

Daily Local-Level Estimates of Ambient Wildfire Smoke PM_{2.5} for the Contiguous US

Marissa L. Childs,* Jessica Li, Jeffrey Wen, Sam Heft-Neal, Anne Driscoll, Sherrie Wang, Carlos F. Gould, Minghao Qiu, Jennifer Burney, and Marshall Burke



Cite This: *Environ. Sci. Technol.* 2022, 56, 13607–13621



Read Online

ACCESS |

Metrics & More

Article Recommendations

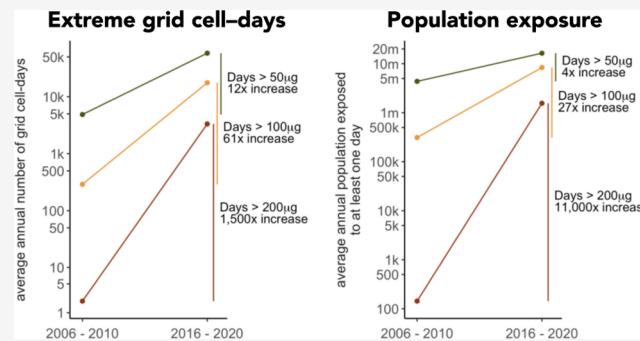
Supporting Information

ABSTRACT: Smoke from wildfires is a growing health risk across the US. Understanding the spatial and temporal patterns of such exposure and its population health impacts requires separating smoke-driven pollutants from non-smoke pollutants and a long time series to quantify patterns and measure health impacts. We develop a parsimonious and accurate machine learning model of daily wildfire-driven PM_{2.5} concentrations using a combination of ground, satellite, and reanalysis data sources that are easy to update. We apply our model across the contiguous US from 2006 to 2020, generating daily estimates of smoke PM_{2.5} over a 10 km-by-10 km grid and use these data to characterize levels and trends in smoke PM_{2.5}. Smoke contributions to daily PM_{2.5} concentrations have increased by up to 5 µg/m³ in the Western US over the last decade, reversing decades of policy-driven improvements in overall air quality, with concentrations growing fastest for higher income populations and predominantly Hispanic populations. The number of people in locations with at least 1 day of smoke PM_{2.5} above 100 µg/m³ per year has increased 27-fold over the last decade, including nearly 25 million people in 2020 alone. Our data set can bolster efforts to comprehensively understand the drivers and societal impacts of trends and extremes in wildfire smoke.

KEYWORDS: particulate matter, wildfires, smoke, aerosols, machine learning

INTRODUCTION

Exposure to ambient fine particulate matter (PM_{2.5}) has long been recognized as a leading environmental determinant of health outcomes and is estimated to cause millions of premature deaths globally and 48,000 deaths in the US every year.¹ Efforts to reduce this health burden require understanding the main sources of PM_{2.5} and how pollutant concentrations from these sources are distributed across human populations. While many countries have made remarkable strides in reducing key anthropogenic emission sources and thus PM_{2.5} concentrations, albeit sometimes from very high levels,^{2,3} other PM_{2.5} sources appear to be growing rapidly. Of key concern in many parts of the world is the growing contribution of wildfire smoke to pollution concentrations.^{4–9} Increases in wildfire smoke are being driven in a substantial part by a warming climate, which increases the flammability of fuels and in turn the occurrence of larger, more extreme wildfires which emit more smoke.^{10–12} Lofted high into the atmosphere, resulting pollutants can travel long distances from their source fire, potentially affecting ground pollution levels and health outcomes thousands of kilometers away.¹³ Because smoke from wildfires can also generate abrupt extreme pollutant concentrations and because emitted pollutants might differ in their toxicity relative to analogous



non-wildfire species,¹⁴ accurate measurement of the location and level of smoke-attributable surface pollutant concentrations is key for understanding the societal impacts of growing wildfire risk.

However, accurate attribution and measurement remain empirically challenging. Ground monitors measure concentrations of total pollutants and cannot be easily used to attribute pollutants to their sources without additional information. Atmospheric chemical transport models (CTMs) offer one common approach to linking wildfire activity to concentrations of key pollutants and downstream human impacts,^{15–20} but their use faces a number of difficulties.²¹ First, uncertainties in wildfire emission inventories have been shown to lead to substantial differences in CTM-estimated smoke PM_{2.5} concentrations, with up to 20-fold differences in estimated regional wildfire-attributed PM_{2.5} concentrations²² when different leading inventories are fed

Received: April 25, 2022

Revised: September 6, 2022

Accepted: September 6, 2022

Published: September 22, 2022



ACS Publications

© 2022 American Chemical Society

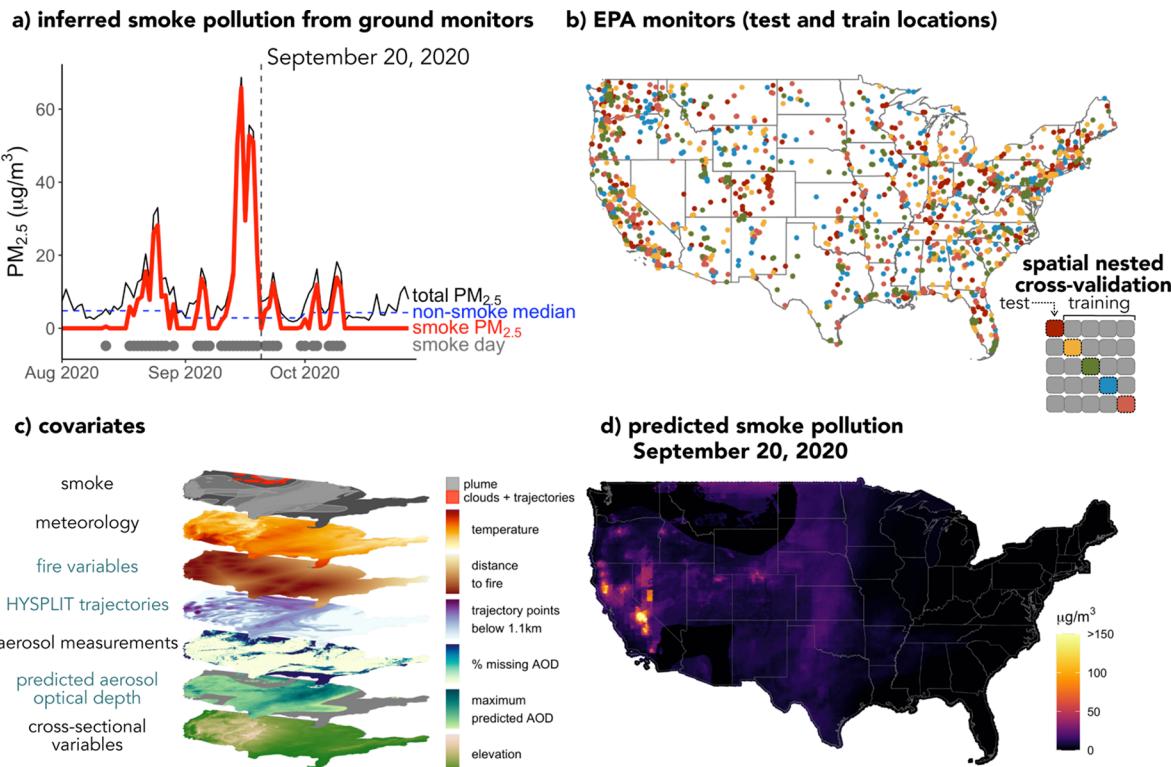


Figure 1. Model predictions are derived from inferred smoke pollution at ground monitors and remotely sensed covariates. (a) Total fine particulate matter (PM_{2.5}, black line) is observed at ground monitors. Plumes and trajectories from fires are used to identify days with smoke (gray points). Non-smoke median PM_{2.5} (blue dashed line) is the station- and month-specific median of PM_{2.5} on non-smoke days, and smoke PM_{2.5} (red line) is total PM_{2.5} above the non-smoke median on days with smoke overhead. (b) Smoke PM_{2.5} is inferred at EPA monitor stations (points) throughout the US, which are then grouped into five disjoint folds for model training and validation to perform spatial nested cross-validation (inset). (c) Smoke days (top layer) are defined based on the presence of smoke plumes (light gray areas) or the presence of 50 HYSPLIT trajectory points below 1.1 km and AOD missingness over 75% (red areas), as a proxy for cloud cover that would prevent the identification of smoke plumes. Other covariates included in the model are used to predict smoke PM_{2.5} on smoke days and include both time-varying and cross-sectional variables. Covariates labeled in black are directly measured by other products, while those in blue are derived. (d) Resulting predictions are a 10 km resolution gridded product of daily smoke PM_{2.5} over the contiguous U.S. from 2006 to 2020. All time-varying covariates and predictions shown are from September 20, 2020. State outlines are reproduced with permission from the US Census Bureau TIGER/Line Shapefiles.⁵¹

into the same transport model, although recent efforts have shown that satellite-based emission calibration can improve the simulation accuracy.²³ Second, the complex chemistry regimes during wildfire (in particular, production of organic aerosols) and hyperlocalized meteorology are often not well-captured by CTMs, leading to concerns over their ability to correctly model the transport of wildfire smoke.^{24–26} Third, parameterized heights of plume injections and the vertical allocations of emissions differ considerably across different CTMs and often compare poorly with observed injection heights, leading to discrepancies in surface PM_{2.5} concentrations when compared with in situ observations.^{27,28}

As a complement to CTM-based approaches, recent efforts have sought to use statistical approaches to directly estimate smoke PM_{2.5} concentrations without explicitly parameterizing the underlying physical processes. The rapid expansion in the frequency and availability of satellite imagery has led to numerous satellite-based estimates of wildfire smoke movement,^{29,30} but commonly used satellite products (e.g., aerosol optical depth or satellite-derived plume boundary estimates) do not provide precise information on where in the atmospheric column the smoke occurs, making it difficult to use this information alone to infer surface concentrations. Instead, non-CTM-based approaches typically include the use of ground monitor data to infer wildfire-attributable pollutant

concentrations. The main empirical challenges of non-CTM-based approaches for estimating wildfire-attributable air pollution are the accurate partitioning of smoke- and non-smoke-sourced pollutants and the estimation of pollution concentrations in locations where ground monitors are not available. Studies have taken multiple approaches to solving the partitioning problem, including building statistical models of all the main sources of pollution and estimating the model with and without wildfire variables,⁴ estimating smoke PM_{2.5} at a given monitor location as anomalous deviations from estimated seasonal non-smoke background PM_{2.5} concentrations,^{5,31} using particle trajectory models to estimate wildfire-influenced and non-influenced surface pollution,³² and simply attributing extreme positive PM_{2.5} anomalies during summer and fall wildfire seasons in the US West to wildfires.⁶ Alternate approaches have also been used to estimate smoke pollutant concentrations for locations without monitors, including fitting statistical models that relate monitor observations to input variables and then using the model to estimate concentrations in non-monitor locations⁴ or interpolating monitor observations across space and inferring the smoke contribution using one of the abovementioned techniques.^{5,6,31} The primary goal of most of these analyses has been to shed light on the longer-term trends in smoke-

derived PM_{2.5} and how smoke contributions to total PM_{2.5} have changed over space and time.

Here, we build on these non-CTM-based approaches to estimate daily, local-level wildfire-smoke-attributable surface PM_{2.5} across the contiguous US. We combine information from satellite-based smoke plume identification and simulations of air trajectories from fire locations to identify when smoke is in the air. Then, similar to other studies, we attribute anomalous deviations from background levels of PM_{2.5} to smoke when smoke is plausibly in the air. To estimate smoke PM_{2.5} at locations without monitors, we take advantage of the additional available information from satellite and reanalysis products and build a machine learning model to predict daily smoke PM_{2.5} over the contiguous US. This combines the strengths of non-CTM-based approaches, which carefully attribute observed ground PM_{2.5} concentrations to smoke, and satellite data which provide additional information in locations without monitors. In contrast to many past machine learning-based efforts predicting total PM_{2.5}, our goal is to isolate smoke-driven changes in PM_{2.5} from other changes in PM_{2.5}. Our efforts are thus a complement to recent machine learning-based efforts at predicting variation in total PM_{2.5}, for example, Di et al.³³ and Reid et al.³⁴

These smoke PM_{2.5} predictions are designed with downstream applications and inference tasks in mind. We sought predictions that accurately captured local short-run variation in smoke PM_{2.5} levels and extremes over sufficiently long time series and across a large spatial domain. Simultaneously, we sought a tractable model with inputs that would be easy to update in the future. These dual goals led us to produce daily predictions of smoke PM_{2.5} at a 10 km resolution using a model with high predictive performance at both low and extreme levels of smoke PM_{2.5}, which we then used to understand the levels, trends, and changing daily extremes in smoke PM_{2.5} concentrations across the contiguous US. We also connected these estimates to data on income, race, and ethnicity to understand differential patterns of exposure and how these patterns are evolving over time.

METHODS

Our approach has three main steps. First, we identify days when smoke was overhead (“smoke days”) from satellite imagery-based plume classification and when clouds may be obscuring plumes, from simulated air trajectories originating at fires (Figure 1c, smoke). Second, we construct a ground-based measure of smoke PM_{2.5} by calculating PM_{2.5} anomalies at Environmental Protection Agency (EPA) monitoring stations (Figure 1a,b), measured as deviations from recent location- and month-specific median PM_{2.5} on non-smoke days and then attribute positive anomalies to smoke if our approach in the first step indicated that there was smoke overhead on that day. Third, because pollution monitoring stations are infrequent in space and typically have many missing observations, we train a model that predicts the station-based ground smoke PM_{2.5} estimated in the second step, based on a set of spatially and temporally consistent inputs (Figure 1c), validating the model on daily time series from held-out EPA stations (i.e., stations not used in model training) and on daily time series from an independent set of private monitors that were not used in model development. Finally, we use the model to produce daily 10 km gridded estimates of smoke pollution over the contiguous US (Figure 1d). Unless noted otherwise, analyses were performed using the R programming language.³⁵

Defining Smoke Days. To understand when smoke from fires may be affecting ground pollution levels, we construct a binary classification of smoke days for each cell of a 10 km grid covering the contiguous US based on two sources of information: hand-annotated smoke plumes from satellite imagery and modeled air particle trajectories from fire locations to aid in identifying smoke when clouds may obscure plume identification. First, we use data on smoke plumes from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS),³⁶ which are analyst-identified plume boundaries based on visible bands of satellite imagery.^{30,37,38} A grid cell is classified as a smoke day if it has any intersection with a smoke plume on a given day (Figure S2a,b). The first full year for which the HMS plume data are available is 2006, which limits the start date of our study period.

Second, given the potential for smoke plume boundaries to miss areas affected by smoke, especially when clouds hinder identification, we build on recent work^{29,32} and simulate air packet trajectories from smoke-producing fire points detected by HMS using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPPLIT) model.^{29,38,39} Using these runs, we classify grid cell days as smoke days if they are missing more than 75% of 1 km aerosol optical depth observations (AOD, 0.47 μm; based on a moderate resolution imaging spectroradiometer (MODIS) multi-angle implementation of atmospheric correction (MAIAC) daily observations) and have a count of at least 50 HYSPPLIT trajectory points in the lowest height quintile (0–1.1 km above ground level) within a 50 km buffer of the location of interest. These thresholds are selected to yield a set of smoke days with anomalous PM_{2.5} values similar to the original set of days (Figure S2e,f; see the Supporting Information for more details).

Calculating Ground-Based Measures of Smoke PM_{2.5}. We then combine classification of smoke days with data on daily average PM_{2.5} concentrations from 2019 EPA monitoring stations throughout the US to define daily time series of smoke PM_{2.5} at each station.⁴⁰ We first define PM_{2.5} anomalies as deviations from recent month- and location-specific median values on non-smoke days (Figure 1a)

$$\tilde{PM}_{idmy} = PM_{idmy} - \overline{PM}_{imy}^{NS} \quad (1)$$

where PM_{idmy} is the PM_{2.5} at station *i* on day *d* in month *m* and year *y* and \overline{PM}_{IMY}^{NS} is the 3 year location- and month-specific median PM_{2.5} on non-smoke days. This median is calculated as

$$\begin{aligned} \overline{PM}_{IMY}^{NS} = \text{median}(\{PM_{idmy}|i = I, m = M, Y - 1 \leq y \\ \leq Y + 1, \text{smoke}_{idmy} = 0\}) \end{aligned} \quad (2)$$

with smoke_{idmy} being a binary variable indicating smoke day classification. We use medians rather than means to prevent days with extreme PM_{2.5} that are not smoke days from affecting the background PM_{2.5} estimates, as is occasionally the case in our data. Furthermore, using 3 year medians, we allow the measure of background non-smoke PM_{2.5} to change over time in each location to capture trends in non-smoke PM_{2.5} over time, including potential declines in anthropogenic emissions. We then define ground-based smoke PM_{2.5} as anomalies above the median on days in which smoke was overhead

$$\text{smokePM}_{idmy} = \max(\tilde{PM}_{idmy} \times \text{smoke}_{idmy}, 0) \quad (3)$$

Our approach to identifying smoke PM_{2.5} at monitoring stations is similar to other recent studies.^{5,31} Similar to previous non-CTM efforts, these estimates rely on the HMS plume boundaries for identification of when smoke is affecting PM_{2.5}. We find that having a smoke plume overhead is associated with an average of 4.5 µg/m³ increase in PM_{2.5} after controlling for monitor-specific averages and average differences in PM_{2.5} between states, months, and years (Table S1). We also find that in monitor time series, plumes align temporally with spikes in PM_{2.5} (Figure S5). Furthermore, to counter omissions when clouds may obscure smoke plumes,²⁹ we included locations with potential cloud cover and air trajectories from known fires (see the “Defining Smoke Days” section mentioned above). Nevertheless, smoke days may be a conservative estimate of the locations with air quality impacted by smoke due to undetected plumes under cloud cover, during nighttime when satellite-based plume segmentations are unavailable, or where smoke is dilute and difficult to identify in satellite imagery.^{5,29} See more detailed discussion in the Supporting Information (“Plume accuracy”).

To further confirm that our method of constructing smoke PM_{2.5} from ground station anomalies is indeed picking up PM_{2.5} from smoke and not from local time-varying sources of PM_{2.5} unrelated to smoke, we apply our method to harmonized speciated data from Interagency Monitoring of Protected Visual Environments (IMPROVE)⁴¹ and Chemical Speciation Network (CSN)⁴² monitors.^{43–46} If our approach is identifying smoke-sourced PM_{2.5} and not PM_{2.5} from other sources, then species most likely to be present in smoke PM_{2.5}—which includes organic carbon throughout the US and perhaps additionally sulfates from agricultural fires in the southeastern US^{47,48}—will increase on smoke days but other non-fire-associated species will not increase. This is indeed what we find: the share of anomalous PM_{2.5} made up by organic carbon increases substantially, particularly on days that our method would predict are very high smoke days and particularly in settings where background sources of other PM_{2.5} are low (such as in the western US) (Figure S6). In areas where background PM_{2.5} levels are higher and where agricultural burning is more common, such as in much of the southeastern US and in the southern Central Valley of CA, both organic carbon and SO₄ increase in importance on smoke days—although, as expected,²¹ their contribution to total PM_{2.5} on that day is still smaller than in Western areas where background PM_{2.5} is low. In both settings, non-wildfire sources of PM_{2.5} (such as dust and elemental carbon) do not increase on smoke days. These results provide confirmatory evidence that our method of assigning anomalous PM_{2.5} to smoke on days with smoke plumes overhead is indeed picking up wildfire-sourced PM_{2.5} and not some other correlated PM_{2.5} source.

Predicting Smoke PM_{2.5}. Because of the limited spatial and intermittent temporal coverage of ground-based PM_{2.5} monitors in the US, estimates of smokePM_{idmy} from eq 3 with time series for more than 5 years are only available at roughly 1400 ground locations. In addition, the average person in the US lives more than 20 km from the nearest pollution monitor.⁴⁹ To capture local short-run variation in smokePM_{idmy} over space and time, we therefore incorporate additional sources of information. One option is to use existing high-resolution gridded daily estimates of PM_{2.5}, from which anomalous estimates of P̃PM_{idmy} could be constructed to

plug into eq 3. Numerous machine-learning-based efforts have succeeded in generating such estimates, but using them faces a number of challenges. First, many estimates are not updated after their initial publication and are available only through earlier years (e.g., Di et al.³³) and/or for a geographic region such as the Western U.S. (e.g., Reid et al.³⁴), making them difficult to use to estimate up-to-date countrywide smoke pollution. Second, these PM_{2.5} predictions are from a model trained to predict total PM_{2.5}, not smoke PM_{2.5}, and as such could potentially not be optimized for our particular task of interest. Finally, estimates could be hard to update, as highest performing model runs depend on a large number of inputs or outputs from other models that themselves are infrequently updated, making updating computationally burdensome.^{33,34}

A second option is to train a model to predict smokePM_{idmy} directly, using inputs from satellite, ground-measured, and reanalysis data sets that are straightforward to update. Because in this approach the model can be optimized to predict the outcome of interest—including focusing on inputs that predict smoke PM_{2.5} (e.g., distance to fire) rather than total PM_{2.5} (e.g., road density)—and can be carefully validated with downstream inference tasks in mind, we take this second option as our main approach.

Model Inputs. Building on earlier statistical-model-based smoke pollution prediction efforts,^{4,5} we extract or compute a set of model inputs that include meteorology, derived fire variables from HMS fire points, counts of HYSPLIT trajectory points, direct aerosol measurements, AOD predictions, and cross-sectional land use and elevation (Figure 1c and Table S3). Model inputs were merged to a consistent 10 km grid for smoke PM_{2.5} training and prediction. The grid is constructed to cover the contiguous US, based on US Census Bureau TIGER/Line county borders.^{50,51}

Detailed information on model inputs is provided in the Supporting Information. Briefly, meteorological inputs to the model include daily mean, minimum, and maximum of the planetary boundary layer, mean wind speed in the eastward and northward directions, mean air temperature and dewpoint temperature at 2 meters, total precipitation, and mean sea level and surface pressure, all drawn from European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5th Generation (ERAS) land or global products.^{52,53} Second, to capture the potential for characteristics of proximate fires to affect smoke PM_{2.5}, we used fire points from NOAA HMS³⁶ identified by trained analysts and used distance to these points as a model input. Third, counts of HYSPLIT trajectory points within a 50 km buffer by quintiles of height above the ground level were used as the input. Fourth, we used two complementary approaches for measuring aerosols: a reanalysis-based approach with consistent data but coarse spatial resolution, based on Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) aerosol optical thickness (AOT) data,⁵⁴ and a satellite-based approach with higher resolution but many missing observations from MODIS MAIAC AOD.^{55–57} Observations in the MAIAC product were first predicted using a gradient boosted tree model⁵⁸ with AOT anomalies on smoke days, meteorology, fire variables, elevation, and land cover as inputs (Table S2), and the resulting predicted AOD measures were used as the input to the smoke prediction model. Finally, we used time-invariant data on land use and elevation from USGS National Elevation Dataset⁵⁹ and National Land Cover Dataset⁶⁰ as additional inputs.

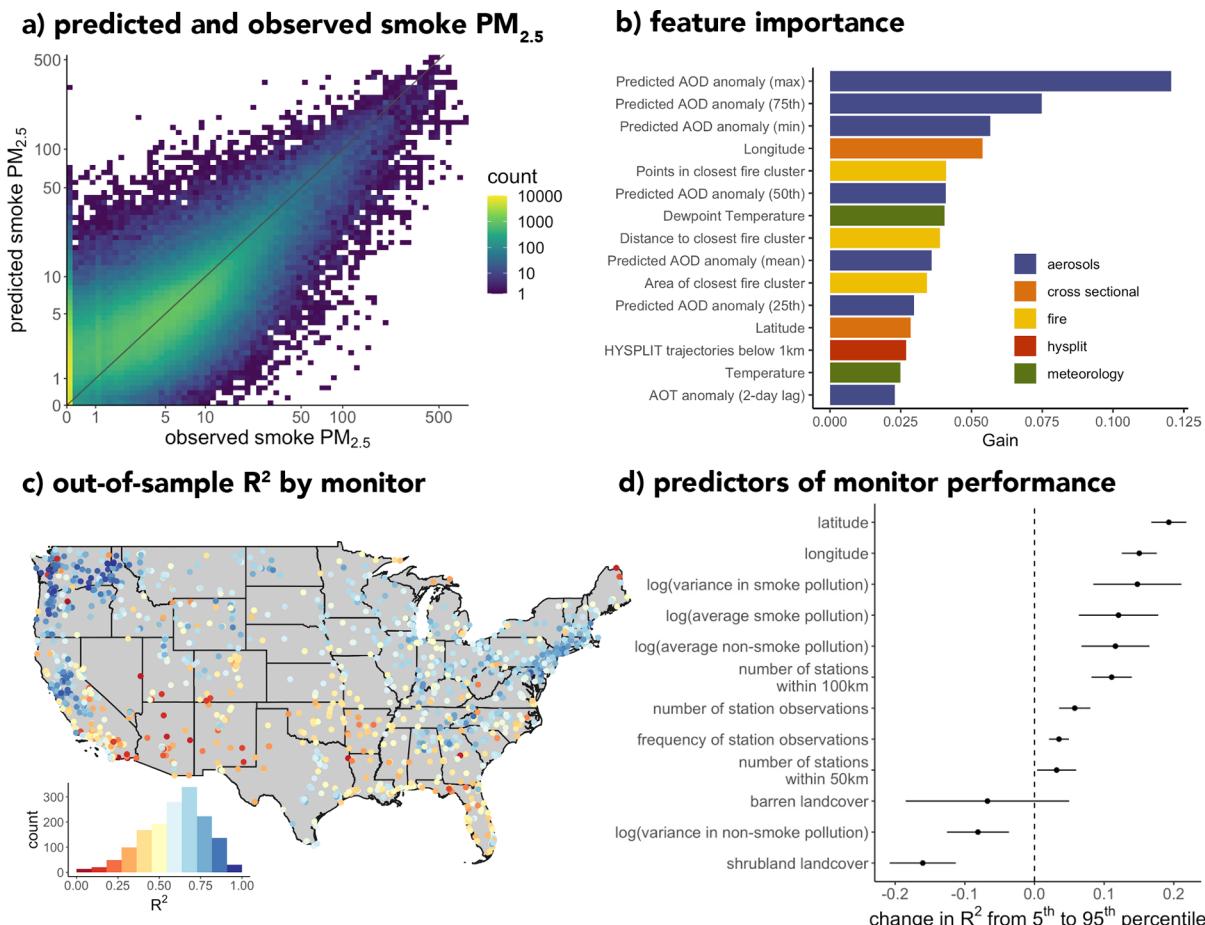


Figure 2. Model performs well out-of-sample and across the range of observed smoke PM_{2.5} with predictable spatial variation in performance. (a) Color indicates count of monitor smoke days within bins of observed (horizontal axis) and predicted (vertical axis) smoke PM_{2.5}. Axes are pseudo-log-transformed, and color scale is log-transformed. The black line indicates the 1–1 line or where predictions perfectly match observations. (b) Feature importance for the top 15 features (vertical axis) from the final model, as measured by gain (horizontal axis) and colored by a broad category of the feature type, includes aerosols, cross-sectional information on elevation and land cover, fire variables, HYSPLIT, and meteorology. (c) For each monitor with at least 50 observations (points on map), R^2 is calculated over all smoke days with available smoke PM_{2.5} using predictions from the model in which that station was out-of-sample. The inset histogram shows the distribution of R^2 values over monitors. (d) To explain the variation in model performance across monitors shown in (c), we fit a cross-sectional linear model relating monitor-specific performance (R^2) shown in (c) to monitor/location characteristics. Predictive power of each characteristic is calculated as the estimated change in monitor R^2 when each characteristic is increased from the 5th to 95th percentile of its distribution. Points show central estimates, and line segments show 95% confidence intervals. State outlines are reproduced with permission from the US Census Bureau TIGER/Line Shapefiles.⁵¹

Model Tuning and Validation. We aimed to predict smoke pollution for a 10 km grid over the conterminous US, so our measure of model performance needed to account for the fact that we would be predicting for out-of-sample locations and that those locations would have a median distance of about 50 km (population-weighted average of about 18 km) from EPA stations (Figure S9). Given concerns of information leakage between training and testing sets for proximate EPA stations, we used grid cells from the coarsest input (MERRA-2, 0.5° latitude \times 0.625° longitude, ~50 km) to define spatial folds, that is, the disjoint sets of training and testing stations used, respectively, for model training and model evaluation. Splitting train and test data sets by station rather than the more conventional method of random splitting by observation (in which a given station can contribute data to both train and test) is a more demanding prediction task^{34,61}—and using coarser spatial blocks further increases the difficulty of the prediction task⁶²—but is a more realistic test of how well the

model would do predicting time series of smoke PM_{2.5} in a new location with no training data.

For model architecture, we fit gradient boosted trees,⁵⁸ which balance nicely our twin goals of model parsimony and high predictive power in related applications (e.g., Chen et al.,⁶³ Zamani Joharestani et al.,⁶⁴ and Xu et al.⁶⁵). We performed fivefold nested spatial cross-validation, with hyperparameter tuning in the inner loop performed with fourfold cross-validation (Figure 1b; see the Supporting Information). All model tuning and training was performed on observations with smoke overhead. Based on preliminary tests, we used regression with the root mean squared error (RMSE) as the objective function, which performed better than pseudo-Huber loss and Tweedie regression—loss functions that, in principle, could respectively help with outliers in the data that the squared error is sensitive to and help with skewed non-negative distribution of outcomes. To measure variable importance, we use gain or the contribution to improvements in model performance from splits on each feature.

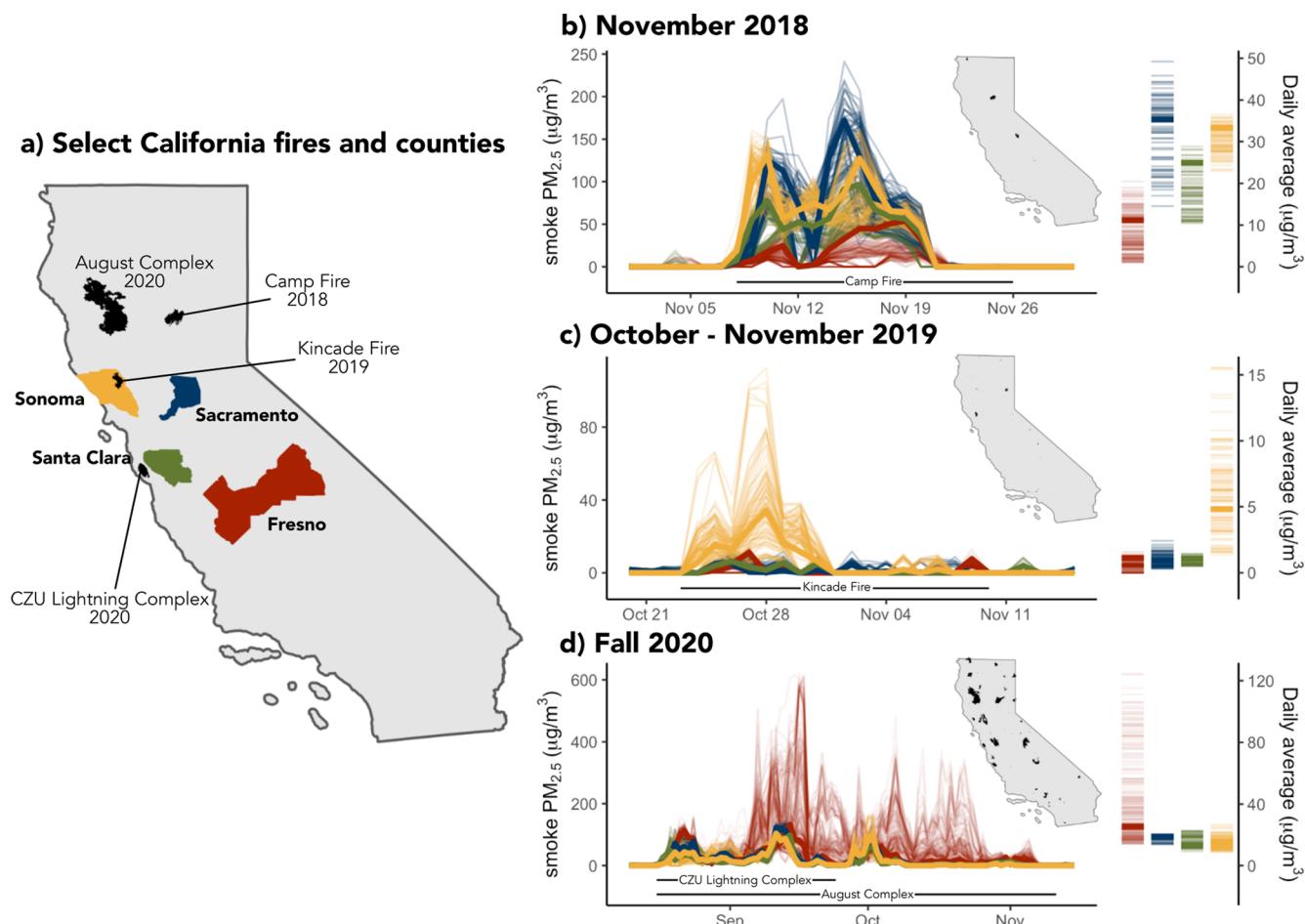


Figure 3. Predictions show remarkable spatial and temporal variation in smoke pollution from recent California fires. (a) Black shapes are select fires from November 2018, October to November 2019, and Fall 2020, and colored areas are four select California counties. (b–d) Daily smoke pollution varies between and within counties, and increases in smoke pollution temporally match with fire events. Thin lines show smoke pollution in grid cells within the county, while thick lines show population-weighted average for the county. Time ranges of select fires are shown along the horizontal axis. Inset maps show all fires burning during the time range of the panel. To the right, dashes show average smoke pollution over the time range in the grid cell (thin dashes) and county (thick line). Fire perimeters and time ranges are reproduced with permission from the CAL FIRE Fire Perimeter data set.⁷² State and county outlines are reproduced with permission from the US Census Bureau TIGER/Line Shapefiles.⁵¹

Assessing Model Performance. We measured model performance by comparing observed smoke PM_{2.5} with model predictions after truncating model predictions at zero. We calculate three metrics for evaluation: the overall R^2 , the “within” R^2 after netting out time-invariant differences in smoke PM_{2.5} across stations and changes in smoke over time common to all stations, and the RMSE on the held-out test set for each of the five folds. The “within” R^2 , which is calculated by regressing observed smoke PM_{2.5} on predicted smoke PM_{2.5} while including sets of station and year fixed effects (i.e., separate intercepts for each station and each year), is meant to measure performance in the context of a common downstream inference task in which within-location variation over time, rather than variation between locations, is used to isolate the impact of pollutants or other environmental exposures from other factors that might also shape human outcomes. To understand performance across days with any smoke, and across days with dense smoke, we calculate these metrics on the full sample of smoke days and the set of observations with smoke pollution of at least 50 $\mu\text{g}/\text{m}^3$.

RESULTS

Model Performance. Spatial out-of-sample model performance, measured over all observations using predictions from models trained on the other four folds, was an R^2 of 0.67, that is, our model explained two-thirds of the variation in smoke PM_{2.5} at stations not used in training. Our “within” performance ($R^2 = 0.65$) approached our overall R^2 , indicating that our model is capably predicting local, temporal variation in smoke and not simply differences in average smoke across locations or between years. The model performed well over the entire range of observed smoke PM_{2.5} (Figure 2a and Table S4), including accurate prediction without saturation at very high daily PM_{2.5} levels, which has historically been a challenge for both numerical models and statistical models that often focus on PM_{2.5} observations below a certain threshold^{33,61,66} (although, see Reid et al.³⁴ for an exception). We also compared model predictions to an alternative data set of ambient PM_{2.5} at private, non-reference-grade PurpleAir monitors⁶⁷ and found similar performance ($R^2 = 0.70$) (Figure S18); this additional data set was not used in training, so these results again demonstrate that our model performs well on completely new data and locations. Although the presence of

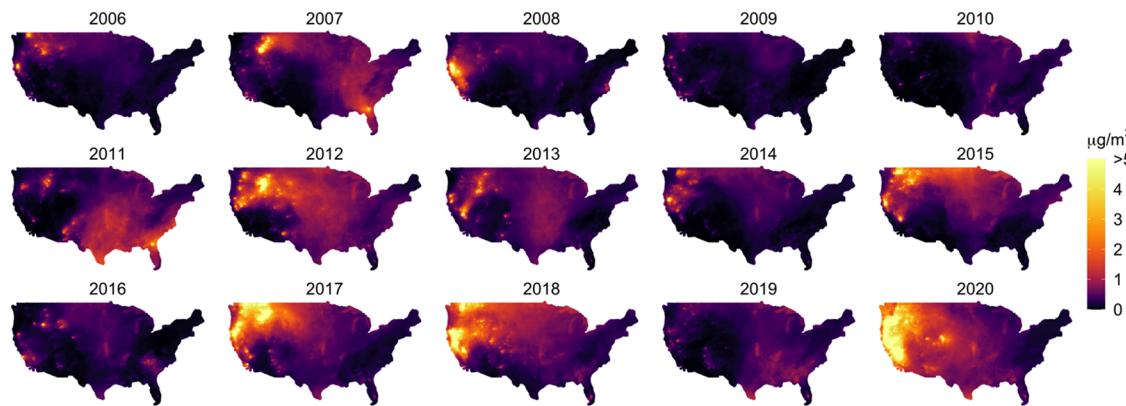


Figure 4. Daily average PM_{2.5} from smoke by year. Each panel shows average daily smoke PM_{2.5} in each location and each year, computed as the average over all days in each grid cell in each year.

satellite-based smoke plumes alone can be an imperfect indicator of surface-level pollution,⁶⁸ the performance of the model in predicting held-out surface PM_{2.5} data suggests that the included features allow us to link changes in satellite measurements of aerosols and meteorological conditions to changes in surface PM_{2.5}. However, there remain a subset of smoke days where our model struggles to predict variation in surface PM_{2.5}, including days when a plume is overhead but observed smoke PM_{2.5} values are near zero—likely cases when smoke is overhead but not mixing to the surface in a way that is predictable with our model features (Figures 2 and S18). However, among days with observed smoke PM_{2.5} <1 μg/m³, 94% of out-of-sample predictions are less than 5 μg/m³ and less than 1% of predictions exceed 10 μg/m³.

Predicted AOD contributed most to model performance, followed by longitude, size of the nearest fire cluster, and dewpoint temperature (Figure 2b). To test the added predictive value from the two most computationally intensive feature sets, we also fit models without AOD predictions and without HYSPLIT features. Including AOD predictions had a higher positive impact on model performance (increase of 0.057 in R²) than HYSPLIT features (increase of 0.014 in R², Figure S10).

We calculated monitor-specific performance when each monitor was not used in model training. We found that the median station performance was comparable to overall model performance ($R^2 = 0.63$), with 90% of monitor-specific R^2 values falling between 0.21 and 0.88. Model performance varied spatially, with often very high performance at EPA monitors throughout California, the Pacific Northwest, the upper Midwest, and the Northeast and lower performance at monitors in the Southwest and the South (Figure 2c). To better understand this spatial variation in model performance, we then fit simple linear models between station-level R^2 and cross-sectional covariates, including new covariates from an alternative land cover classification (Figure S11).^{69–71} We found that after latitude and longitude, shrubland land cover and average and variance in smoke pollution were most predictive of model performance at individual stations, as measured by the absolute predicted change in R^2 when a covariate is changed from its 5th to 95th percentile (Figure 2d). Model performance was higher in locations with higher average and variance in smoke PM_{2.5} and lower in locations with higher percentage shrubland land cover. Higher variance in non-smoke pollution was also associated with worse model performance. Shrubland areas may have less variation in smoke

PM_{2.5}, more variation in non-smoke PM_{2.5}, leading to less precise estimates of smoke PM_{2.5}, or a different relationship between satellite AOD and ground PM_{2.5} due to land cover, any of which could result in lower performance in smoke PM_{2.5} predictions. These results help account for why performance was substantially higher in the Pacific Northwest (high average and variance in smoke PM_{2.5}, forest landcover) versus the desert Southwest (low average and variance in smoke PM_{2.5}, shrubland landcover); other efforts to predict total PM_{2.5} have also performed substantially worse in the desert Southwest.^{53,34} By examining individual station time series, we also found that our lowest performing stations were often characterized by a small number of extreme outliers in the ground measurements (Figure S12).

Patterns and Trends in Predicted Smoke PM_{2.5}. Predicted daily smoke PM_{2.5} shows remarkable temporal and spatial variation around fire events, consistent with observed smoke behavior around individual fires (Figure S13). For example, Figure 3 shows model predictions for time periods surrounding three specific fire events⁷² in California over multiple years. Predicted smoke PM_{2.5} showed increases corresponding to the onset of known fires, with variation in smoke PM_{2.5} within fire events over time and across locations within counties (Figure 3b–d). These heterogeneities aggregate to marked differences in total smoke PM_{2.5} concentrations between nearby locations and highlight the differences lost when using binary smoke measures or when interpolating between monitors.

Daily gridded estimates can also be aggregated to larger temporal or spatial scales to characterize broader patterns and trends in smoke concentrations. We measured the contribution of smoke to annual PM_{2.5} by aggregating daily predictions to the annual level across the contiguous US and found that some locations experienced over 2000 μg/m³ of daily accumulated PM_{2.5} from smoke in the span of a year, equivalent to average annual PM_{2.5} levels 5 μg/m³ higher (Figure 4). This level is equivalent to roughly half of the overall annual average PM_{2.5} concentrations from all sources across much of the US.⁷³ Annual hotspots of high smoke PM_{2.5} correspond to locations of large fires (Figures S15 and S16), although impacts often extend beyond the burned areas. The locations most affected varied by year but were primarily concentrated in the West, with larger areas affected in recent years, particularly 2017, 2018, and 2020. The Southwest and Northeast experienced the least smoke pollution over the study period.

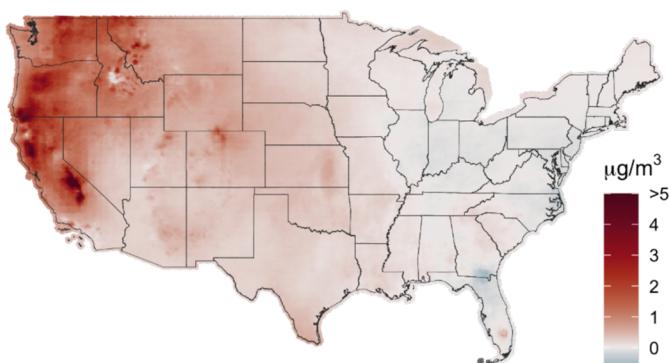
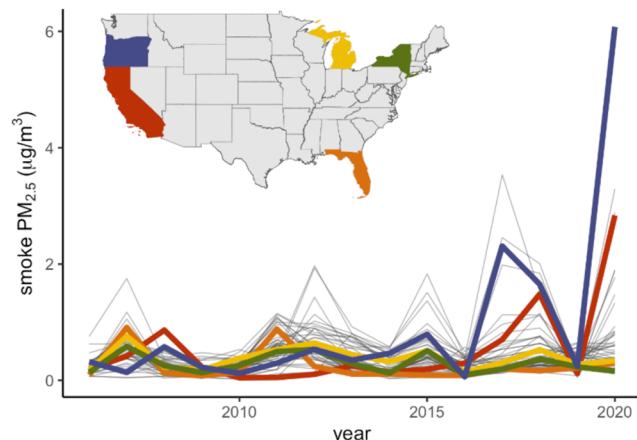
a) Decadal change in smoke PM_{2.5}**b) Annual smoke PM_{2.5} by state**

Figure 5. Over the last decade, smoke PM_{2.5} has increased in much of the US, particularly in Western states, but some areas in the South and East have seen modest declines. (a) Decadal change in smoke PM_{2.5} is the difference in daily average smoke PM_{2.5} during 2006–2010 and 2016–2020. (b) Population-weighted average smoke PM_{2.5} shows marked increases in Western states and little change in Eastern states. Each line indicates a state, with the inset map showing highlighted states whose colors match the lines corresponding to the states in the main panel. State outlines are reproduced with permission from the US Census Bureau TIGER/Line Shapefiles.⁵¹

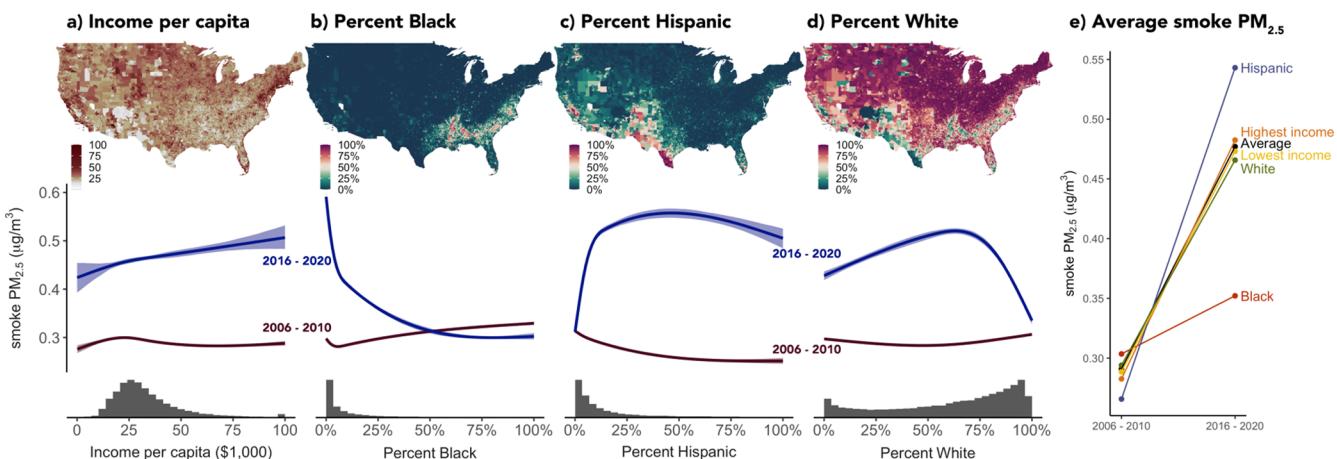


Figure 6. One decade ago, smoke PM_{2.5} levels did not differ meaningfully by income, race, or ethnicity, but recent exposure patterns now differ by race, ethnicity, and, to a smaller extent, income. (a) All income levels experienced similar smoke PM_{2.5} concentrations from 2006 to 2010 and increases in smoke PM_{2.5} to recent years (2016–2020), with the greatest increases occurring at the highest income levels. (b) Smoke PM_{2.5} concentrations have fallen in heavily non-Hispanic Black tracts, consistent with the modest declines seen in the Southeastern region. (c) Concentrations have increased most in tracts with Hispanic populations, corresponding to higher percent Hispanic in Western and Southwestern regions. (d) Smoke PM_{2.5} increases were the smallest in tracts that were heavily non-Hispanic white, concordant with the more modest smoke PM_{2.5} increases in the Midwest and Northeast. For all panels, lines are spline fits between income/race/ethnicity and average smoke concentrations in 2006–2010 (purple) and 2016–2020 (blue) in US Census tracts, with shaded areas showing bootstrapped 95% confidence intervals, while histograms show the distribution across tracts. Tract-level smoke PM_{2.5} is an area-weighted average of smoke PM_{2.5} in intersecting grid cells. Income per capita is top-coded to \$100,000. (e) We also calculate the average annual smoke PM_{2.5} concentrations for the average Hispanic individual (blue), White individual (green), Black individual (red), and US resident (black) and individuals living in census tracts in the highest (orange) and lowest (yellow) income quintiles. Census tract outlines are reproduced with permission from the US Census Bureau TIGER/Line Shapefiles.⁵¹

To better understand longer-run changes in smoke PM_{2.5} concentrations, we calculated the decadal change in smoke pollution as the difference in average annual smoke PM_{2.5} from 2006–2010 to 2016–2020, with 5 year windows used to avoid undue influence from extreme years, such as 2020. Locations west of the Mississippi River saw increases in smoke pollution in the last decade, with the greatest increases in Washington, Oregon, and California (Figure 5a). Some of these Western regions saw decadal increases in an annual smoke PM_{2.5} of 5 $\mu\text{g}/\text{m}^3$ or greater, an amount comparable in absolute magnitude to the reduction in PM_{2.5} brought about by the

Clean Air Act in the US.^{74,75} Some locations in the Southeast and Northeast saw modest ($<1 \mu\text{g}/\text{m}^3$) declines in smoke PM_{2.5}, consistent with a decline in burned area observed in existing fire products in many states in the Southeast, East, and Midwest (i.e., Monitoring Trends in Burn Severity,⁷⁶ Figure S14) and a decline in days with heavy smoke plumes in the air in the Southeast.³¹ The notable declines on the Georgia-Florida border and in central Idaho may be due to the 2007 fires in those areas, which were associated with elevated annual smoke PM_{2.5} (Figures 4 and S16). We also quantify population-weighted concentrations by state for each year

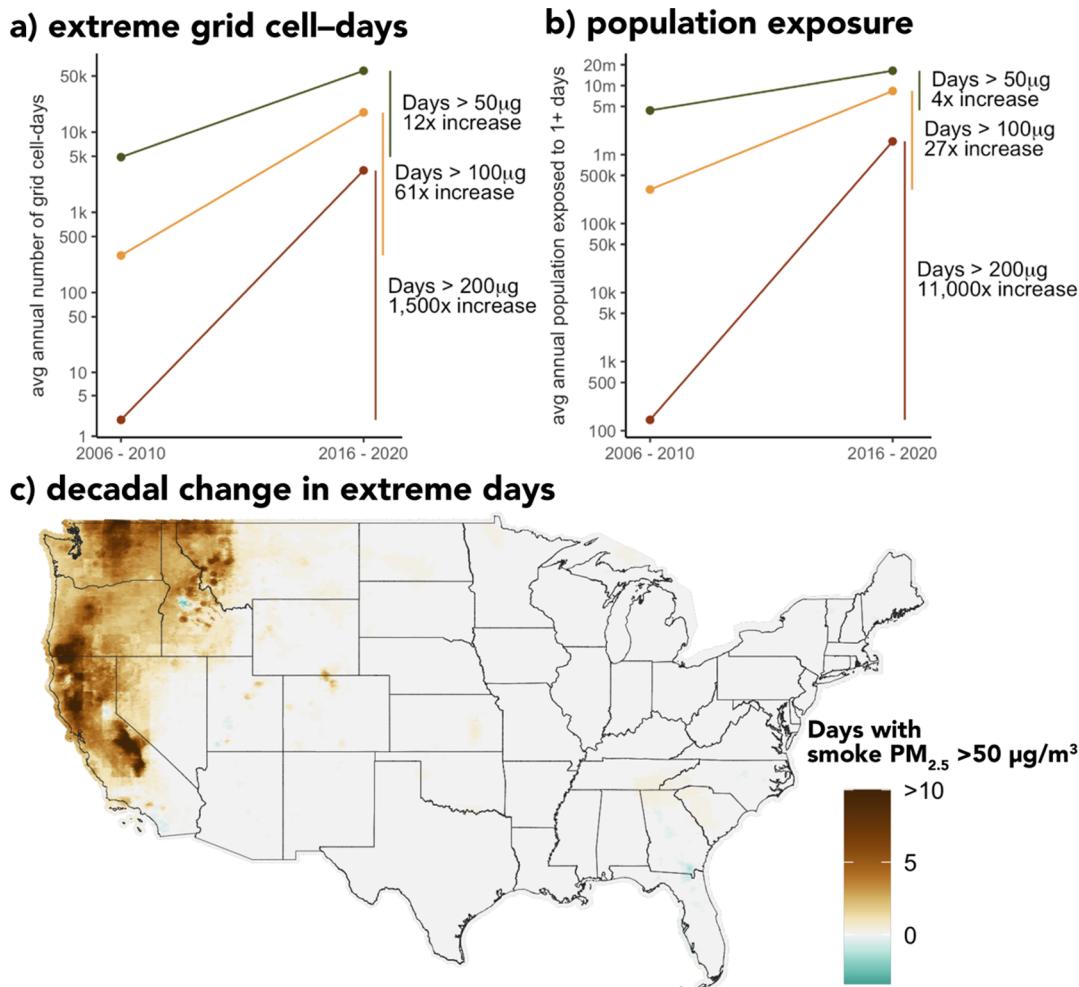


Figure 7. Changing occurrence of smoke PM_{2.5} extremes. (a) Decadal change in the number of grid cell days with smoke PM_{2.5} above 50 (green), 100 (orange), and 200 $\mu\text{g}/\text{m}^3$ (red), computed as the difference in average annual counts during 2006–2010 and during 2016–2020. Annotations show the change in multiples of the baseline rate. (b) Decadal change in the population in the US living in places with at least 1 day per year of smoke above 50, 100, or 200 $\mu\text{g}/\text{m}^3$. For instance, over 16 million people on average in the US lived in places with at least 1 day above 50 $\mu\text{g}/\text{m}^3$ per year in the last 5 years, a fourfold increase from a decade ago. (c) Map of decadal change in extreme days with smoke PM_{2.5} over 50 $\mu\text{g}/\text{m}^3$. State outlines are reproduced with permission from the US Census Bureau TIGER/Line Shapefiles.⁵¹

and find that concentrations were worst for the average Oregon resident in 2020, with annual smoke PM_{2.5} levels over 50 times higher than a decade previous (Figure 5b). On the other hand, residents in Midwestern, Northeastern, and Southern states had similar levels of smoke PM_{2.5} over the last 15 years.

Differences in Smoke Pollution by Race, Ethnicity, and Income. Although PM_{2.5} from smoke is growing throughout most of the country, the geographic patterns in smoke PM_{2.5} may result in differential exposure for different populations. Understanding the magnitudes and sources of disparities in environmental exposures across income and racial/ethnic groups is a key question in environmental justice. We merge our gridded data with census tract level data on income, race, and ethnicity from the US Census Bureau American Community Survey (ACS)⁷⁷ to quantify the levels and trends in ambient concentrations. From 2006 to 2010, average annual smoke PM_{2.5} did not differ meaningfully by income or by the percent of tract population represented by non-Hispanic black, non-Hispanic white, or Hispanic individuals (Figure 6). Over the last decade, smoke PM_{2.5} concentrations have grown fastest for predominantly Hispanic

and non-Hispanic white populations, while predominantly non-Hispanic black census tracts have seen a slight decline in smoke PM_{2.5} (Figure 6). Across all income levels, smoke PM_{2.5} has increased, but that increase has been slightly larger in higher income census tracts. These changes reflect the broad geographic patterns in smoke PM_{2.5} trends (Figure 5), as well as the geographic concentrations of different racial and ethnic groups in the country. We also compare average annual smoke PM_{2.5} levels to gross domestic product (GDP) per capita by county⁷⁸ and to population density per grid cell.⁷⁹ We find that smoke PM_{2.5} concentrations have increased more in counties with higher GDP per capita and have been the smallest in intermediate population density areas, larger in high population density areas, and the largest in very low density areas (Figure S17).

Changing Occurrence of Daily Extremes. Finally, the primary goal of our analysis was to ensure that our model had low bias in predicting not only moderate (and more common) daily smoke PM_{2.5} concentrations but also extreme levels of daily smoke PM_{2.5}. Quantifying exposures to extremes is critical for understanding health and related impacts, both because impacts might be non-linear in exposure and because

compensatory behavior (e.g., staying indoors) differs substantially by the level of exposure.³¹ Whether resulting concentration–response functions are concave, convex, or linear is not well established in the literature⁴ but has important implications for the magnitude of societal impacts and the optimal policy response.

We estimate a substantial increase in exposure to extremes in daily smoke PM_{2.5} over the last decade. Using thresholds of 50, 100, or 200 µg/m³ of daily smoke PM_{2.5} concentrations to denote extremes, we calculate a remarkable 12–1500× decadal increase in the annual average count of grid cell days with concentrations above these thresholds (Figure 7a). Because many of these grid cells might be in relatively unpopulated areas of the Western US, we also calculate the number of people residing in locations where at least a day per year exceeded these thresholds, using population estimates from WorldPop.⁷⁹ We calculate that each year, on average, 16.4 million people in the US lived in places with at least 1 day of smoke PM_{2.5} above 50 µg/m³ during the 2016–2020 period, a fourfold increase from the 2006 to 2010 average (Figure 7b). While less than half a million people lived in areas experiencing a day per year of smoke PM_{2.5} concentrations over 100 µg/m³ a decade ago, this number increased to over 8 million in recent years. In proportional terms, increases were the largest for the most extreme threshold, with almost nobody experiencing a day per year above 200 µg/m³ a decade ago, but now, over 1.5 million people are residing in locations routinely exposed to these conditions. The locations experiencing the greatest increase in days with extreme smoke PM_{2.5} are concentrated in the Western US, particularly Washington, Oregon, California, Idaho, Montana, and Nevada (Figure 7c).

DISCUSSION

Here, we produce 10 km resolution estimates of smoke PM_{2.5} over the contiguous US from 2006 to 2020 on a daily basis. These predictions perform well over the range of observed smoke PM_{2.5} and vary predictably in performance by region (Figure 2). These predictions capture small-scale variation in smoke PM_{2.5} within counties and within fire events (Figure 3) and larger scale interannual variation in smoke pollution (Figure 4). We find steep increases in average smoke pollution and days with smoke PM_{2.5} extremes over the last decade, particularly in the Western US (Figures 5 and 7), resulting in a changing profile of smoke PM_{2.5} concentrations (Figure 6). Consistent with recent work,^{4–6} these predictions suggest that the increases in PM_{2.5} from wildfire smoke are rapidly undoing much of the improvements in air quality from the last few decades, at least throughout many areas of the Western US.

In comparison to many existing efforts to estimate smoke PM_{2.5} using CTMs with and without emissions from fires or through sensitivity analyses embedded in CTMs,⁸⁰ our approach uses statistical, machine-learning models fit to inferred smoke PM_{2.5} at EPA monitors. Although CTM-based smoke PM_{2.5} estimates trade-off between the computational cost, spatial coverage, and spatial resolution, our statistical approach can achieve high resolution (10 km) estimates over the entire contiguous US, can be validated against long time series of monitor observations, and can easily scale to large areas due to the fast prediction speeds after models have been trained. On the other hand, CTM-based estimates can characterize subdaily variation in smoke PM_{2.5}, while our estimates are currently limited to daily resolution. Finally, CTMs can provide speciated pollutant estimates of

PM_{2.5}, albeit with substantial uncertainty in concentration estimates,²² while our focus is on total smoke PM_{2.5}.

Our work is related to a recent interpolation-based approach used to estimate wildfire-attributable PM_{2.5} across the US.⁵ While we take a similar approach to measuring smoke PM_{2.5} in ground data, we diverge in using a range of satellite- and model-based inputs, rather than interpolation, to estimate smoke PM_{2.5} in locations without stations. Because interpolation by design smooths the input data, such an approach could underestimate extreme concentrations, both in locations without monitors and on the large number of smoke days when specific monitors do not report concentrations. Finally, we validate our approach against 15 year time series of held-out station observations and against independent private sensor data, which stands in contrast to the single-season evaluation in earlier work.⁵ Our work complements recent machine learning-based efforts to use satellites and other inputs to predict total PM_{2.5} concentrations over time.^{33,34}

As with most available data sets on specific pollutants, variation in estimated smoke PM_{2.5} in our data is likely correlated with variation in other pollutants including NO₂ and ozone,^{47,81} although the emission, formation, and evolution of those other pollutants are an evolving area of research.^{82,83} Downstream applications that wish to use our data to isolate the impact of PM_{2.5}, specifically on outcomes, must then take care to account for co-varying pollutants that could also affect outcomes. Such applications should also consider accounting for other covarying meteorological variables such as temperature and precipitation, although how best to account for the role of these variables is not necessarily clear, as these variables are plausibly both a driver of wildfire activity (and thus not a confound) and an independent source of impact (and thus possibly a confound).

Future advancements to smoke PM_{2.5} estimates could include improvements to both the monitor-based training data and to our machine learning-based smoke prediction pipeline. Precision of smoke PM_{2.5} estimates at monitors—our training data—is a function of the precision of the non-smoke counterfactual, that is, the estimated background rate of PM_{2.5} absent smoke. We currently use median PM_{2.5} from days without smoke, which accounts for station-specific differences, seasonal variation within the station, and trends over time in PM_{2.5} levels but does not account for more granular variation in other time-varying non-smoke sources of PM_{2.5}. This may result in imprecision in our training smoke PM_{2.5} estimates, as anomalous PM_{2.5} may be a noisy estimate of the concentrations from smoke, especially in locations with high variation in background non-smoke PM_{2.5} which was associated with poorer model performance (Figure 2). Future efforts could more explicitly model background non-smoke PM_{2.5}, perhaps using machine learning and other information on time variation in other PM_{2.5} sources. Future model development might also benefit from the increasing availability of monitor data as large numbers of private sensors, such as PurpleAir monitors, come online (Figure S18). In this study, we use these latter data as a source of independent evaluation, but such data could also be useful in model training, although their use should consider that these monitors are neither reference grade nor regularly calibrated. Several procedures have been developed for improving PM_{2.5} estimates derived from PurpleAir monitors.^{84–88} While the most appropriate calibration likely depends on the setting, we utilized the Barkjohn correction⁸⁴ because we found in previous work³¹ that it

performed best at predicting out-of-sample PM_{2.5} at EPA reference grade monitors. As higher spatial and temporal densities of training data were predictive of increased model performance (Figure 2d), future inclusion of these data sources should improve the accuracy of estimates. Other features and data sources such as smoke plume height, spatial lags of meteorology, and indicators of atmospheric mixing such as air temperature at different vertical heights have been found in other settings to improve total PM_{2.5} estimates, predict variation in the relationship between PM_{2.5} and AOD, or have the potential to improve the model's ability to identify when smoke mixes to the surface, something the current model occasionally struggles with, as evidenced by the range of predicted values on days with very low observed smoke PM_{2.5} values.^{89–92} Future advances could also include alternative machine learning models, such as convolutional neural networks, that take advantage of the spatial information instead of features at a single point and have been found to provide good performance on total PM_{2.5}.⁹³ While our estimates rely on plume boundaries drawn by NOAA analysts over the contiguous US, automation of plume identification—a task for which early computer vision work has shown promise^{94–96}—could allow for generalization of this approach to other geographic regions, an effort of increasing importance as wildfires grow in many parts of the world.^{11,97–99} Finally, uncertainty quantification from machine learning models is an active area of research, and future improvements to these estimates could include more granular quantification of uncertainty.

A growing literature estimates the impact of smoke on a range of outcomes including health outcomes such as mortality, hospitalizations, and birth outcomes,^{100,101} economic outcomes including labor productivity and economic output,¹⁰² and cognitive outcomes such as test scores and mental health.⁹⁴ Many of these studies have been limited to short time spans, small geographic ranges, or binary measures of smoke concentrations, in part due to lack of broad-scale validated data on pollutant concentrations attributable to wildfire smoke.¹⁰³ Our new estimates should enable improvements in the breadth and precision of these studies and help refine our understanding of how growing smoke PM_{2.5} concentrations affect a range of societal outcomes and are well suited for studying the impact of more common, low-level smoke concentrations and increasingly frequent periods of extreme concentrations. Our model's strong ability to predict within-location variation in smoke PM_{2.5} over time and to generate long time series of concentration estimates are particularly beneficial for understanding societal impacts, given the frequent reliance of modern causal inference approaches on temporal rather than spatial variation in estimating the impact of environmental exposures on societal outcomes. Our estimates can thus help establish smoke-specific concentration–response functions across a range of societal responses of interest and, by more accurately measuring extreme exposures, help better characterize potential non-linearities in these functions. Finally, smoke PM_{2.5} can also be linked to antecedent climate conditions to better understand the past local and regional influence of climate on smoke PM_{2.5} concentrations and to inform how smoke pollution might evolve under future climate.

DATA AVAILABILITY

Data and code to replicate all results in the main text and supplementary materials are available at <https://github.com/echolab-stanford/daily-10km-smokePM>.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.2c02934>.

Additional model details including model tuning and model inputs, assessment of smoke plume accuracy and smoke PM_{2.5} estimates using speciated data, additional model performance comparisons, and trends in and annual burned areas ([PDF](#))

AUTHOR INFORMATION

Corresponding Author

Marissa L. Childs — *Emmett Interdisciplinary Program in Environment and Resources, Stanford University, Stanford, California 94305, United States;*  orcid.org/0000-0002-8597-2161; Email: marissac@stanford.edu

Authors

Jessica Li — *Center on Food Security and the Environment, Stanford University, Stanford, California 94305, United States*

Jeffrey Wen — *Department of Earth System Science, Stanford University, Stanford, California 94305, United States;*  orcid.org/0000-0001-9391-6939

Sam Heft-Neal — *Center on Food Security and the Environment, Stanford University, Stanford, California 94305, United States*

Anne Driscoll — *Center on Food Security and the Environment, Stanford University, Stanford, California 94305, United States*

Sherrie Wang — *Goldman School of Public Policy, UC Berkeley, Berkeley, California 94720, United States*

Carlos F. Gould — *Department of Earth System Science, Stanford University, Stanford, California 94305, United States*

Minghao Qiu — *Department of Earth System Science, Stanford University, Stanford, California 94305, United States;*  orcid.org/0000-0002-5224-570X

Jennifer Burney — *Global Policy School, UC San Diego, San Diego, California 92093, United States;*  orcid.org/0003-3532-2934

Marshall Burke — *Center on Food Security and the Environment and Department of Earth System Science, Stanford University, Stanford, California 94305, United States; National Bureau of Economic Research, Cambridge, Massachusetts 02138, United States*

Complete contact information is available at:
<https://pubs.acs.org/10.1021/acs.est.2c02934>

Author Contributions

All authors contributed to the conception and design of the study. M.L.C., J.L., J.W., S.H.-N., and A.D. contributed to data extraction and processing. M.L.C. conducted AOD prediction, and J.L. conducted HYSPLIT simulations. M.L.C. and J.L. performed model tuning and evaluation. M.L.C. led the analyses of model performance, smoke PM_{2.5} patterns, and differential exposures, and M.B. led the analysis of daily

extremes. All authors contributed to analyzing results and writing the paper.

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

We thank seminar participants at Cornell, Columbia, MIT, Stanford, UC Berkeley, and UC Santa Barbara for helpful comments. 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 also thank the NOAA Air Resources Laboratory (ARL) for the provision of the HYSPLIT transport and dispersion model used in this publication. We acknowledge the use of imagery from the Worldview Snapshots application (<https://wvs.earthdata.nasa.gov>), part of the Earth Observing System Data and Information System (EOSDIS). We thank the Robert Wood Johnson Foundation for funding. M.L.C. was supported by the Illich-Sadowsky Fellowship through the Stanford Interdisciplinary Graduate Fellowship program at Stanford University. S.W. was supported by a Ciriacy-Wanrup Postdoctoral Fellowship at the UC Berkeley Rausser College of Natural Resources. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

REFERENCES

- (1) GBD 2019 Risk Factors Collaborators. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet* **2020**, *396*, 1223–1249.
- (2) Zhang, Q.; Zheng, Y.; Tong, D.; Shao, M.; Wang, S.; Zhang, Y.; Xu, X.; Wang, J.; He, H.; Liu, W.; Ding, Y.; Lei, Y.; Li, J.; Wang, Z.; Zhang, X.; Wang, Y.; Cheng, J.; Liu, Y.; Shi, Q.; Yan, Y.; Geng, G.; Hong, C.; Li, L.; Liu, F.; Zheng, B.; Cao, J.; Ding, A.; Gao, J.; Fu, Q.; Huo, J.; Liu, B.; Liu, Z.; Yang, F.; He, K.; Hao, J. Drivers of improved PM 2.5 air quality in China from 2013 to 2017. *Proc. Natl. Acad. Sci. U.S.A.* **2019**, *116*, 24463–24469.
- (3) Aldy, J. E.; Auffhammer, M.; Cropper, M.; Fraas, A.; Morgenstern, R. Looking Back at 50 Years of the Clean Air Act. *J. Econ. Lit.* **2022**, *60*, 179–232.
- (4) Burke, M.; Driscoll, A.; Heft-Neal, S.; Xue, J.; Burney, J.; Wara, M. The changing risk and burden of wildfire in the United States. *Proc. Natl. Acad. Sci. U.S.A.* **2021**, *118*, No. e2011048118.
- (5) O'Dell, K.; Ford, B.; Fischer, E. V.; Pierce, J. R. Contribution of wildland-fire smoke to US pm2.5 and its influence on recent trends. *Environ. Sci. Technol.* **2019**, *53*, 1797–1804.
- (6) Jaffe, C. D.; Jaffe, D. A. US particulate matter air quality improves except in wildfire-prone areas. *Proc. Natl. Acad. Sci. U.S.A.* **2018**, *115*, 7901–7906.
- (7) Meng, J.; Martin, R. V.; Li, C.; van Donkelaar, A.; Tzompa-Sosa, Z. A.; Yue, Y.; Xu, J.-W.; Weagle, C. L.; Burnett, R. T. Source contributions to ambient fine particulate matter for Canada. *Environ. Sci. Technol.* **2019**, *53*, 10269–10278.
- (8) Liu, J. C.; Mickley, L. J.; Sulprizio, M. P.; Dominici, F.; Xu, Y.; Ebisu, K.; Anderson, G. B.; Khan, R. F. A.; Bravo, M. A.; Bell, M. L. Particulate air pollution from wildfires in the western US under climate change. *Climatic Change* **2016**, *138*, 655–666.
- (9) Chen, Y.; Cao, C.; Cao, Y.; Bashir, B.; Xu, M.; Xie, B.; Wang, K. Observed evidence of the growing contributions to aerosol pollution of wildfires with diverse spatiotemporal distinctions in China. *J. Clean. Prod.* **2021**, *298*, 126860.
- (10) Xie, Y.; Lin, M.; Decharme, D.; Delire, C.; Horowitz, L. W.; Lawrence, D. M.; Li, F.; Séferian, S. Tripling of western US particulate pollution from wildfires in a warming climate. *Proc. Natl. Acad. Sci. U.S.A.* **2022**, *119*, No. e2111372119.
- (11) Williams, J. T.; Williams, A. P. Impact of anthropogenic climate change on wildfire across western US forests. *Proc. Natl. Acad. Sci. U.S.A.* **2016**, *113*, 11770–11775.
- (12) Hurteau, M. D.; Westerling, A. L.; Wiedinmyer, C.; Bryant, B. P. Projected effects of climate and development on California wildfire emissions through 2100. *Environ. Sci. Technol.* **2014**, *48*, 2298–2304.
- (13) O'Dell, K.; Bilsback, K.; Ford, B.; Martenies, S. E.; Magzamen, S.; Fischer, E. V.; Pierce, J. R. Estimated mortality and morbidity attributable to smoke plumes in the United States: Not just a western US problem. *GeoHealth* **2021**, *5*, No. e2021GH000457.
- (14) Aguilera, R.; Corrington, T.; Gershunov, A.; Benmarhnia, T. Wildfire smoke impacts respiratory health more than fine particles from other sources: observational evidence from southern California. *Nat. Commun.* **2021**, *12*, 1493.
- (15) Liu, J. C.; Mickley, L. J.; Sulprizio, M. P.; Dominici, F.; Yue, Y.; Ebisu, K.; Anderson, G. B.; Khan, R. F. A.; Bravo, M. A.; Bell, M. L. Particulate air pollution from wildfires in the western US under climate change. *Climatic Change* **2016**, *138*, 655–666.
- (16) Rappold, A. G.; Reyes, J.; Pouliot, P.; Cascio, W. E.; Diaz-Sanchez, D. Community vulnerability to health impacts of wildland fire smoke exposure. *Environ. Sci. Technol.* **2017**, *51*, 6674–6682.
- (17) Munoz-Alpizar, R.; Pavlovic, R.; Moran, M. D.; Chen, J.; Gravel, S.; Henderson, S. B.; Ménard, S.; Racine, J.; Duhamel, A.; Gilbert, S.; Beaulieu, P.-A.; Landry, H.; Davignon, D.; Cousineau, S.; Bouchet, V. Multi-Year (2013–2016) PM2.5 wildfire pollution exposure over North America as determined from operational air quality forecasts. *Atmosphere* **2017**, *8*, 179.
- (18) Koman, P. D.; Billmire, M.; Baker, K. R.; de Majo, R.; Anderson, F. J.; Hoshiko, S.; Thelen, B. J.; French, N. H. F. Mapping modeled exposure of wildland fire smoke for human health studies in California. *Atmosphere* **2019**, *10*, 308.
- (19) Larsen, A.; Yang, S.; Reich, B. J.; Rappold, A. G. A spatial causal analysis of wildland fire-contributed pm2.5 using numerical model output. March 12, 2020, Statistics, Methodology, arXiv:2003.06037 accessed on April 1, 2022.
- (20) Neumann, J. E.; Meredith, A.; Anenberg, S.; Kinney, P. L.; Marcus, S.; Martinich, J.; Lukens, J.; Xu, J.-W.; Henry, R. Estimating PM2.5-related premature mortality and morbidity associated with future wildfire emissions in the western US. *Environ. Res. Lett.* **2021**, *16*, 035019.
- (21) Jaffe, D. A.; O'Neill, S. M.; Larkin, N. K.; Holder, A. L.; Peterson, D. L.; Halofsky, J. E.; Rappold, A. G. Wildfire and prescribed burning impacts on air quality in the United States. *J. Air Waste Manage. Assoc.* **2020**, *70*, 583–615.
- (22) Koplitz, S. N.; Nolte, C. G.; Pouliot, G. A.; Vukovich, J. M.; Beidler, J. Influence of uncertainties in burned area estimates on modeled wildland fire PM2.5 and ozone pollution in the contiguous US. *Atmos. Environ.* **2018**, *191*, 328–339.
- (23) Li, Y.; Tong, D.; Ma, S.; Zhang, X.; Kondragunta, S.; Li, F.; Saylor, R. Dominance of wildfires impact on air quality exceedances during the 2020 record-breaking wildfire season in the United States. *Geophys. Res. Lett.* **2021**, *48*, No. e2021GL094908.
- (24) Herron-Thorpe, F. L.; Mount, G. H.; Emmons, L. K.; Lamb, B. K.; Jaffe, D. A.; Wigder, N. L.; Chung, S. H.; Zhang, R.; Woelfle, M. D.; Vaughan, J. K. Air quality simulations of wildfires in the Pacific Northwest evaluated with surface and satellite observations during the summers of 2007 and 2008. *Atmos. Chem. Phys.* **2014**, *14*, 12533–12551.
- (25) Gunsch, M. J.; May, N. W.; Wen, M.; Bottnerus, C. L. H.; Gardner, D. J.; VanReken, T. M.; Bertman, S. B.; Hopke, P. K.; Ault, A. P.; Pratt, K. A. Ubiquitous influence of wildfire emissions and secondary organic aerosol on summertime atmospheric aerosol in the forested Great Lakes region. *Atmos. Chem. Phys.* **2018**, *18*, 3701–3715.
- (26) Carter, T. S.; Heald, L. H.; Jimenez, J. L.; Campuzano-Jost, P.; Kondo, Y.; Moteki, N.; Schwarz, J. P.; Wiedinmyer, C.; Darmenov, A. S.; da Silva, A. M.; Kaiser, J. W. How emissions uncertainty influences

- the distribution and radiative impacts of smoke from fires in north america. *Atmos. Chem. Phys.* **2020**, *20*, 2073.
- (27) Paugam, R.; Wooster, M.; Freitas, S.; Val Martin, M. V. A review of approaches to estimate wildfire plume injection height within large-scale atmospheric chemical transport models. *Atmos. Chem. Phys.* **2016**, *16*, 907–925.
- (28) Ye, X.; Arab, P.; Ahmadov, R.; James, E.; Grell, G. A.; Pierce, P.; Kumar, A.; Makar, M.; Chen, J.; Davignon, D.; Carmichael, G. R.; Ferrada, G.; McQueen, J.; Huang, J.; Kumar, R.; Emmons, L.; Herron-Thorpe, F. L.; Parrington, M.; Engelen, R.; Peuch, V.-H.; da Silva, A.; Soja, A.; Gargulinski, E.; Wiggins, E.; Hair, J. W.; Fenn, M.; Shingler, S.; Kondragunta, S.; Lyapustin, A.; Wang, Y.; Holben, H.; Giles, D. M.; Saide, P. E. Evaluation and intercomparison of wildfire smoke forecasts from multiple modeling systems for the 2019 williams flats fire. *Atmos. Chem. Phys.* **2021**, *21*, 14427–14469.
- (29) Brey, S. J.; Ruminski, M.; Atwood, S. A.; Fischer, E. V. Connecting smoke plumes to sources using hazard mapping system (hms) smoke and fire location data over north america. *Atmos. Chem. Phys.* **2018**, *18*, 1745–1761.
- (30) Ruminski, M.; Kondragunta, S.; Roland, D.; Zeng, J. Recent changes to the hazard mapping system. *Proceedings of the 15th International Emission Inventory Conference*, 2006; Vol. 15, p 18.
- (31) Burke, M.; Heft-Neal, S.; Li, J.; Driscoll, A.; Baylis, P.; Stigler, M.; Weill, J. A.; Burney, J. A.; Wen, J.; Childs, M. L.; Gould, C. F. Exposures and behavioural responses to wildfire smoke. *Nat. Human Behav.* **2022**, *1*.
- (32) Schneider, S. R.; Lee, K.; Santos, G.; Abbatt, J. P. D. Air Quality Data Approach for Defining Wildfire Influence: Impacts on PM_{2.5}, NO₂, CO, and O₃ in Western Canadian Cities. *Environ. Sci. Technol.* **2021**, *55*, 13709–13717.
- (33) Di, Q.; Amini, H.; Shi, L.; Kloog, I.; Silvern, R.; Kelly, J.; Sabath, M.; Choirat, C.; Koutrakis, P.; Lyapustin, A.; Wang, Y.; Mickley, L. J.; Schwartz, J. An ensemble-based model of pm_{2.5} concentration across the contiguous united states with high spatiotemporal resolution. *Environ. Int.* **2019**, *130*, 104909.
- (34) Reid, C. E.; Considine, E. M.; Maestas, M. M.; Li, G. Daily PM_{2.5} concentration estimates by county, ZIP code, and census tract in 11 western states 2008–2018. *Sci. Data* **2021**, *8*, 112.
- (35) R Core Team *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2020. <https://www.R-project.org/> (accessed on June 22, 2020).
- (36) National Oceanic and Atmospheric Administration Hazard mapping system fire and smoke product. <https://www.ospo.noaa.gov/Products/land/hms.html#about> (accessed on Nov 22, 2021).
- (37) Schroeder, W.; Ruminski, M.; Csiszar, I.; Giglio, L.; Prins, E.; Schmidt, C.; Morisette, J. Validation analyses of an operational fire monitoring product: The hazard mapping system. *Int. J. Rem. Sens.* **2008**, *29*, 6059–6066.
- (38) Rolph, G. D.; Draxler, R. R.; Stein, A. F.; Taylor, A.; Ruminski, M. G.; Kondragunta, S.; Zeng, J.; Huang, H.-C.; Manikin, G.; McQueen, J. T.; Davidson, P. M. Description and verification of the noaa smoke forecasting system: the 2007 fire season. *Weather Forecast.* **2009**, *24*, 361–378.
- (39) Stein, A. F.; Draxler, R. R.; Rolph, G. D.; Stunder, B. J. B.; Cohen, M. D.; Ngan, F. NOAA's HYSPLIT Atmospheric Transport and Dispersion Modeling System. *Bull. Am. Meteorol. Soc.* **2015**, *96*, 2059–2077.
- (40) US Environmental Protection Agency Outdoor air quality data. <https://www.epa.gov/outdoor-air-quality-data/download-daily-data> (accessed on June 8, 2021).
- (41) US Environmental Protection Agency. Interagency monitoring of protected visual environments (improve). <http://vista.cira.colostate.edu/Improve/> (accessed on Dec 10, 2020).
- (42) US Environmental Protection Agency. Chemical speciation network (csn). <https://www.epa.gov/amtic/chemical-speciation-network-csn> (accessed on March 11, 2021).
- (43) Malm, W. C.; Sisler, J. F.; Huffman, D.; Eldred, R. A.; Cahill, T. A. Spatial and seasonal trends in particle concentration and optical extinction in the united states. *J. Geophys. Res. Atmos.* **1994**, *99*, 1347–1370.
- (44) Gorham, K. A.; Raffuse, S. M.; Hyslop, N. P.; White, W. H. Comparison of recent speciated pm_{2.5} data from collocated csn and improve measurements. *Atmos. Environ.* **2021**, *244*, 117977.
- (45) Hand, J. L.; Schichtel, B. A.; Malm, W. C.; Frank, N. H. Spatial and temporal trends in pm_{2.5} organic and elemental carbon across the united states. *Adv. Meteorol.* **2013**, *2013*, 1.
- (46) Hand, J. L.; Prentiss, A. J.; Schichtel, B. A.; Malm, W.; Chow, J. C. Trends in remote PM_{2.5} residual mass across the United States: Implications for aerosol mass reconstruction in the IMPROVE network. *Atmos. Environ.* **2019**, *203*, 141–152.
- (47) Liu, X.; Zhang, Y.; Huey, L. G.; Yokelson, R. J.; Wang, Y.; Jimenez, J. L.; Campuzano-Jost, P.; Beyersdorf, A. J.; Blake, D. R.; Choi, Y.; St Clair, J. M.; Crounse, J. D.; Day, D. A.; Diskin, G. S.; Fried, A.; Hall, S. R.; Hanisco, T. F.; King, L. E.; Meinardi, S.; Mikoviny, T.; Palm, B. B.; Peischl, J.; Perring, A. E.; Pollack, I. B.; Ryerson, T. B.; Sachse, G.; Schwarz, J. P.; Simpson, I. J.; Tanner, D. J.; Thornhill, K. L.; Ullmann, K.; Weber, R. J.; Wennberg, W.; Wisthaler, A.; Wolfe, G. M.; Ziembka, L. D. Agricultural fires in the southeastern U.S. during SEAC 4 RS: Emissions of trace gases and particles and evolution of ozone, reactive nitrogen, and organic aerosol. *J. Geophys. Res. Atmos.* **2016**, *121*, 7383–7414.
- (48) Rickly, P.; Guo, H.; Campuzano-Jost, P.; Jimenez, J. L.; Wolfe, G. M.; Bennett, R.; Bourgeois, I.; Crounse, J. D.; Dibb, J. E.; DiGangi, J. P.; Diskin, G. S.; Dollner, M.; Gargulinski, E. M.; Hall, S. R.; Halliday, T. F.; Hanisco, R. A.; Hannun, J.; Liao, R.; Moore, A.; Nault, J. B. N.; Nault, C. E.; Nowak, T.; Robinson, K. J.; Ryerson, M.; Sanchez, A. J.; Schöberl, M.; Soja, S.; St Clair, K. L.; Thornhill, U.; Ullmann, P. O.; Wennberg, B.; Weinzierl, E. B.; Wiggins, E. L.; Winstead, A. W.; Rollins, A. W. Emission factors and evolution of SO₂ measured from biomass burning in wild and agricultural fires. *Atmos. Chem. Phys. Discuss.* **2022**, *1*.
- (49) Martin, R. V.; Brauer, M.; van Donkelaar, A.; Shaddick, S.; Narain, U.; Dey, S. No one knows which city has the highest concentration of fine particulate matter. *Atmos. Environ.: X* **2019**, *3*, 100040.
- (50) Walker, K. tigris: Load Census TIGER/Line Shapefiles, 2021. R package version 1.4. <https://CRAN.R-project.org/package=tigris> (accessed on May 16, 2021).
- (51) US Census Bureau 2019 TIGER/Line Shapefiles, 2019. Accessed using the R package tigris. Shapefiles are also available from <https://www.census.gov/cgi-bin/geo/shapefiles/index.php>.
- (52) Hersbach, H.; Bell, B.; Berrisford, P.; Biavati, G.; Horányi, A.; Sabater, J. M.; Nicolas, J.; Peubey, C.; Radu, R.; Rozum, I.; Schepers, D.; Simmons, A.; Soci, C.; Dee, D.; Thépaut, J.-N. Era5 hourly data on pressure levels from 1979 to present. *Copernicus Climate Change Service (C3S) Climate Data Store (Cds)*, *10*, 2018 (accessed on February 20, 2022).
- (53) Sabater, J. M. *Era5-land Hourly Data from 1981 to Present, Copernicus Climate Change Service (C3S) Climate Data Store (Cds) [data Set]*, 2019.
- (54) Global Modeling and Assimilation Office (GMAO) *MERRA-2 tavg1_2d_aer_Nx: 2d,1-Hourly, Time-averaged, Single-Level, Assimilation, Aerosol Diagnostics V5.12.4*; Goddard Earth Sciences Data and Information Services Center (GES DISC): Greenbelt, MD, USA, 2015.
- (55) Li, L.; Franklin, M.; Girguis, M.; Lurmann, F.; Wu, J.; Pavlovic, N.; Breton, C.; Gilliland, G.; Habre, R. Spatiotemporal imputation of maiac aod using deep learning with downscaling. *Remote Sens. Environ.* **2020**, *237*, 111584.
- (56) Lyapustin, A.; Wang, Y.; Korkin, S.; Huang, D. Modis collection 6 maiac algorithm. *Atmos. Meas. Tech.* **2018**, *11*, 5741–5765.
- (57) Bi, J.; Belle, H. B.; Wang, Y.; Lyapustin, A. I.; Wildani, A.; Liu, Y. Impacts of snow and cloud covers on satellite-derived PM_{2.5} levels. *Remote Sens. Environ.* **2019**, *221*, 665–674.
- (58) Chen, T.; Guestrin, C. XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference*

- on Knowledge Discovery and Data Mining, KDD '16; ACM, 2016; pp 785–794.
- (59) US Geological Survey National Elevation Dataset 1/3 Arc-Second (Ned 1/3); Courtesy of The US Geological Survey, 2009.
- (60) Dewitz, J. *National Land Cover Database (NLCD) 2016 Products*; US Geological Survey Data Release, 2019.
- (61) Hu, X.; Belle, H. B.; Meng, M.; Wildani, A.; Waller, L. A.; Strickland, M. J.; Liu, Y. Estimating PM_{2.5} Concentrations in the Conterminous United States Using the Random Forest Approach. *Environ. Sci. Technol.* **2017**, *51*, 6936–6944.
- (62) Just, A. C.; Arfer, K. B.; Rush, J.; Dorman, M.; Shtein, A.; Lyapustin, A.; Kloog, I. Advancing methodologies for applying machine learning and evaluating spatiotemporal models of fine particulate matter (PM_{2.5}) using satellite data over large regions. *Atmos. Environ.* **2020**, *239*, 117649.
- (63) Chen, Z.-Y.; Jin, J.-Q.; Zhang, R.; Zhang, T.-H.; Chen, J.-J.; Yang, J.; Ou, C.-Q.; Guo, Y. Comparison of Different Missing-Imputation Methods for MAIAC (Multiangle Implementation of Atmospheric Correction) AOD in Estimating Daily PM_{2.5} Levels. *Remote Sens.* **2020**, *12*, 3008.
- (64) Zamani Joharestani, M.; Cao, C.; Ni, X.; Bashir, B.; Talebianfandarani, S. PM_{2.5} Prediction Based on Random Forest, XGBoost, and Deep Learning Using Multisource Remote Sensing Data. *Atmosphere* **2019**, *10*, 373.
- (65) Xu, Y.; Ho, C.; Wong, M. S.; Deng, C.; Shi, S.; Chan, T.-C.; Knudby, K. Evaluation of machine learning techniques with multiple remote sensing datasets in estimating monthly concentrations of ground-level PM_{2.5}. *Environ. Pollut.* **2018**, *242*, 1417–1426.
- (66) Geng, G.; Murray, N. L.; Tong, J. S.; Fu, X.; Hu, P.; Lee, M.; Meng, H. H.; Chang, Y.; Liu, Y. Satellite-Based Daily PM 2.5 Estimates During Fire Seasons in Colorado. *J. Geophys. Res. Atmos.* **2018**, *123*, 8159–8171.
- (67) Purpleair sensor data. <https://thingspeak.com/>, Via JSON in accordance with PurpleAir terms and conditions (accessed on Feb 11, 2021).
- (68) Buysse, C. E.; Kaulfus, A.; Nair, U.; Jaffe, D. A. Relationships between particulate matter, ozone, and nitrogen oxides during urban smoke events in the western us. *Environ. Sci. Technol.* **2019**, *53*, 12519–12528.
- (69) Friedl, M.; Sulla-Menashe, D. *MCD12Q1-MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006 [Data Set]* (NASA Eosdis Land Processes Daac, 2019), 2020.
- (70) Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, I.; Thau, D.; Moore, R. Google earth engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27.
- (71) Aybar, C.; Wu, Q.; Bautista, L.; Yali, Y.; Barja, B. rgee: An r package for interacting with google earth engine. *J. Open Source Software* **2020**, *5*, 2272.
- (72) CAL FIRE, California Department of Forestry and Fire Protection Fire perimeters. <https://frap.fire.ca.gov/frap-projects/fire-perimeters/> (accessed on Feb 7, 2022).
- (73) US Environmental Protection Agency. Particulate matter (pm_{2.5}) trends, 2022. <https://www.epa.gov/air-trends/particulate-matter-pm25-trends> (accessed on March 24, 2022).
- (74) Chay, K.; Greenstone, M. *Air Quality, Infant Mortality, and the Clean Air Act of 1970*, NBER Working Paper, 2003.
- (75) Heft-Neal, S.; Burney, J.; Bendavid, E.; Burke, M. Robust relationship between air quality and infant mortality in africa. *Nature* **2018**, *559*, 254–258.
- (76) Monitoring Trends in Burn Severity (MTBS) Project (USDA Forest Service/U.S. Geological Survey). MTBS data access: Burned areas boundaries dataset, 1984–2020 <https://www.mtbs.gov/direct-download> (accessed on July 22, 2022).
- (77) US Census Bureau American community survey 5-year estimates. Accessed via R package tidy census.
- (78) Regional Economic Accounts Cagdp9: Real gdp in Chained Dollars by County and msa; Bureau of Economic Analysis, US Department of Commerce, 2022. <https://apps.bea.gov/regional/downloadzip.cfm> (accessed on July 6, 2022).
- (79) Stevens, F. R.; Gaughan, A. E.; Linard, C.; Tatem, A. J. Disaggregating census data for population mapping using random forests with remotely-sensed and ancillary data. *PLoS One* **2015**, *10*, No. e0107042.
- (80) Huang, R.; Qin, M.; Hu, Y.; Russell, A. G.; Odman, M. T. Apportioning prescribed fire impacts on PM_{2.5} among individual fires through dispersion modeling. *Atmos. Environ.* **2020**, *223*, 117260.
- (81) Jaffe, C. D.; Jaffe, D. A. Investigation of high ozone events due to wildfire smoke in an urban area. *Atmos. Environ.* **2018**, *194*, 146–157.
- (82) Calahorrano, J. F. J.; Lindaas, J.; O'Dell, K.; Palm, B. B.; Peng, Q.; Frank, F.; Pollack, I. B.; Garofalo, L. A.; Farmer, D. K.; Pierce, J. R.; Collett, J. L., Jr.; Weinheimer, A.; Campos, T.; Hornbrook, R. S.; Hall, S. R.; Kirk, U.; Pothier, M. A.; Eric, C. A.; Wade, P.; Hu, L.; Hills, A. J.; Montzka, D.; Tyndall, G.; Thornton, J. A.; Fischer, E. V. Daytime oxidized reactive nitrogen partitioning in western us wildfire smoke plumes. *J. Geophys. Res. Atmos.* **2021**, *126*, No. e2020JD033484.
- (83) Xu, L.; Crounse, J. D.; Vasquez, K. T.; Allen, H.; Wennberg, P. O.; Bourgeois, I.; Brown, S. S.; Campuzano-Jost, P.; Coggon, M. M.; Crawford, J. H.; DiGangi, J. P.; Diskin, G. S.; Fried, A.; Gargulinski, E. M.; Gilman, J. B.; Gkatzelis, G. I.; Guo, H.; Hair, J. W.; Hall, S. R.; Halliday, H. A.; Hanisco, T. F.; Hannun, R. A.; Holmes, C. D.; Huey, L. G.; Jimenez, J. L.; Lamplugh, A.; Lee, Y. R.; Liao, J.; Lindaas, J.; Neuman, J. A.; Nowak, J. B.; Peischl, J.; Peterson, D. A.; Piel, F.; Richter, D.; Rickly, P.; Robinson, M. A.; Rollins, A. W.; Ryerson, T. B.; Sekimoto, K.; Selimovic, V.; Shingler, S.; Soja, A. J.; St Clair, J. M.; Tanner, D. J.; Ullmann, U.; Veres, P. R.; Walega, W.; Warneke, C.; Washenfelder, R. A.; Weibring, P.; Wisthaler, A.; Wolfe, W. M.; Womack, C. C.; Yokelson, R. J. Ozone chemistry in western U.S. wildfire plumes. *Sci. Adv.* **2021**, *7*, No. eab13648.
- (84) Barkjohn, K. K.; Gantt, B.; Clements, A. L. Development and application of a United States-wide correction for PM_{2.5} data collected with the PurpleAir sensor. *Atmos. Meas. Tech.* **2021**, *14*, 4617–4637.
- (85) Wallace, L.; Bi, J.; Ott, W. R.; Sarnat, J.; Liu, Y. Calibration of low-cost PurpleAir outdoor monitors using an improved method of calculating PM. *Atmos. Environ.* **2021**, *256*, 118432.
- (86) Bi, J.; Wallace, L. A.; Sarnat, J. A.; Liu, Y. Characterizing outdoor infiltration and indoor contribution of PM2.5 with citizen-based low-cost monitoring data. *Environ. Pollut.* **2021**, *276*, 116763.
- (87) Krebs, B.; Burney, J.; Zivin, J. G.; Neidell, M. Using crowdsourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter. *Environ. Sci. Technol.* **2021**, *55*, 6107–6115.
- (88) Singer, W. W.; Singer, B. C. Wildfire Smoke Adjustment Factors for Low-Cost and Professional PM_{2.5} Monitors with Optical Sensors. *Sensors* **2020**, *20*, 3683.
- (89) Lyapustin, A.; Wang, Y.; Korkin, S.; Kahn, R.; Winker, D. Maiac thermal technique for smoke injection height from modis. *Geosci. Rem. Sens. Lett. IEEE* **2019**, *17*, 730–734.
- (90) Cheeseman, M.; Ford, B.; Volckens, J.; Lyapustin, A.; Pierce, J. R. The relationship between maiac smoke plume heights and surface pm. *Geophys. Res. Lett.* **2020**, *47*, No. e2020GL088949.
- (91) Qiu, M.; Zigler, C.; Selin, E. S. Statistical and machine learning methods for evaluating trends in air quality under changing meteorological conditions. *Atmos. Chem. Phys.* **2022**, *22*, 10551–10566.
- (92) Tai, A. P. K.; Mickley, L. J.; Jacob, D. J.; Leibensperger, L.; Zhang, J. A.; Fisher, H. O. T.; Pye, H. O. T. Meteorological modes of variability for fine particulate matter (PM_{2.5}) air quality in the United States: implications for PM_{2.5} sensitivity to climate change. *Atmos. Chem. Phys.* **2012**, *12*, 3131–3145.
- (93) Park, Y.; Kwon, B.; Heo, J.; Hu, X.; Liu, Y.; Moon, T. Estimating PM_{2.5} concentration of the conterminous United States via interpretable convolutional neural networks. *Environ. Pollut.* **2020**, *256*, 113395.
- (94) Wen, J.; Burke, M. Wildfire smoke plume segmentation using geostationary satellite imagery. September 3, 2021. arXiv (Computer Science, Computer Vision and Pattern Recognition),

arXiv:2109.01637. <https://doi.org/10.48550/arXiv.2109.01637> (accessed April 14, 2022).

- (95) Ramasubramanian, M.; Kaulfus, A.; Maskey, M.; Ramachandran, R.; Gurung, I.; Freitag, B.; Christopher, S. Pixel level smoke detection model with deep neural network. *Image and Signal Processing for Remote Sensing XXV*; International Society for Optics and Photonics, 2019; Vol. 11155, p 1115515.
- (96) Larsen, A.; Hanigan, I.; Reich, B. J.; Qin, Y.; Cope, M.; Morgan, G.; Rappold, A. G. A deep learning approach to identify smoke plumes in satellite imagery in near-real time for health risk communication. *J. Expo. Sci. Environ. Epidemiol.* **2021**, *31*, 170–176.
- (97) Gillett, N. P.; Weaver, A. J.; Zwiers, F. W.; Flannigan, M. D. Detecting the effect of climate change on canadian forest fires. *Geophys. Res. Lett.* **2004**, *31*, L18211.
- (98) Balch, J. K.; Abatzoglou, J. T.; Joseph, M. B.; Koontz, M. J.; Mahood, A. L.; McGlinchy, M. G.; Cattau, M. E.; Williams, A. P. Warming weakens the night-time barrier to global fire. *Nature* **2022**, *602*, 442–448.
- (99) Jolly, W.; Cochrane, M. A.; Freeborn, P. H.; Holden, Z. A.; Brown, T. J.; Williamson, G. J.; Bowman, D. M. J. S. Climate-induced variations in global wildfire danger from 1979 to 2013. *Nat. Commun.* **2015**, *6*, 7537.
- (100) Reid, C. E.; Brauer, M.; Johnston, F. H.; Jerrett, M.; Balmes, J. R.; Elliott, C. T. Critical review of health impacts of wildfire smoke exposure. *Environ. Health Perspect.* **2016**, *124*, 1334–1343.
- (101) Heft-Neal, S.; Driscoll, A.; Yang, W.; Shaw, G.; Burke, M. Associations between wildfire smoke exposure during pregnancy and risk of preterm birth in california. *Environ. Res.* **2022**, *203*, 111872.
- (102) Borgschulte, M.; Molitor, D.; Zou, E. *Air Pollution and the Labor Market: Evidence from Wildfire Smoke*, NBER Working Paper Series, Rev Econ Stat, 2018.
- (103) Liu, C.; Pereira, G.; Uhl, S. A.; Bravo, M. A.; Bell, M. L. A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environ. Res.* **2015**, *136*, 120–132.

□ Recommended by ACS

Evaluation of Model-Based PM_{2.5} Estimates for Exposure Assessment during Wildfire Smoke Episodes in the Western U.S.

Ellen M. Considine, Rachel C. Nethery, *et al.*

JANUARY 24, 2023

ENVIRONMENTAL SCIENCE & TECHNOLOGY

READ ▾

National Exposure Models for Source-Specific Primary Particulate Matter Concentrations Using Aerosol Mass Spectrometry Data

Provrat K. Saha, Allen L. Robinson, *et al.*

SEPTEMBER 26, 2022

ENVIRONMENTAL SCIENCE & TECHNOLOGY

READ ▾

Identification of Factors Determining Household PM_{2.5} Variations at Regional Scale and Their Implications for Pollution Mitigation

Xinlei Liu, Shu Tao, *et al.*

FEBRUARY 24, 2023

ENVIRONMENTAL SCIENCE & TECHNOLOGY

READ ▾

Air Pollution Over India: Causal Factors for the High Pollution with Implications for Mitigation

Nimish Singh, Veerabhadran Ramanathan, *et al.*

NOVEMBER 23, 2021

ACS EARTH AND SPACE CHEMISTRY

READ ▾

[Get More Suggestions >](#)