more stagnant conditions over California, whereas low-impact days exhibit weaker anomalies and circulation patterns more favorable to dispersion (Figure 4C). Sacramento Valley atmospheric patterns show a similar contrast between high- and low-impact days, although the anomalies are somewhat weaker and more spatially diffuse than in the San Joaquin Valley (Figure S7).

Many historical nonburn days exhibit large-scale atmospheric patterns similar to those associated with lower-impact Ag burning days, suggesting that favorable dispersion conditions may have occurred more often than historical burning patterns indicate. The classification CNN identifies 247 of 1,041 nonburn days in the Sacramento Valley (24%) and 282 of 648 in the San Joaquin Valley (44%) as resembling lower-impact atmospheric conditions (Figure 4D). Because operational burn windows also depend on local winds, fuel moisture, staffing, permitting, and management objectives, these results should be interpreted as identifying potentially favorable large-scale meteorological conditions rather than retrospective missed burn opportunities.

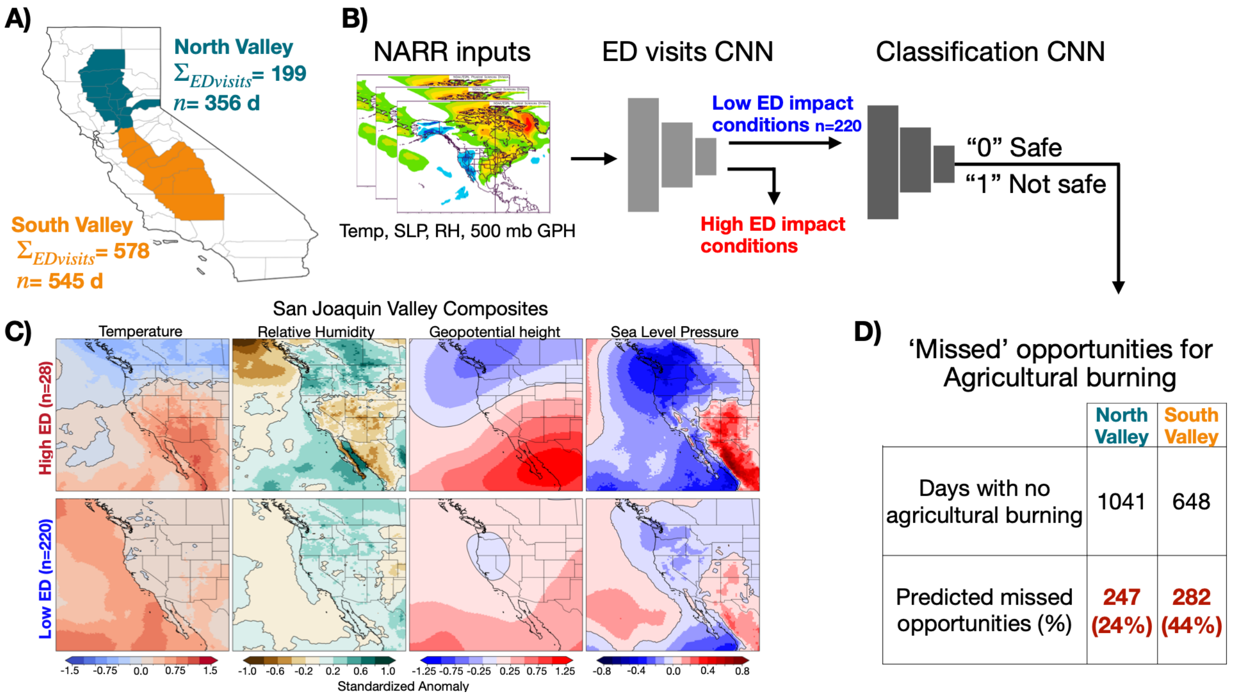

Figure 4. Atmospheric conditions are associated with large differences in Ag burning-related asthma ED impacts and identify historical opportunities for lower-impact burning. (A) Study regions and cumulative Ag burning-related ED visits and burn days in the Sacramento Valley and San Joaquin Valley. (B) Schematic of the CNN workflow including NARR meteorological inputs, specifically temperature, sea level pressure (SLP), relative humidity (RH), and 500-hPa geopotential height (GPH) used to predict asthma ED visits and classify days as lower- or higher-impact burn conditions. (C) Composite standardized anomalies for the San Joaquin Valley showing distinct meteorological patterns on high-ED and low-ED Ag burning days across atmospheric variables. (D) Number and fraction of nonburn days classified as lower impact burn opportunities.

DISCUSSION

Our results show that although wildfire smoke dominates the statewide burden, multiple fire sources contribute to asthma-related ED visits during California's fire season. Wildfire smoke accounts for the largest annual number of asthma-related ED visits during 2014 to 2020, while Ag burning contributes 24% of total visits, particularly in the Central Valley where exposures are most concentrated. In contrast, Rx fire smoke is associated with smaller and more uncertain health impacts, reflecting potentially weaker health responses and greater uncertainty in source attribution. Despite the higher uncertainty, we find that RX smoke also contributes to a non-negligible fraction of smoke-related asthma ED visits (11%). We also find that large-scale atmospheric conditions are associated with substantial variation in the health impacts of intentional burning. Meteorologically driven high-impact days account for 20% to 25% of total Ag-burning-related ED visits in the San Joaquin and Sacramento Valleys, despite representing only 5% to 7% of burn days. These results show that wildland fire smoke sources contribute to asthma-related health impacts during California's fire season and that the public health consequences of Ag burning depend strongly on when burning occurs.

Smoke from all three fire sources is associated with increased asthma-related ED visits. Because these sources can overlap in space and time, exposed communities may experience a combined smoke burden from wildfire, Ag burning, and Rx fire. In addition to the well-established association between wildfire smoke $PM_{2.5}$ and asthma ED visits, we find that exposure to smoke $PM_{2.5}$ from Ag burning is also strongly associated with increased asthma ED visits. We also do not find clear disparities in health burden across race or income groups (Figure S5). This finding is consistent with smoke affecting broad segments of the population during California's fire season rather than a single demographic group. However, because ED visits reflect healthcare utilization rather than health status, the absence of differences in ED visit responses does not necessarily imply that underlying asthma impacts are similar across groups. Differences in healthcare-seeking behavior or access to care could result in similar ED visit responses to smoke despite differences in the underlying health impacts of smoke.

At the same time, the estimated health impacts of Rx fire smoke are smaller than those of wildfire and Ag burning on a per $\mu g/m^3$ $PM_{2.5}$ basis, although the 95% confidence intervals overlap and the Rx estimates are more uncertain. Several mechanisms could contribute to this pattern. Because Rx fires are planned events subject to extensive review and permitting, communities may be better able to anticipate and avoid exposure than during more episodic wildfire events (Clark et al., 2024). Differences in fuel composition may also matter, as Rx fires often consume less dense or less accumulated biomass than wildfires, while some wildfires also burn structures and other built materials that may alter smoke composition and toxicity (Krasovich Southworth et al., 2025; Marsavin et al., 2023). In addition, land managers may make efforts to conduct Rx burns at times and in locations that reduce smoke impacts, including avoiding especially unfavorable meteorological conditions or more densely populated areas, which could reduce the realized health burden of Rx smoke relative to less controlled fire sources (Kelp et al., 2025). Future work is therefore needed to determine whether Rx fire smoke is intrinsically less harmful and to estimate more reliably how Rx fire smoke affects health under increasing burning. Even if the mechanisms remain uncertain, evidence of lower Rx fire smoke impacts under operational conditions would still be useful for land managers comparing treatment options.

The Ag burning results provide empirical evidence that the health impacts of planned burning can vary sharply with atmospheric conditions even within existing permitting systems. In a future where California aims to treat nearly one million acres annually, burn managers may need to conduct treatments more frequently and under a wider range of conditions than those that have traditionally defined burn windows because climate change is shrinking those windows (Swain et al., 2023). Our results suggest that this expansion does not necessarily imply uniformly higher health impacts. Instead, we find that the highest impact Ag burning days are more closely tied to unfavorable weather than to burn size alone. We also find that many nonburn days had weather conditions similar to lower impact burn days. These results suggest that health benefits may come from better identifying atmospheric conditions associated with lower smoke impacts and from avoiding the small number of burn days when conditions are especially conducive to poor air quality and elevated health impacts. However, these findings should not be interpreted as directly identifying missed Rx fire windows. Ag burns in the Central Valley differ from wildland Rx fires in fuel conditions, topography, and go/no-go criteria. Optimizing Rx fire timing, location, and treatment type remains an open question that involves burn operations, local meteorology, community response, National Environmental Policy Act (NEPA) mitigation requirements and other permitting requirements, and tradeoffs among health impacts, cost, and staffing capacity (Deak et al., 2024; Higuera-Mendieta and Burke, 2026; Kelp et al., 2025; Strabo et al., 2026).

We acknowledge that our study has several limitations related to smoke estimation and fire-source attribution. First, estimating fire-source smoke is subject to multiple sources of uncertainty, especially for estimating smoke pollution originating from Rx fires. Some fires classified in the CTM model data as Ag burning may instead reflect wildfires occurring on Ag croplands (Schollaert et al., 2024a). The reclassified FINNv2.2 emissions inventory used to drive the GEOS-Chem CTM is derived from MODIS and VIIRS active fire detections and therefore inherits known limitations of active fire products, including a bias toward hotter, larger, and more persistent fires and reduced sensitivity to smaller or shorter-duration burns. As a result, only a subset of actual Rx fire activity is likely captured, especially for treatments that are small or poorly aligned with satellite overpass times (Schollaert et al., 2024a). In addition, Rx fire inventories rely on management reporting, which may contain inaccuracies or omissions in burn location, timing, or extent. Because unmatched fire detections in the reclassified emissions inventory are ultimately classified as wildfire, incomplete reporting or missed satellite detections may preferentially result in Rx fire emissions being attributed to wildfire rather than Rx fire.

Second, although our hybrid smoke framework improves source attribution by combining an empirical wildfire smoke product with CTM-based fire typing, neither component can be treated as ground truth for Rx fire smoke. The CTM relies on emissions inputs that may omit many smaller Rx fires, while the empirical ML product is also unlikely to capture Rx smoke reliably because these burns are often too small to generate detectable satellite plume signatures and too localized or distant to be captured by monitoring networks. Because direct observational data for Rx fire smoke remain limited, it is difficult to determine whether our hybrid approach overestimates or underestimates true Rx smoke exposure. To reflect this uncertainty, we report results across a range of source-specific $PM_{2.5}$ datasets rather than relying on a single exposure estimate. Future work should prioritize improved monitoring and validation of source-specific smoke exposures, especially for smaller and more intermittent Rx fires.

Third, the ED data span only 2014 to 2017 due to the lag in health data processing and reporting, which is shorter than the 2014 to 2020 smoke exposure record used for burden estimation. Applying exposure-response estimates from 2014 to 2017 to later years assumes that the relationship between smoke exposure and asthma-related ED visits remained stable through 2020. This assumption introduces uncertainty especially because 2018 to 2020 included severe wildfire smoke years and potential changes in population exposure, vulnerability, and health care utilization. Extending source-specific health analyses with longer-run health outcome data will be an important direction for future work.

CONCLUSION

We combine an empirical wildfire smoke product, CTM-based source attribution, and statewide ED visit records to quantify the competing asthma-related health impacts of wildfire, Ag burning, and Rx fire smoke during California's fire season. We find that a 10 $\mu g/m^3$ increase in smoke $PM_{2.5}$ is associated with an increase of 3.04% [95% CI: 2.58%, 3.49%] in asthma-related ED visits for wildfire smoke, 2.73% [95% CI: 1.21%, 4.25%] for Ag burning smoke, and 1.50% [95%CI:

-0.14%, 3.13%] for Rx fire smoke. Applying these source-specific relationships to the 2014-2020 smoke record, we estimate that wildfire smoke accounts for 2,455 annual asthma-related ED visits [95% CI: 2,087, 2,823], while Ag burning accounts for 922 visits per year [95% CI: 408, 1,436] and Rx fire accounts for 420 visits per year [95% CI: -38, 877]. Wildfire smoke therefore dominates the statewide burden, but Ag burning still accounts for 24% of the average annual asthma burden in our sample and produces a concentrated regional burden in the Central Valley. Rx fire smoke is also associated with increased asthma-related ED visits, although the estimated effects are smaller and more uncertain than those for wildfire and Ag burning. We further show that the public health impacts of intentional burning vary sharply with atmospheric conditions with only 5% to 7% of Ag burning days accounting for 20% to 25% of total Ag burning ED visits, while many historical nonburn days exhibit conditions associated with lower burden burning. These impacts exceed those associated with the largest burn days determined by either biomass burning emissions or burned area.

These results indicate that California's smoke health burden is not driven by wildfires alone and that, even when meteorological conditions are considered in burn planning, there may still be major opportunities to better avoid the small number of days with especially poor smoke air quality and elevated near-term health impacts. In particular, California's plans to expand Rx burning will require a clearer understanding of how the timing, location, and type of burning affect smoke-related health outcomes. Although the current scale of Rx fire in California remains modest relative to the state's goal of treating one million acres annually, our results suggest that the public health consequences of this expansion will depend not only on how much burning occurs, but also on when and where it occurs relative to population exposure and atmospheric conditions. As California moves toward larger-scale use of Rx fire, integrating source-specific smoke estimates with health data and operational burn planning may help identify treatment windows that balance land management goals with public health protection. More broadly, future progress will require better observational constraints on Rx fire smoke and more systematic evaluation of the tradeoffs among wildfire risk reduction, smoke exposure, and near-term health impacts.

Open Research Section

Processed data and CNN model code used in this work can be found at Zenodo (https://zenodo.org/records/21384716). Code to reproduce figures and tables will be made available upon publication.

Conflict of Interest declaration

The authors declare there are no conflicts of interest for this manuscript.

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Supplementary Materials for

Competing Health Impacts of Smoke from Wildfires, Agricultural Burning, and Prescribed Fires in California

Authors: Makoto Kelp[1, 2, ^*], Minghao Qiu[3,4, ^*], Sam Heft-Neal[1], Rebecca Sandoval[5], Claire Schollaert[6], Miriam E. Marlier[6], Marshall Burke[1], and Noah S. Diffenbaugh[1]
^Equal contribution

[1] Doerr School of Sustainability, Stanford University, Stanford, CA, USA
[2] Department of Atmospheric Sciences, University of Utah, Salt Lake City, UT, USA
[3] School of Marine and Atmospheric Sciences, Stony Brook University, Stony Brook, NY, USA
[4] Program in Public Health, Stony Brook University, Stony Brook, NY, USA
[5] Environmental Studies Program, University of California, Santa Barbara, Santa Barbara, CA, USA
[6] Department of Environmental Health Sciences, UCLA Fielding School of Public Health, Los Angeles, CA, USA

^ These authors contributed equally.
*Corresponding authors: Makoto Kelp (makoto.kelp@utah.edu), Minghao Qiu (minghao.qiu@stonybrook.edu)

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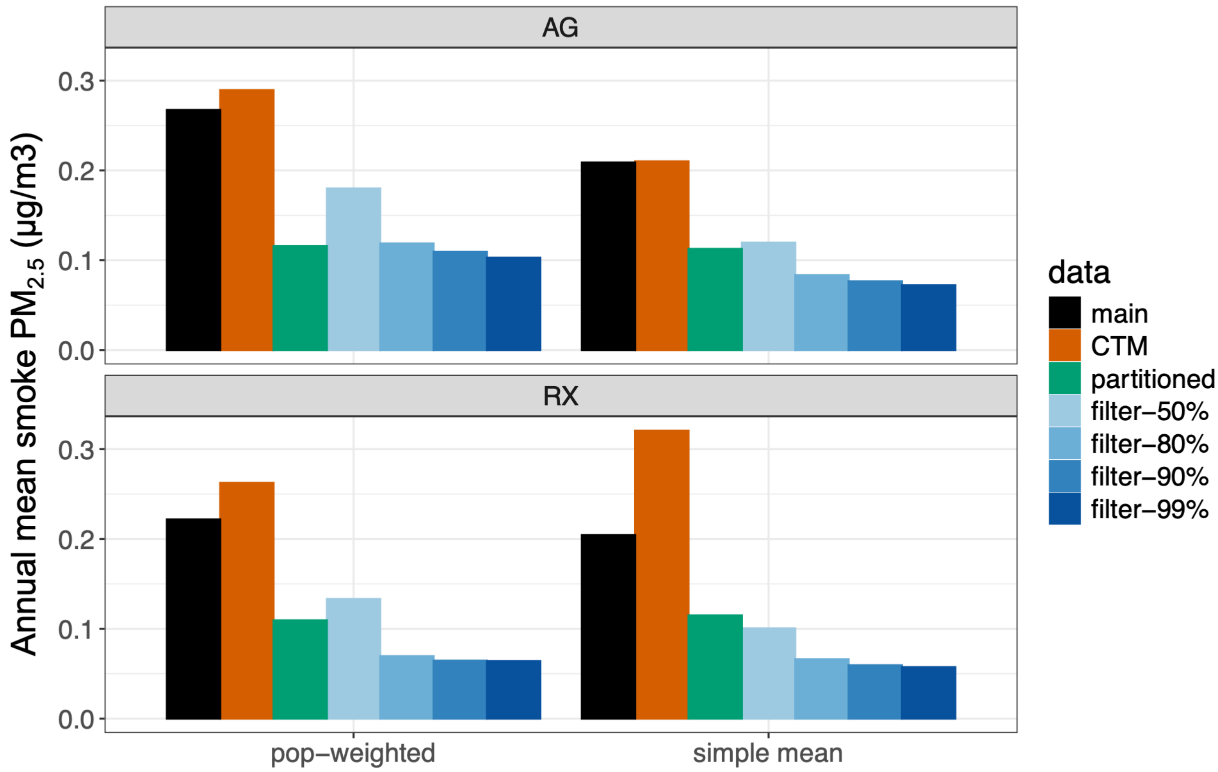

Figure S1. Annual mean agricultural burning (AG) and prescribed fire (RX) smoke $PM_{2.5}$ ($\mu g/m^3$) across California (2014-2020) under alternative source attribution approaches. Smoke $PM_{2.5}$ exposures are shown as both averages and population weighted. 'Main' refers to the concentration-weighted blended estimate used in the primary analysis. 'CTM' denotes the GEOS-Chem chemical transport model estimates; partitioned refers to the ML-based source-apportioned estimate using Childs et al. (2024). Filter-50% through filter-99% indicate blended estimates retained only on grid cell-days where the attributed source comprises at least 50%, 80%, 90%, or 99% of total co-located smoke $PM_{2.5}$ from all three fire types combined. More restrictive filters progressively isolate days and locations of near-exclusive source dominance, resulting in lower mean concentrations as mixed-source grid cells are excluded.

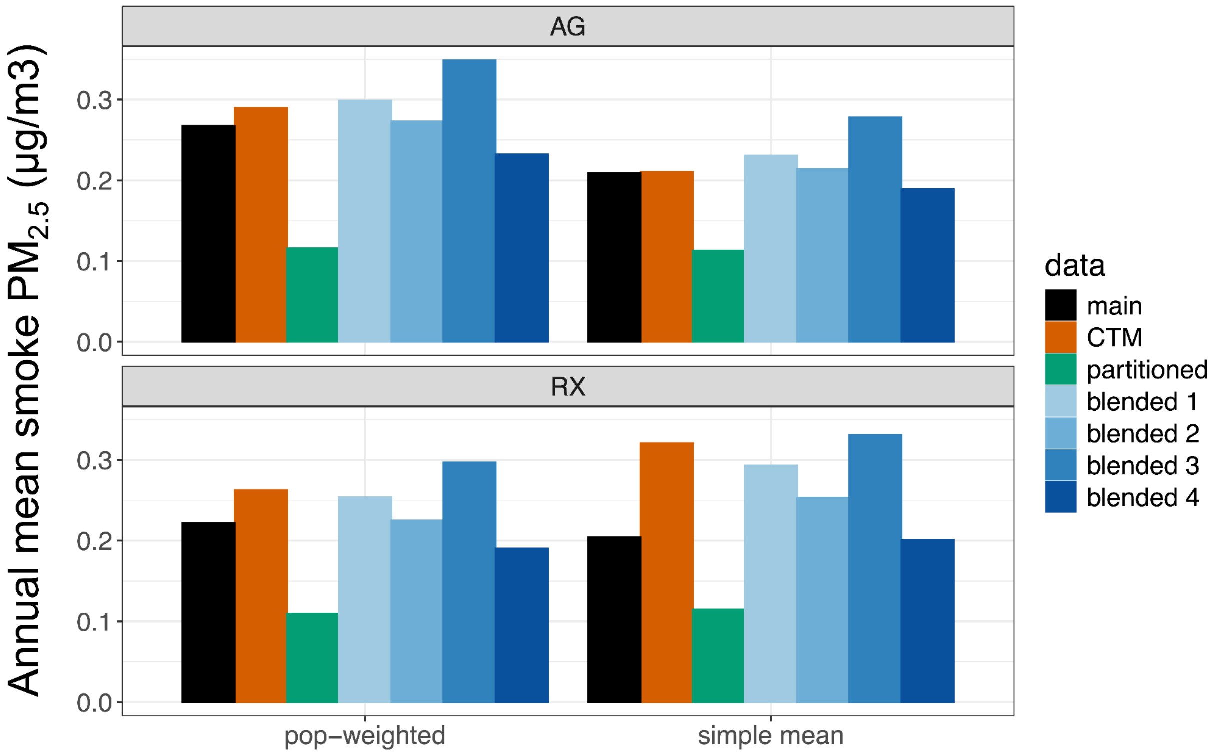

Figure S2. Annual mean agricultural burning (AG) and prescribed fire (RX) smoke $PM_{2.5}$ (µg/m^3) across California (2014-2020) under alternative source attribution approaches as in Figure S1, but for blended product definitions.

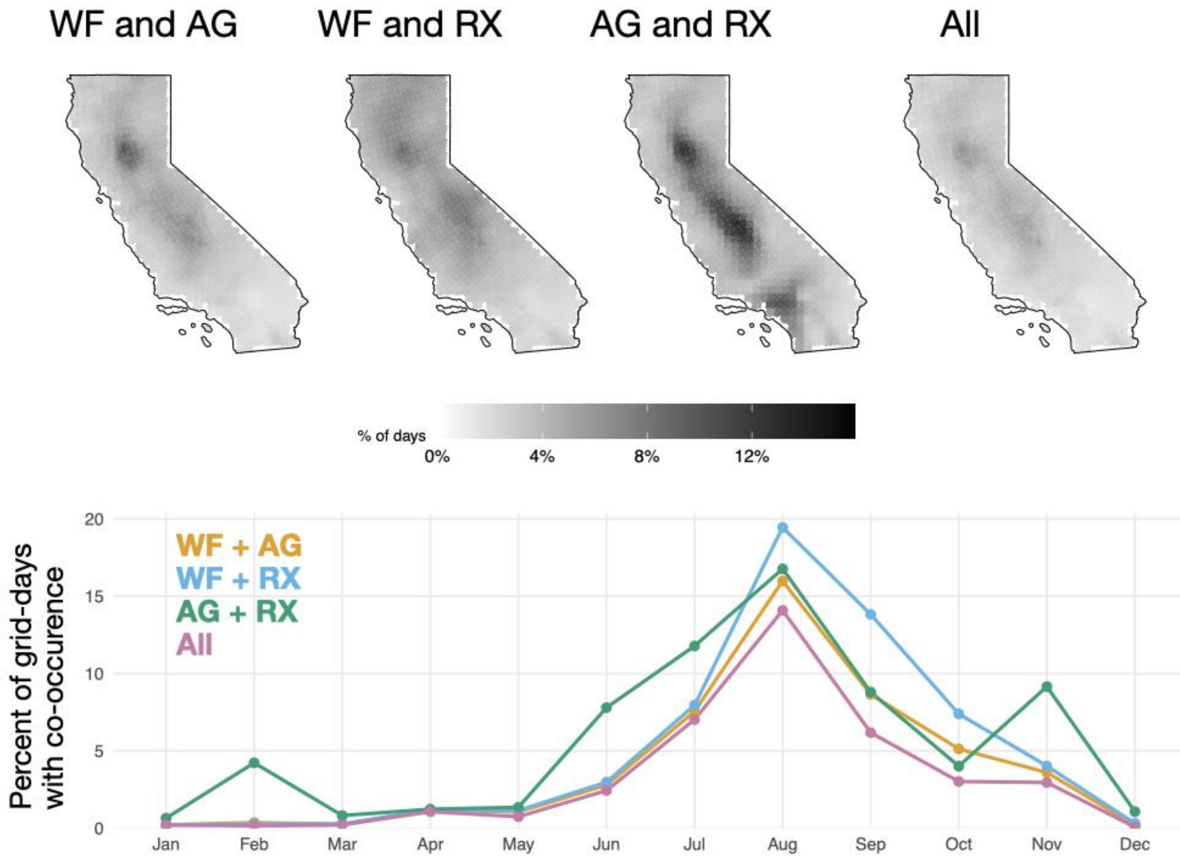

Figure S3. Spatial and temporal co-occurrence of wildfire (WF), agricultural (AG), and prescribed (RX) fire smoke across California from 2014 to 2020. Maps show the fraction of days at each 10 km grid cell on which two or more smoke sources were simultaneously active (defined as $PM_{2.5}$ > 0.1 μg/m^3). All four maps share a common colorbar. The bottom plot shows the monthly frequency of each co-occurrence type expressed as the percentage of California grid-days.

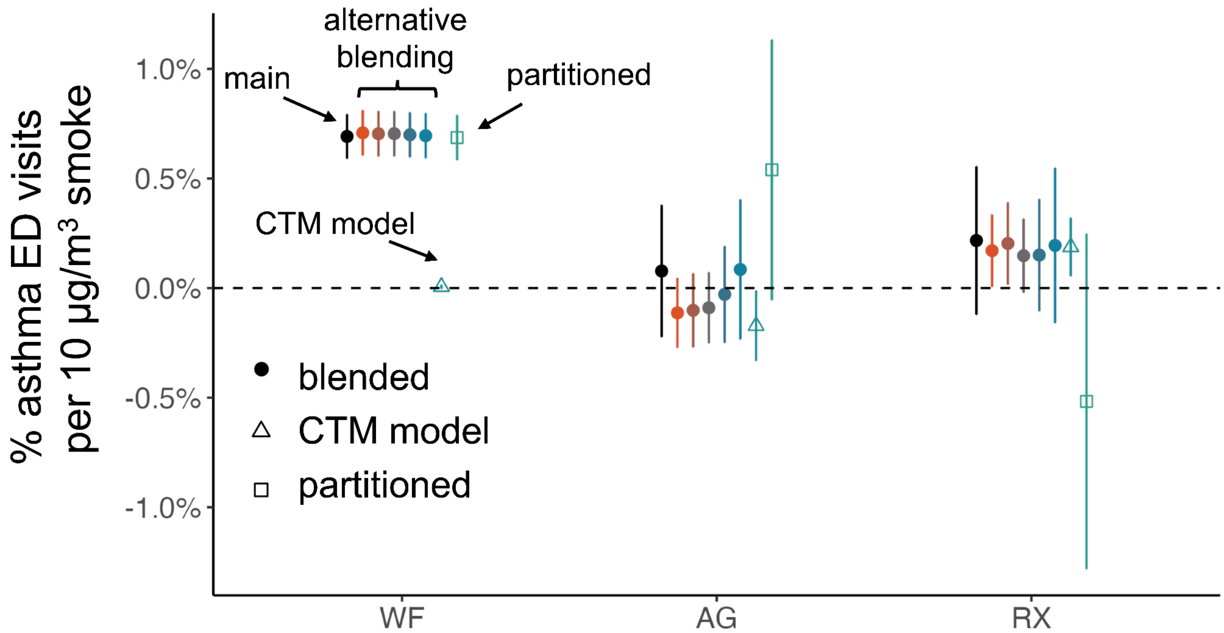

Figure S4. ED visit rate as in Figure 2, but using data from all months in 2014 to 2017.

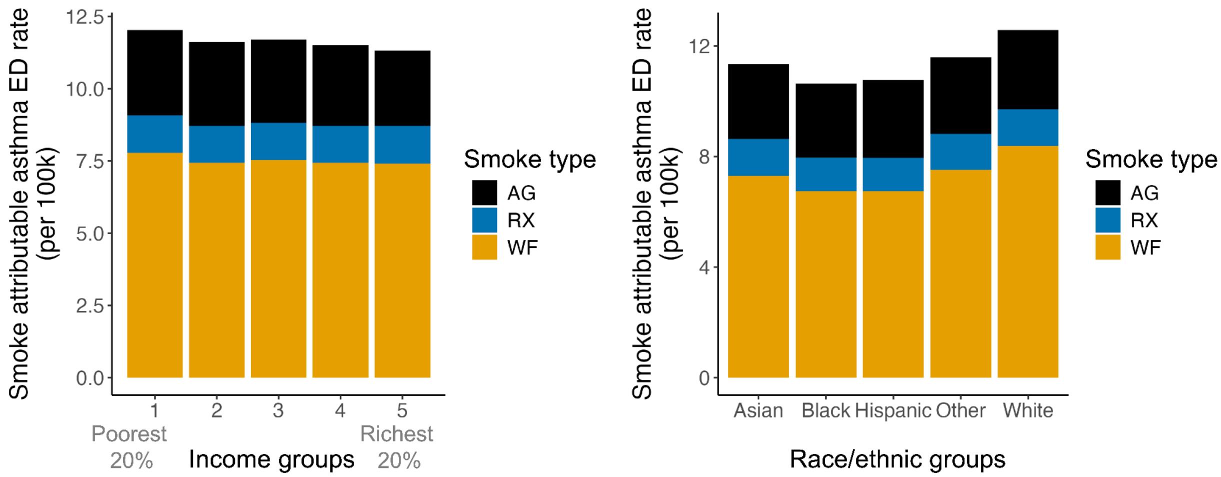

Figure S5. Asthma ED visit rates (per 100,000 people) attributable to agricultural burning (AG), prescribed fire (RX), and wildfire (WF) smoke by income quintile (left) and race/ethnicity (right), California 2014-2020. No statistically significant differences in smoke-attributable ED burden across subgroups were detected for any fire type.

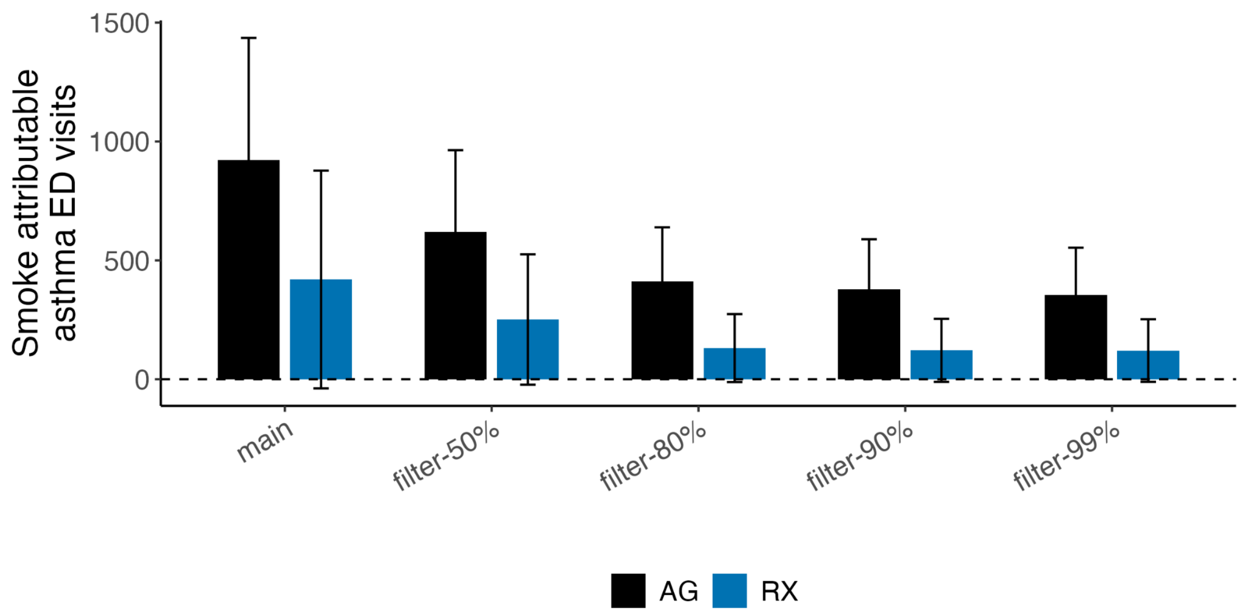

Figure S6. Total statewide asthma ED visits attributable to agricultural burning (AG) and prescribed fire (RX) smoke under alternative source attribution datasets in California from 2014-2020. 'Main' is the concentration-weighted blended estimate used in the primary analysis; filter-50% through filter-99% retain blended contributions only on grid cell-days where the attributed source comprises at least that fraction of total co-located smoke $PM_{2.5}$. Bars represent means; error bars are 95% confidence intervals.

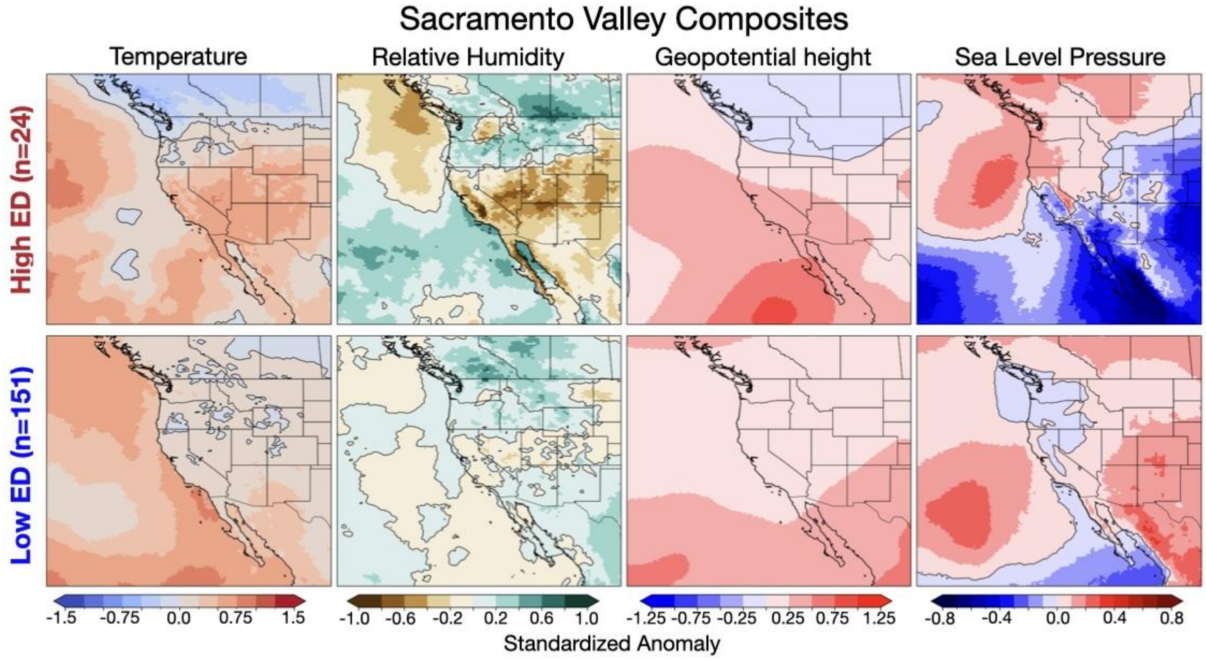

Figure S7. Composite standardized anomalies as in Figure 4C, but for the Sacramento Valley.

Table S1. Sensitivity of monitor-validation regression coefficients across alternative smoke $PM_{2.5}$ products.

Main vs. CTM vs. partitioned[1]				
	main	**partitioned**	**CTM model**	
WF	1.075 (0.033)	1.076 (0.033)	0.022 (0.004)	
AG	1.377 (0.051)	1.041 (0.033)	2.455 (0.669)	
RX	0.880 (0.085)	0.978 (0.088)	-0.445 (0.130)	
Different blended thresholds[2]				
	blended 1	**blended 2**	**blended 3**	**blended 4**
WF	1.083 (0.032)	1.076 (0.032)	1.081 (0.032)	1.076 (0.033)
AG	1.153 (0.038)	1.964 (0.090)	1.510 (0.057)	1.381 (0.049)
RX	0.658 (0.099)	0.698 (0.099)	0.568 (0.099)	0.842 (0.081)
Different filters on contributions from AG and RX[3]				
	filter-50%	**filter-80%**	**filter-90%**	**filter-99%**
WF	1.107 (0.033)	1.103 (0.033)	1.102 (0.033)	1.101 (0.033)
AG	1.495 (0.055)	1.300 (0.152)	1.246 (0.128)	-0.224 (0.427)
RX	0.748 (0.138)	-0.131 (0.267)	-0.075 (0.454)	-4.164 (0.591)

[1]The table reports the slope coefficient (standard error) from regressing EPA station-measured smoke $PM_{2.5}$ on modeled smoke $PM_{2.5}$, separately for wildfire (WF), agricultural burns (AG), and prescribed fire (RX) sources, restricted to April-October. A coefficient near 1 indicates that the modeled product is, on average, unbiased relative to the monitor; deviations from 1 quantify under- or over-prediction. Standard errors are reported in the parentheses.
[2]Alternative blended estimates vary the bounds applied to CTM and ML inputs before concentration-weighting. The main analysis clamps CTM to [0.5, 5] $\mu g/m^3$ and ML to [0, 50] $\mu g/m^3$. Blended 1 removes the upper ceiling on the ML estimate, with CTM clamped to [0.5, 50] $\mu g/m^3$. Blended 2 lowers the CTM floor to 0.1 $\mu g/m^3$, testing sensitivity to the standard 0.5 $\mu g/m^3$ minimum. Blended 3 raises both CTM bounds to [1, 10] $\mu g/m^3$ to improve detection of point sources. Blended 4 changes the upper ceiling on both inputs to [0.5, 25] $\mu g/m^3$ and [0, 25] $\mu g/m^3$ for CTM and ML, respectively, to reduce potential top-coding artifacts.
[3]Source dominance filters retain a blended AG or RX contribution only on grid cell-days where that source accounts for at least X% of total co-located smoke $PM_{2.5}$ from all three fire types combined. Otherwise, the contribution is set to zero.

Table S2. Comparison of agricultural burning day groups used in the CNN sensitivity analysis for the San Joaquin Valley and Sacramento Valley.

Valley	Day group	N days	Percent of burn days	Mean ED visits per day	Percent of total ED visits
San Joaquin Valley	All burn days	545	100.0	1.06	100.0
San Joaquin Valley	[1]Top 10% Ag emissions	55	10.1	1.59	15.1
San Joaquin Valley	[1]Top 10% Ag burned area	55	10.1	1.58	15.0
San Joaquin Valley	[2]Meteorologically driven high-impact days	28	5.1	4.20	20.4
Sacramento Valley	All burn days	356	100.0	0.56	100.0
Sacramento Valley	[1]Top 10% Ag emissions	36	10.1	0.81	14.7
Sacramento Valley	[1]Top 10% Ag burned area	36	10.1	0.78	14.2
Sacramento Valley	[2]Meteorologically driven high-impact days	24	6.7	2.04	24.6

[1]Defined by reclassified FINN v2.2 agricultural emissions

[2]Corresponding to days classified as high-impact by the valley-specific CNN framework