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Wildland fire smoke and respiratory health outcomes among elderly populations in California: comparison of exposure and health impact estimates

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Wildland fire smoke and respiratory health outcomes among elderly populations in California: comparison of exposure and health impact estimates

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of the requirements for the degree Master of Science
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by

Jenny Trinh Nguyen

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ABSTRACT OF THE THESIS

Wildland fire smoke and respiratory health outcomes

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by

Jenny Trinh Nguyen

Master of Science in Environmental Health Sciences

University of California, Los Angeles, 2024

Professor Miriam Elizabeth Marlier, Chair

The advancement of new exposure assessment techniques has facilitated the development of several wildland fire smoke datasets employing varied smoke estimation methods. Exposure to wildland fire smoke can increase respiratory health risks, particularly among vulnerable groups such as the elderly. This study compares estimates of wildland fire smoke fine particulate matter ("smoke $PM_{2.5}$") in California from 2008 to 2018 across three datasets and quantifies differences in the attributable respiratory health burden among elderly populations from utilizing smoke estimates from different datasets. Smoke $PM_{2.5}$ estimates were obtained from a chemical transport model dataset, the Community Multiscale Air Quality (CMAQ) dataset, and two machine learning datasets, the Childs and Casey datasets. Respiratory health burdens attributable to smoke $PM_{2.5}$ were quantified using smoke estimates from the three datasets through health impact assessments conducted in the US Environmental Protection Agency's (EPA) Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) program. Smoke estimates from Childs and Casey, which rely on similar input datasets, were more similar than those from CMAQ in terms of correlation, spatial distributions, and temporal trends. Approximately 1,300-5,400 respiratory hospitalizations and emergency department (ED)/emergency room (ER) visits among the elderly are attributable to smoke $PM_{2.5}$ exposure in California during the study period. Using smoke estimates from different datasets and different dose-response values from the literature yielded discrepancies in health impact estimates, with discrepancies of approximately 3,500-4,000 respiratory hospitalizations and ED/ER visits between CMAQ with Childs and Casey in the main analysis and discrepancies of approximately 1,000-4,000 respiratory hospitalizations and ED/ER visits between dose-response values from the main and sensitivity analyses. Differences in smoke $PM_{2.5}$ and health impact estimates can affect future wildland fire policies and strategies that rely on these estimates to address health burdens, especially among vulnerable populations such as the elderly.

The thesis of Jenny Trinh Nguyen is approved.

Lara J. Cushing

Michael Leo B. Jerrett

Miriam Elizabeth Marlier, Committee Chair

University of California, Los Angeles

2024

DEDICATION

To my family and friends, for always

encouraging and supporting me throughout this journey.

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LIST OF ACRONYMS

AQS	**Air Quality System** A repository, maintained by the Environmental Protection Agency, of ambient air pollution monitoring data collected by several air quality control agencies in the United States
BenMAP-CE	**Environmental Benefits Mapping and Analysis Program – Community Edition** An open-source software program used to estimate health and economic impacts attributed to changes in air pollution
CARB	**California Air Resources Board** An agency of the California government responsible for implementing and overseeing air pollution control measures in the state
CI	**Confidence interval** An interval that an estimated parameter is expected to fall within, based on a given confidence level
CMAQ	**Community Multiscale Air Quality Modeling System** An open-source system of programs, developed by the Environmental Protection Agency, used to run air quality modeling simulations
COPD	**Chronic obstructive pulmonary disease** Lung diseases that restrict airflow and cause difficulties in breathing
CSV	**Comma-separated values** A plain text file that stores data in a tabular format, with values separated by commas
ED	**Emergency department** A hospital facility that provides emergency medical care to patients who arrive without prior appointments and present with serious health conditions
EPA	**Environmental Protection Agency** An agency of the US government responsible for handling environmental protection issues in the nation
ER	**Emergency room** Similar to emergency department
FEM	**Federal Equivalent Method** A method for sampling and analyzing ambient air pollution concentrations that is consistent and equivalent with the Federal Reference Method, designated by the Environmental Protection Agency
FRM	**Federal Reference Method** The main method for sampling and analyzing ambient air pollution concentrations, designated by the Environmental Protection Agency
GEOS-Chem	**Goddard Earth Observing System chemical transport model**

	A three-dimensional chemical transport model that simulates atmospheric composition using meteorological inputs from the Goddard Earth Observing System
HA	**Hospitalization** Admission of a patient to a hospital for medical care
HCUP	**Healthcare Cost and Utilization Project** A suite of healthcare databases that includes data on inpatient stays, ambulatory care, and emergency department visits in the United States
HMS	**Hazard Mapping System** A tool, developed by the National Oceanic and Atmospheric Administration, for identifying and mapping wildfires and smoke emissions in the United States
ICD	**International Classification of Disease** A medical classification system, developed by the World Health Organization, used to classify and code diagnoses and procedures
MAIAC	**Multi-Angle Implementation of Atmospheric Correction** An algorithm, developed to be used with the Moderate Resolution Imaging Spectroradiometer, that employs time series analysis and image-based processing for atmospheric correction
MODIS	**Moderate Resolution Imaging Spectroradiometer** A satellite sensor, aboard the National Aeronautics and Space Administration's Terra and Aqua satellites, that captures remote sensing data of Earth's surfaces, such as the atmosphere, oceans, and land
NASA	**National Aeronautics and Space Administration** An agency of the US government responsible for aeronautic research and space exploration
NEDS	**National Emergency Department Sample** An emergency department database in the United States that provides national data on emergency department visits, as part of the suite of databases from the Healthcare Cost and Utilization Project
NIS	**National Inpatient Sample** An inpatient healthcare database in the United States that provides regional and national data on inpatient hospitalizations, as part of the suite of databases from the Healthcare Cost and Utilization Project
NOAA	**National Oceanic and Atmospheric Administration** A scientific agency of the US government responsible for weather forecasting, climate monitoring, and oceanic and coastal management
OR	**Odds ratio**

	A measure of association between two events, typically the exposure and outcome, that compares the odds of the outcome given exposure to the odds of the outcome given no exposure
$PM_{2.5}$	**Fine particulate matter** Small, inhalable particles with a diameter equal to or less than 2.5 μm
RMSE	**Root mean square error** A measurement of the average differences between observed values and predicted values from a model
RR	**Relative risk** A measure of risk that compares the risk of the outcome in the exposed group to the risk of the outcome in the unexposed group
SEDD	**State Emergency Department Databases** An emergency department database in the United States that provides state-level data on emergency department visits, as part of the suite of databases from the Healthcare Cost and Utilization Project
SES	**Socioeconomic status** A measure of a person's economic and sociological standing, usually a combination of indicators including income, education, housing status and more
SID	**State Inpatient Databases** An inpatient healthcare database in the United States that provides state-level data on inpatient hospitalizations, as part of the suite of databases from the Healthcare Cost and Utilization Project
US/USA	**United States of America** Country in North America
WRF-Chem	**Weather Research and Forecasting with Chemistry model** A chemical transport model that integrates atmospheric chemistry and meteorology to simulate atmospheric processes and chemical reactions of aerosols and trace gases
WUI	**Wildland-urban interface** An area between human development and undeveloped vegetation

LIST OF SYMBOLS

β	Beta coefficient
$\beta_{2.5\ percentile}$	Beta coefficient associated with the lower confidence interval
$\beta_{97.5\ percentile}$	Beta coefficient associated with the upper confidence interval
ΔPM	Increment change in wildland fire smoke $PM_{2.5}$ concentration response function as estimated by the literature
ΔQ	Change in air pollution from wildland fire smoke $PM_{2.5}$ concentrations
H	Estimated health impact
R^2	Coefficient of determination
ρ	Spearman correlation coefficient
σ_{β}	Standard error for the Beta coefficient
$\sigma_{\beta,\ 2.5\ percentile}$	Standard error for the Beta coefficient associated with the lower confidence interval
$\sigma_{\beta,\ 97.5\ percentile}$	Standard error for the Beta coefficient associated with the upper confidence interval

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INTRODUCTION

Wildland fires are increasing in frequency, intensity, and duration, as a result of changes in temperature and aridity influenced by human-caused climate change (Abatzoglou & Williams, 2016; Westerling et al., 2006), changes in land management (Calkin et al., 2015; Keane et al., 2002), and development in the wildland-urban interface (WUI) (Radeloff et al., 2018). Increases in wildland fire activity pose threats to human health, through exposure to the direct fire as well as associated smoke pollution, with smoke transport in the atmosphere contributing to regional exposures in addition to local exposures (Heilman et al., 2014). Fine particulate matter ($PM_{2.5}$), an inhalable mixture of small particles with a diameter of 2.5 μm or less, from wildland fire smoke (hereafter referred to as smoke $PM_{2.5}$) can penetrate deep into the lungs and enter the bloodstream due to its small size, contributing to wide-ranging adverse health effects (Feng et al., 2016; Pope & Dockery, 2006; US EPA, 2019). Epidemiological studies have linked smoke $PM_{2.5}$ exposure to increased risk of mortality and respiratory morbidity, with mixed but suggestive evidence for cardiovascular morbidity (Cascio, 2018; Reid, Brauer, et al., 2016). Specifically, in California, approximately 52,000-56,000 premature deaths are attributable to smoke $PM_{2.5}$ between 2008 to 2018, which highlights the large mortality burdens associated with wildland fires (Connolly et al., 2024). Emerging evidence suggests higher toxicity from smoke $PM_{2.5}$ compared to $PM_{2.5}$ from other sources (Aguilera et al., 2021), further emphasizing wildland fire smoke as a pertinent public health issue.

Health impacts from smoke $PM_{2.5}$ exposure are often not distributed evenly. Highly susceptible populations include children, the elderly, pregnant people, people with pre-existing health conditions, people with lower socioeconomic status (SES), and people of color (Cascio, 2018). In particular, elderly populations are more susceptible to wildland fires due to declining health with increasing age (Liu, Wilson, Mickley, Ebisu, et al., 2017). Exposure to smoke $PM_{2.5}$ is likely to exacerbate health risks among elderly populations who may already suffer from health complications. Wildland fires also often occur in rural areas where large proportions of the elderly reside (Masri et al., 2021), which can increase this population's exposure to smoke $PM_{2.5}$. As such, assessing health impacts attributable to smoke $PM_{2.5}$ among the elderly will support the characterization of this population's vulnerability to wildland fires.

Existing studies have used different methods to characterize smoke $PM_{2.5}$ exposure, which include the use of surface air pollutant monitors, satellite-based observations, and various atmospheric models, as well as a mixture of different approaches (Cascio, 2018; Liu et al., 2015; Youssouf et al., 2014). Historically, studies have often utilized air pollutant monitoring data from stationary Federal Reference Method (FRM)/Federal Equivalent Method (FEM) monitors when assessing exposure (Liu et al., 2015), though recent studies have shifted towards using satellite-based observations and models instead as these methods yielded more comprehensive exposure assessments (Gan et al., 2017; Liu et al., 2015). The availability of diverse methods to develop pollution exposure surfaces naturally raises questions of how smoke $PM_{2.5}$ estimates from different methods compare to one another. Notably, estimates of health risks in epidemiological studies can be influenced by the exposure estimation method used (Gan et al., 2017). Gan et al. found differing results of health risks for chronic obstructive pulmonary disease (COPD) from smoke $PM_{2.5}$ exposure across various smoke exposure models, with increased risk observed using kriging of in situ surface monitors and geographically weighted regression, which combines surface monitor and satellite data and simulated estimations from chemical transport models, and no associated risk observed using the chemical transport model alone (Gan et al., 2017). Consequently, understanding how exposure assessments of smoke $PM_{2.5}$ through different methods compare and affect health estimates is crucial, especially with the continuous development of new smoke $PM_{2.5}$ datasets.

Several studies have characterized and examined the exposure distribution of smoke $PM_{2.5}$ (Aguilera et al., 2023; Childs et al., 2022; Koman et al., 2019; Wilkins et al., 2018; Yao et al., 2018), but few studies have compared differences in smoke $PM_{2.5}$ across datasets that have used different exposure estimation methods. Moreover, the current literature on potential differences in smoke $PM_{2.5}$ estimates affecting health impact or risk estimates is limited, and no studies have analyzed this issue in elderly populations, specifically. California constitutes an ideal area to investigate such issues as the state has historically and frequently continues to experience wildland fires (Dennison et al., 2014; Li & Banerjee, 2021; Palinkas, 2020).

To address these knowledge gaps, this study assesses smoke $PM_{2.5}$ exposure estimates from three modeled datasets in California from 2008 to 2018 at the census tract-level and compares whether smoke $PM_{2.5}$ estimates vary in space, time, and magnitude. Then, I conducted a health impact assessment to investigate how smoke $PM_{2.5}$ estimates from different datasets impact the attributable respiratory health burden among elderly populations in California. Understanding how health impact estimates vary based on the dataset used is critical for determining the health burden of wildland fires and appropriately allocating resources, especially when considering susceptible populations such as the elderly.

METHODS

Data sources

Modeled smoke $PM_{2.5}$ estimates in California from 2008 to 2018 were obtained from three publicly available datasets (Casey et al., 2024; Childs et al., 2022; Wilkins et al., 2018).

The first dataset was developed from a chemical transport model, specifically the Community Multiscale Air Quality (CMAQ) modeling system, using SMARTFIRE emissions (Sullivan et al., 2008) that produced air pollution estimates with and without the wildland fire contribution, with the difference between the two corresponding to pollution attributable to wildland fire smoke (Wilkins et al., 2018). This dataset provides daily gridded smoke $PM_{2.5}$ estimates across the US from 2008 to 2018 at a 12-km spatial resolution (Wilkins et al., 2018); however, only estimates for California were used for this study.

The second dataset, developed by Childs et al., provides daily smoke $PM_{2.5}$ concentrations across the US from 2006 to 2020 at both the census tract-level and at a 10-km grid (Childs et al., 2022). This dataset utilized machine learning methods, specifically gradient boosting, and multiple inputs, including monitor data from the US Environmental Protection Agency (EPA) and several covariates, to predict smoke $PM_{2.5}$ concentrations (Childs et al., 2022). Only census-tract level estimates for California from 2008 to 2018 were used in this study to align with the study area of interest and the years available in the CMAQ dataset.

The third dataset, developed by Casey et al., provides both daily all-source $PM_{2.5}$ concentrations and smoke $PM_{2.5}$ concentrations in California from 2006 to 2020 at the census tract-level (Casey et al., 2024). This dataset, previously developed by Aguilera et al. at the zip code-level using the same methodology (Aguilera et al., 2023), also used machine learning methods, specifically an ensemble model of deep learning, random forests, and gradient boosting, to estimate smoke $PM_{2.5}$ concentrations, incorporating monitor data from the US EPA's Air Quality System (AQS) and several predictor variables (Casey et al., 2024). Only estimates from 2008 to 2018 were used for consistency with the CMAQ dataset.

Model performance for all the datasets were evaluated in the respective studies. The model for the CMAQ dataset was compared to observations from AQS. During months where model differences were largest, the model estimated higher monthly mean $PM_{2.5}$ than observed mean $PM_{2.5}$ (Wilkins et al., 2018). Simulations with the fire contribution yielded a root mean square error (RMSE) of 5.22. The model performed well when fires have been identified and recorded in emissions inventories but overpredicted $PM_{2.5}$ for atypical fire events, such as fire activity during winter months or megafires (Wilkins et al., 2018). The model for the Childs dataset was validated on daily time series data from both private and held-out EPA monitors not used for model training or development, with an R^2 value of 0.67 and a RMSE of 9.57 for smoke days for the "out-of-sample" test (Childs et al., 2022). The authors emphasized the model's high performance through its accurate predictions of observed $PM_{2.5}$, even at high concentrations. The ensemble model for the Casey dataset was validated on monitoring data from five held-out monitoring sites not used for model training, with an R^2 value of 0.78 and a RMSE of 3.51 for the hold-out test (Aguilera et al., 2023). The ensemble model underpredicted high observed $PM_{2.5}$ concentrations, though the authors discussed that these underpredictions were common for exposure estimation through statistical methods (Aguilera et al., 2023). Given that the datasets have been validated against observed $PM_{2.5}$, the subsequent step is to conduct a comparative analysis between the datasets.

To align spatial resolutions across all datasets, the gridded estimates from CMAQ were transformed into census tract-level estimates in R using the "exactextractr" package, which averages the gridded estimates over census tract areas.

Smoke exposure comparisons

Statistical analysis

A range of statistical approaches, including correlations, the Kruskal-Wallis test, and the Dunn test, were applied to evaluate the extent that smoke $PM_{2.5}$ concentrations from the datasets correlated with one another and to assess statistical variation in the estimates across datasets. I calculated descriptive statistics, specifically the mean and standard deviation, of statewide smoke $PM_{2.5}$ concentrations for the overall study period and each year within by averaging the daily estimates across all California census tracts for each dataset. Using daily census tract-level smoke $PM_{2.5}$ concentrations, I computed Spearman correlation coefficients between pairs of datasets (CMAQ and Childs, CMAQ and Casey, Childs and Casey) for each year within the study period to examine the magnitude and direction of correlation between smoke estimates from different datasets.

To determine whether smoke $PM_{2.5}$ concentrations from the datasets statistically differed, I applied the Kruskal-Wallis test, a non-parametric method that tests for differences in the mean rank across certain groups (McKight & Najab, 2010). Census tract-level annual average smoke $PM_{2.5}$ concentrations, which I calculated by averaging daily estimates across the overall study period and for each year within, were used for this test. For each year and across the overall study period, I performed the Kruskal-Wallis test to assess for differences in the mean ranks of smoke $PM_{2.5}$ concentrations for all census tracts between the datasets, with a null hypothesis of no differences in the mean ranks between the datasets and an alternative hypothesis of at least one dataset has a different mean rank.

Differences across the California Fourth Climate Change Assessment Regions (hereafter referred to as climate regions) were tested as well, with shapefiles obtained from the California

Natural Resources Agency (California Natural Resources Agency, n.d.). The climate regions were developed as part of the Fourth Assessment's goal to report climate impacts and solutions in specific regions across California (State of California, n.d.), which include the North Coast, Sacramento Valley, Sierra Nevada, San Francisco Bay Area, San Joaquin Valley, Central Coast, Los Angeles, Inland Deserts, and San Diego regions. I intersected climate region boundaries with census tract boundaries using the "sf" package in R to assign each census tract to a climate region. If a census tract was located within two climate regions, it was assigned the climate region in which a larger area of the census tract fell in. Similarly, for each year and across the overall study period, I performed the Kruskal-Wallis test to test for differences in the mean ranks of smoke $PM_{2.5}$ concentrations by climate regions between the datasets, with similar null and alternative hypotheses described earlier.

Following the Kruskal-Wallis test, I applied the Dunn test, a non-parametric pairwise multiple comparisons procedure (Dinno, 2015), to determine which of the three datasets differed from each other. For each year and across the overall study period, I performed the Dunn test to test for multiple pairwise differences in the mean ranks by state and climate region between each pair of the datasets, with a null hypothesis of no differences in the mean ranks between the pairs and an alternative hypothesis of differences in the mean ranks between the pairs. For both the Kruskal-Wallis and Dunn tests, the null hypothesis was rejected if the p-value was less than 0.05.

Spatial analysis

Spatial distributions of smoke $PM_{2.5}$ concentrations for the overall study period and each year within were visualized by mapping annual and overall smoke estimates at the census tract-level for each dataset using the "ggplot2" package in R. I also examined disparities in spatial distributions by calculating absolute differences in annual and overall smoke estimates for each pair of the datasets (i.e., CMAQ minus Childs, CMAQ minus Casey, Childs minus Casey) at the census tract-level and mapping the differences. Positive values were depicted in blue and indicated that the former dataset in the difference calculation had higher estimates, while negative values were depicted in red and indicated that the latter dataset had higher estimates.

Temporal analysis

Monthly time-series trends of statewide average smoke $PM_{2.5}$ concentrations were plotted to compare potential temporal differences between the datasets across the study period. To analyze trends at finer temporal and spatial resolutions, I assessed daily temporal trends of smoke $PM_{2.5}$ concentrations for all California census tracts, which were plotted alongside the statewide average concentration, during fire season months (June to October) of high fire years (2008 and 2018) for all three datasets. I also evaluated daily temporal trends of the differences in smoke estimates by calculating the absolute differences in the daily concentrations for each pair of the datasets for all census tracts. I plotted these differences alongside the statewide average difference during fire season months of high fire years. Differences were calculated as CMAQ minus Childs, CMAQ minus Casey, and Childs minus Casey, to retain consistency. Positive values indicated the former dataset in the calculation had higher estimates, while negative values indicated the latter dataset had higher estimates.

<u>Health impact assessment</u>

The US EPA's Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE) v1.5.8 was used to estimate the attributable respiratory health burden from smoke $PM_{2.5}$ exposure among elderly populations (65 years or older) using three different smoke datasets and to compare how health impact estimates vary across datasets. BenMAP-CE is an open-source software program used to estimate health and economic impacts attributable to changes in air pollution (US EPA, 2021). The software integrates data across several sources, including air quality, population, health, and economic data and dose-response effect estimates, to quantify impacts. Users can choose to upload their own data or use preloaded datasets provided in the software. To estimate health impacts, BenMAP-CE calculates changes in air pollution concentrations, links those changes to specific health outcomes through a health impact function, and applies the function to a population of interest (US EPA, 2023).

Literature review

To gather and synthesize knowledge from the current literature on wildland fire smoke impacts on respiratory morbidity among elderly populations, I conducted a targeted literature review to identify relevant peer-reviewed journal articles and select a wildland fire- and elderly-specific dose response value that would be used to assess the attributable health burden from smoke exposure. This literature review is an extension of a previous literature review completed by other researchers but has been adapted and updated to fit the needs of this study. Specifically, the focus of the previous literature review was on identifying articles that explored the impact of smoke PM exposure on morbidity for several health endpoints (e.g., respiratory, cardiovascular, and birth outcomes) among the general population, while this literature review is centered on smoke PM exposure effects on only respiratory morbidity among elderly populations.

The timeframe of the first iteration of the previous literature review spanned from 2015 to 2021, with searches conducted on PubMed, Web of Science, Embase, and PsycInfo. Updates to the previous literature review were made in July 2023, with searches conducted on PubMed and Web of Science for articles published between 2021 and July 2023. I obtained a list of all articles that passed the screening process for the previous literature review and further screened these articles based on an inclusion criterion described below. To include the most recent literature, I completed a second update to the literature review, with searches conducted on PubMed and Web of Science for articles published between July 2023 and January 2024. Table 1 details the search terms used for the second update.

Table 1. List of search terms used for the updated search (July 2023 to January 2024) for articles focused on respiratory health effects from smoke PM exposure.

Database	***Search Date***	***Search Terms***
PubMed	1/10/2024	("wildfire*"[Title/Abstract] OR "wild fire*"[Title/Abstract] OR "wildland fire*"[Title/Abstract] OR "peat fire*"[Title/Abstract] OR "bush fire*"[Title/Abstract] OR "bushfire*"[Title/Abstract] OR "brush fire*"[Title/Abstract] OR "brushfire*"[Title/Abstract] OR "landscape fire*"[Title/Abstract] OR "forest fire*"[Title/Abstract] OR "wildfires"[MeSH Terms]) AND ("respiratory"[Title/Abstract] OR "respiratory infection*"[Title/Abstract] OR "respiratory illness*"[Title/Abstract] OR "lung*"[Title/Abstract] OR "lung disease*"[Title/Abstract] OR "chronic lung disease*"[Title/Abstract] OR "asthma"[Title/Abstract] OR "pneumonia"[Title/Abstract] OR "respiratory tract diseases"[MeSH Terms]) AND ("journal article"[Publication Type] AND ("english"[Language] OR "french"[Language] OR "spanish"[Language]))
Web of Science	1/10/2024	(TI=("wildfire*") OR TI=("wild fire*") OR TI=("wildland fire*") OR TI=("peat fire*") OR TI=("bush fire*") OR TI=("bushfire*") OR TI=("brush fire*") OR TI=("brushfire*") OR TI=("landscape fire*") OR TI=("forest fire*")) AND (TI=("respiratory") OR TI=("respiratory infection*") OR TI=("respiratory illness*") OR TI=("lung*") OR TI=("lung disease*") OR TI=("chronic lung disease*") OR TI=("asthma") OR TI=("pneumonia") OR TI=("respiratory tract disease*"))

		(AB=("wildfire*") OR AB=("wild fire*") OR AB=("wildland fire*") OR AB=("peat fire*") OR AB=("bush fire*") OR AB=("bushfire*") OR AB=("brush fire*") OR AB=("brushfire*") OR AB=("landscape fire*") OR AB=("forest fire*")) AND (AB=("respiratory") OR AB=("respiratory infection*") OR AB=("respiratory illness*") OR AB=("lung*") OR AB=("lung disease*") OR AB=("chronic lung disease*") OR AB=("asthma") OR AB=("pneumonia") OR AB=("respiratory tract disease*")) *Notes: Options for English, Spanish, and French articles were manually selected.*

To select relevant articles for this study, I implemented an inclusion criterion to screen articles from the second search and from the list of previously screened articles. Criteria for inclusion included human health-focused peer-reviewed journal articles that assessed the effect of smoke PM exposure on health outcomes and were published in English, Spanish, or French. Specifically, articles that assessed respiratory morbidity as at least one of the health outcomes of interests and that investigated effects in elderly populations, either as the main population of interest or as part of a stratified by age group analysis, were included. Since BenMAP-CE defines their health endpoints using International Classification of Disease 9th edition (ICD-9) codes, only articles that specified ICD codes that could be matched to BenMAP-CE's health endpoints were included. Lastly, the selection of articles was limited to those that reported a quantitative dose-response value.

In screening resultant articles from the second search, I removed duplicate articles first. Then, I screened articles by their titles and abstracts and removed those with irrelevant topics. Following the title and abstract screen, I screened the remaining articles through a review of the full text and implementation of the inclusion criterion to select relevant articles. In screening articles from the list of previously screened articles, I applied the same procedure as detailed above.

Selection of elderly-specific dose-response value

Following the selection of relevant articles, I extracted and recorded information about the study period, study area, pollutant of interest, exposure assessment, respiratory health outcomes, medical care type (e.g., hospitalization [HA], emergency department [ED]/emergency room [ER] visit), ICD codes, dose-response type (e.g., relative risk [RR] or odds ratio [OR]), elderly-specific dose-response values, and elderly age range in a spreadsheet. For articles that reported International Classification of Disease 10th edition (ICD-10) codes, I converted the codes to the ICD-9 equivalent. I obtained groupings of ICD-9 codes used to define respiratory hospitalization and ED/ER visit endpoints in BenMAP-CE from the software's user manual and referenced these groupings in order to determine whether respiratory health outcomes from the articles could be closely matched to respiratory health endpoints from BenMAP-CE. If a close match could be identified, the match was recorded.

The selection of an elderly-specific dose-response value required an additional screening procedure following selection and extraction of relevant articles. I developed an inclusion criterion to select an article with the most appropriate dose-response value. Criteria for inclusion included articles that were US-based and that estimated smoke $PM_{2.5}$ exposure as a concentration response function, i.e. dose-response values were estimated per increment of smoke $PM_{2.5}$. ICD codes from the articles must closely match ICD codes for the health endpoints from BenMAP-CE. Lastly, at least one estimated dose-response value from each health outcome must be statistically significant. If multiple articles satisfied the inclusion criteria, I gave more consideration to articles based in California.

Estimation of health impacts

Datasets required to estimate health impacts were imported into BenMAP-CE for analysis. I created a new grid definition for California census tracts, using boundaries obtained from the US Census Bureau (US Census Bureau, n.d.-b). I computed a grid crosswalk between the new grid definition with preloaded grid definitions to align their spatial scales. For air quality data, I used census tract-level annual smoke $PM_{2.5}$ concentrations from 2008 to 2018 from the CMAQ, Childs, and Casey datasets to estimate changes in air quality attributable to wildland fire smoke in California.

For population data, BenMAP-CE provides preloaded block-level population data from the 2010 US Decennial Census. If the preferred grid definition's spatial scale does not align with the block-level data, users can utilize PopGrid (US EPA, 2014), a software program that assigns the block-level population data to the preferred grid definition and generates data files that can be imported into BenMAP-CE. Using PopGrid, I generated data files with population counts for California census tracts and population weights to forecast changes in population with different years and imported these files into BenMAP-CE.

For health data, BenMAP-CE provides several preloaded incidence and prevalence datasets for mortality and morbidity outcomes. This study focused on respiratory hospitalizations and ED/ER visits, which were calculated from the Healthcare Cost and Utilization Project (HCUP) databases and includes data from the State Inpatient Databases (SID), the State Emergency Department Databases (SEDD), the National Inpatient Sample (NIS), and the

Nationwide Emergency Department Sample (NEDS) (US EPA, 2023). I selected the preloaded county-level "Other Incidence (2014)" dataset, which includes daily incidence rates, for the health data.

For the health impact functions, I used an elderly-specific dose-response value selected from the literature as the effect estimate. I converted selected dose-response values to Beta coefficients using Equation 1 (US EPA, 2023),

$$\beta = \frac{\ln(RR)}{\Delta PM} \tag{1}$$

where β is the Beta coefficient, RR is the relative risk or the elderly-specific dose-response value selected from the literature, and ΔPM is the increment change in the smoke $PM_{2.5}$ concentration response function as estimated by the literature. I converted selected dose-response values' confidence intervals to standard errors using Equations 2-4 (US EPA, 2023),

$$\sigma_{\beta,2.5\ percentile} = \frac{\beta - \beta_{2.5\ percentile}}{1.96} \tag{2}$$

$$\sigma_{\beta,97.5\ percentile} = \frac{\beta_{97.5\ perentile} - \beta}{1.96} \tag{3}$$

$$\sigma_{\beta} \cong \frac{\sigma_{\beta,2.5\ percentile} + \sigma_{\beta,97.5\ percentile}}{2} \tag{4}$$

where $\sigma_{\beta,\ 2.5\ \text{percentile}}$ is the standard error for the Beta coefficient associated with the lower confidence interval, $\sigma_{\beta,\ 97.5\ \text{percentile}}$ is the standard error for the Beta coefficient associated with the upper confidence interval, $\beta_{2.5\ \text{percentile}}$ is the Beta coefficient associated with the lower confidence interval, $\beta_{97.5\ \text{percentile}}$ is the Beta coefficient associated with the upper confidence interval, β is the Beta coefficient, and σ_β is standard error for the Beta coefficient. I performed calculations for each selected health endpoint with a dose-response value. I properly formatted the calculated coefficients in comma-separated values (CSV) files and, per consultation with BenMAP-CE staff, defined inputs for Metric, Seasonal Metric, and Metric Statistic as D24HourMean, QuarterlyMean, and Mean, respectively, to account for an annual calculation. Equation 5 (US EPA, 2023) describes the function used to calculate health impacts,

$$H = \left(1 - \frac{1}{e^{\beta \times \Delta Q}}\right) \times Incidence \times Population \times 365 \quad (5)$$

where H is the estimated health impact, β is the Beta coefficient, ΔQ is the change in air pollution from smoke $PM_{2.5}$ concentrations, Incidence is the daily incidence rate, Population is the population count, and 365 is used to adjust for an annual calculation with daily incidence rates. I imported the CSV files with the coefficients and health impact functions into BenMAP-CE.

Following successful importation of all required files into BenMAP-CE, I computed health impact assessments for each year within the study period for each dataset (11 years x 3 datasets), for a total of 33 runs. Figure 1 depicts an example of the BenMAP-CE interface during a sample run. For each health endpoint evaluated, I exported the health impact estimates as CSV files to later import and summarize in R. In R, I aggregated the health impact estimates across the overall study period and by year as well as across all census tracts to obtain a statewide estimate for each health endpoint and dataset. I visualized spatial distributions of one health endpoint by mapping health impact estimates aggregated across the overall study period at the census tract-level for each dataset.

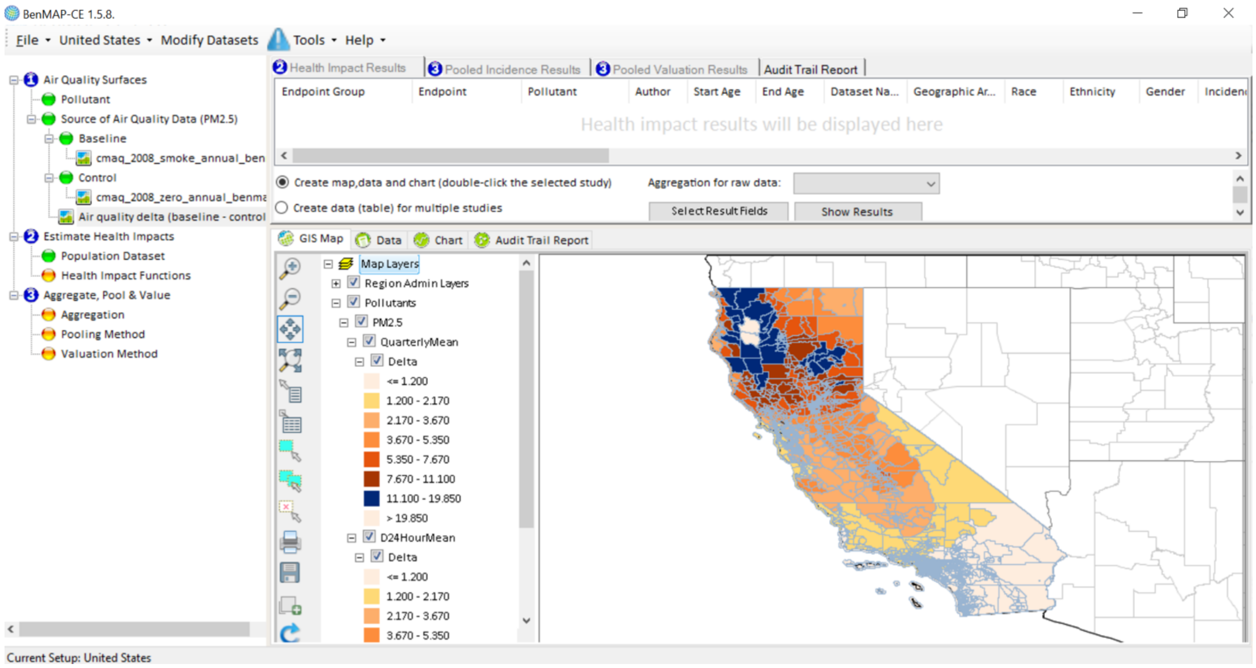


Figure 1. Sample demonstration of the health impact assessment in BenMAP-CE, using smoke estimates from the CMAQ dataset for 2008.

RESULTS

<u>Smoke exposure comparisons</u>

Statistical analysis

The mean value for the 2008-2018 average smoke $PM_{2.5}$ concentrations across all California census tracts were 1.15 μg/m^3, 0.40 μg/m^3, and 0.27 μg/m^3 for the CMAQ, Childs, and Casey datasets, respectively (Table 2). Mean values for the CMAQ dataset were greater than mean values for the Childs and Casey datasets for all years. Similarly, mean values for the Childs dataset were greater than mean values for the Casey dataset for all years; however, mean values between the Childs and Casey datasets were closer in magnitude, compared to mean values for the CMAQ dataset, which is likely due to the similar inputs used by these two datasets in their estimation of smoke $PM_{2.5}$. For all datasets, mean values were higher during high fire years (e.g., 2008, 2017, and 2018) and generally lower during low fire years (e.g., 2010-2012).

Table 2. Descriptive statistics of daily smoke $PM_{2.5}$ ($\mu g/m^3$) across all California census tracts for the overall study period (2008-2018) and stratified by year.

	CMAQ		**Childs**		**Casey**	
	Mean	SD	Mean	SD	Mean	SD
Year						
Overall	1.15	14.79	0.40	4.77	0.27	2.84
2008	2.43	9.39	0.88	1.37	0.70	4.43
2009	0.56	2.59	0.23	0.41	0.13	0.91
2010	0.31	1.77	0.04	0.47	0.03	0.35
2011	0.35	0.99	0.05	1.09	0.03	0.34
2012	0.39	1.20	0.11	1.49	0.06	0.79
2013	0.76	2.75	0.25	1.24	0.16	0.99
2014	0.47	4.23	0.15	1.58	0.08	0.84
2015	0.72	4.43	0.20	1.25	0.14	1.21
2016	1.06	24.91	0.29	4.10	0.21	0.96
2017	2.83	36.30	0.72	9.34	0.30	1.68
2018	2.75	17.66	1.51	3.57	1.14	7.69

Notes: SD = standard deviation

The Childs and Casey datasets were highly correlated for all years within the study period, with the largest Spearman correlation coefficient of 0.97 observed in 2018 (Table 3). In contrast, correlations between the CMAQ dataset with both the Childs and Casey datasets ranged from poor to moderate, with the largest Spearman correlation coefficient of 0.44 between CMAQ and Childs and 0.43 between CMAQ and Casey, both observed in 2018 (Table 3). Correlations between CMAQ with Childs and Casey were close in magnitude. Across all pairs of datasets, correlations were generally higher during high fire years (e.g., 2008 and 2018) and generally lower during low fire years (e.g., 2010-2012).

Table 3. Spearman correlation coefficients (ρ) of daily smoke $PM_{2.5}$ ($\mu g/m^3$) across all California census tracts, stratified by year.

	CMAQ, Childs	CMAQ, Casey	Childs, Casey
Year			
2008	0.38	0.39	0.89
2009	0.26	0.26	0.85
2010	0.13	0.12	0.86
2011	0.12	0.09	0.85
2012	0.17	0.15	0.87
2013	0.20	0.18	0.91
2014	0.19	0.17	0.89
2015	0.21	0.19	0.93
2016	0.37	0.36	0.96
2017	0.39	0.40	0.78
2018	0.44	0.43	0.97

Notes: All values are statistically significant (p-value < 0.05).

Across all California census tracts, the Kruskal-Wallis test yielded p-values <0.05 for the overall study period and all years within when stratified by year (Table S1). I rejected the null hypothesis of no differences in the mean ranks between the CMAQ, Childs, and Casey datasets, which suggests that at least one dataset has a different mean rank. Across all California census tracts, the Dunn test yielded p-values <0.05 for each pairwise comparison for the overall study period and all years within when stratified by year (Table S1). I rejected the null hypothesis of no differences in the mean ranks between each pairwise comparison, which suggests that all three datasets were statistically different from each other.

Across census tracts grouped by climate regions, the Kruskal-Wallis test yielded p-values <0.05 for the overall study period and all years within when stratified by year for all climate regions. This suggests that at least one dataset has a different mean rank for all climate regions. The Dunn test yielded p-values <0.05 for each pairwise comparison for the overall study period for all climate regions (Table S2). When stratified by year, p-values were <0.05 for a majority of the climate regions, years, and pairwise comparisons. This suggests that during most years and in most climate regions, all three datasets statistically differed from each other. Exceptions were observed between Childs and Casey, where p-values were >0.05 during 2008, 2010, 2011, and 2016 in the North Coast, Sierra Nevada Mountains, and Inland regions (Table S2). Additionally, the p-value was >0.05 during 2018 in the San Francisco Bay Area region between CMAQ and Childs. For these cases, I failed to reject the null hypothesis, suggesting that these pairs of datasets did not statistically differ from each other.

Spatial analysis

Spatial heterogeneity was observed in the 2008-2018 average smoke $PM_{2.5}$ concentrations across California census tracts within and between the datasets (Figure 2). Within each dataset, higher average smoke $PM_{2.5}$ concentrations were concentrated in Northern California census tracts, while moderate concentrations were observed in Central California census tracts (Figure 2). Between the datasets, the spatial distribution for CMAQ differed largely from the spatial distributions for Childs and Casey, with higher average concentrations for CMAQ and lower average concentrations for Childs and Casey. When stratified by year, there was spatial heterogeneity across each year, both within and between datasets (Figure S1). Exposure was mostly concentrated in Northern and Central California census tracts during most years. Generally, the variation was more easily observed for CMAQ, given the higher estimates from this dataset.

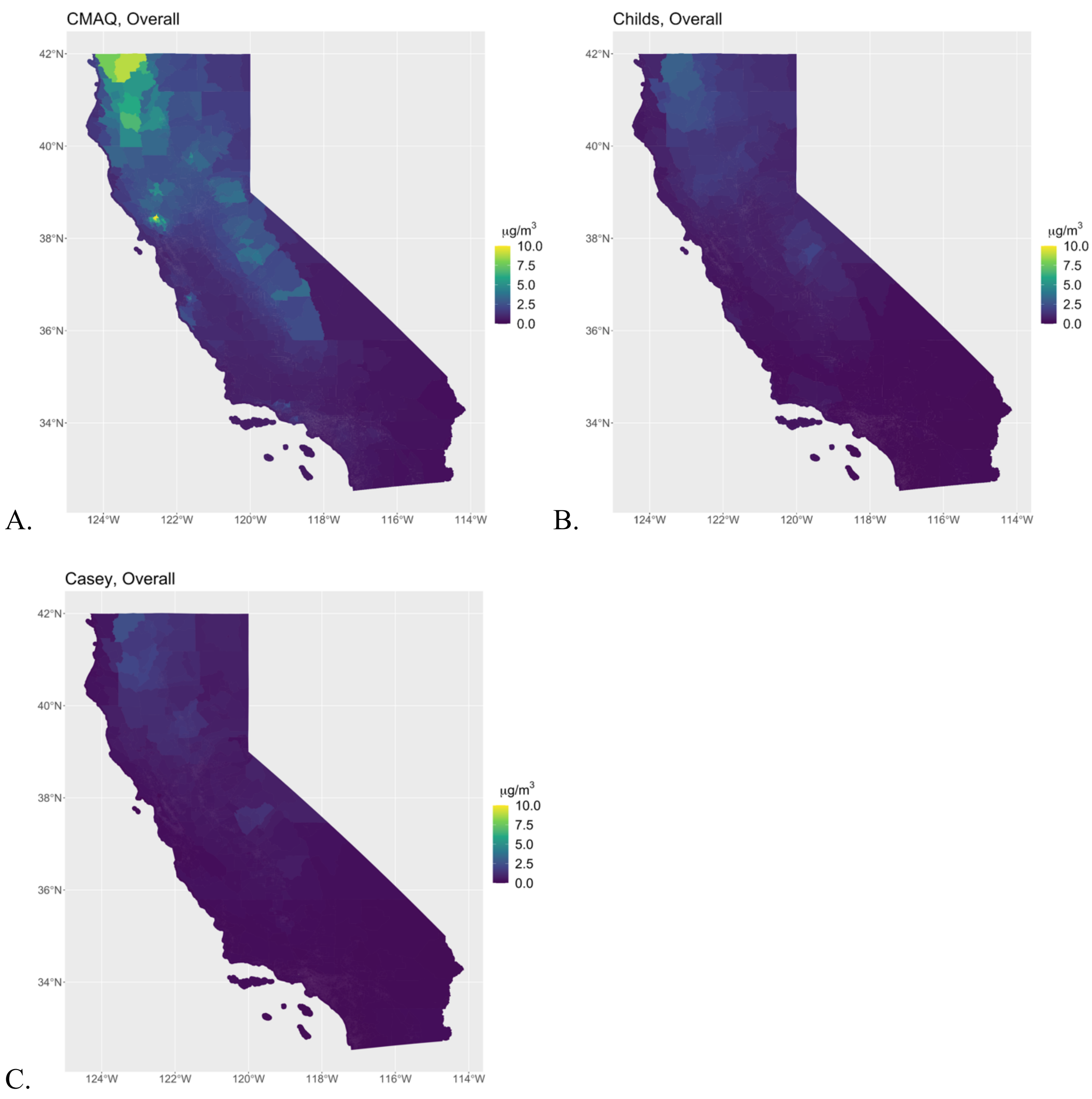
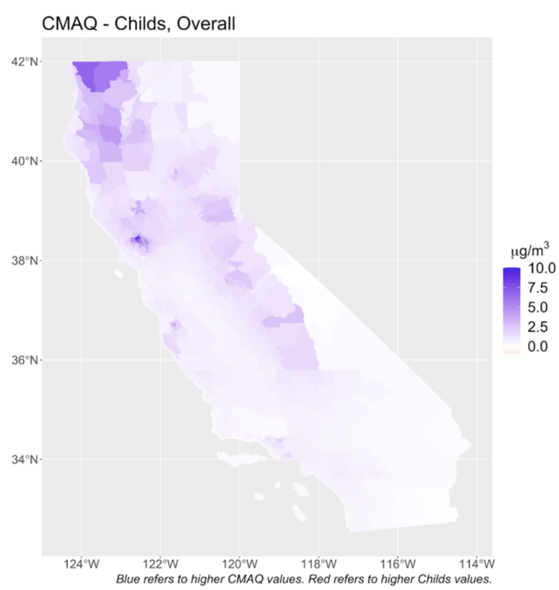
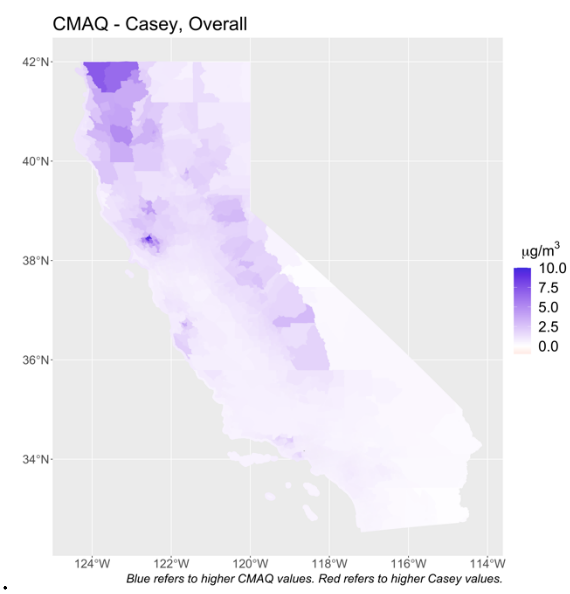


Figure 2. Spatial distribution of the 2008-2018 annual average smoke $PM_{2.5}$ ($\mu g/m^3$) at the census tract-level in California for each dataset.

Spatial heterogeneity was observed in the differences in the 2008-2018 average smoke $PM_{2.5}$ concentrations across California census tracts within and between the pairs of datasets (Figure 3). For each pair of datasets, differences were mainly observed in Northern and Central California census tracts, with larger differences in Northern California. Differences between Childs and Casey were small, with slightly higher estimates from Childs compared to Casey across several census tracts (Figure 3C). Differences between CMAQ with both Childs and Casey were larger (Figure 3A-B), with higher estimates from CMAQ across several census tracts, especially in Northern California. The spatial distribution of CMAQ and Childs and of CMAQ and Casey were relatively similar to each other but differed from the spatial distribution of Childs and Casey. When stratified by year, there was spatial heterogeneity in the differences across each year, both within and between datasets (Figure S2). Generally, CMAQ had higher estimates across several census tracts in all years except for in 2012, where both Childs and Casey had higher estimates in some Northern California census tracts (Figure S2).



A.



B.

C.

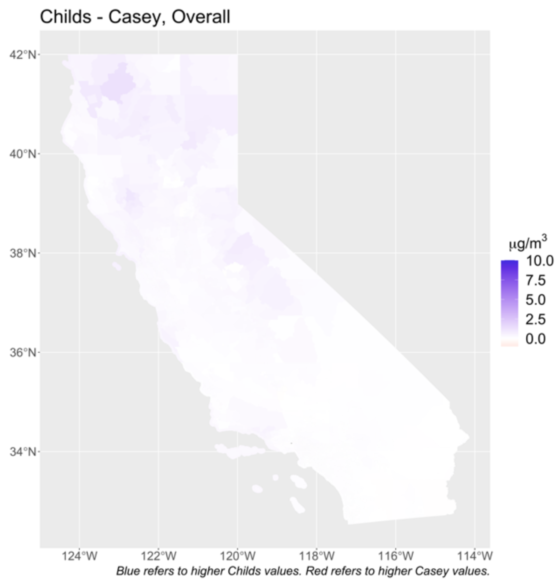


Figure 3. Spatial distribution of the differences in 2008-2018 annual average smoke $PM_{2.5}$ ($\mu g/m^3$) at the census tract-level in California for each dataset.

Notes: Blue refers to higher values for the former dataset, and red refers to higher values for the latter dataset.

Temporal analysis

During the study period, average smoke $PM_{2.5}$ concentrations across all California census tracts varied between datasets over time (Figure 4). There was more agreement in the temporal trends between Childs and Casey, with lower average concentrations consistently observed over time for these two datasets compared to CMAQ. Across all datasets, peaks in average concentrations were observed during summer months, which coincides with the typical fire season (Figure 4). The highest peaks in average concentrations were observed during high fire years in 2008, 2017, and 2018 (Figure 4) for all datasets, but with particularly high peaks for CMAQ during these years.

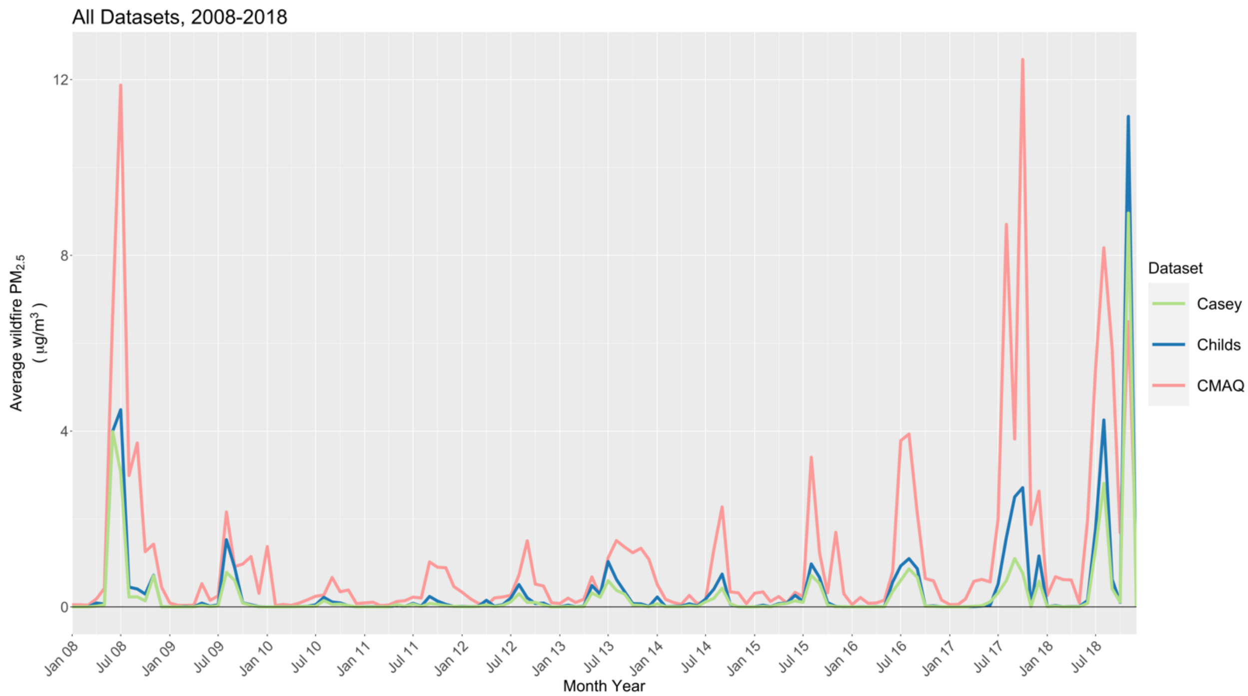
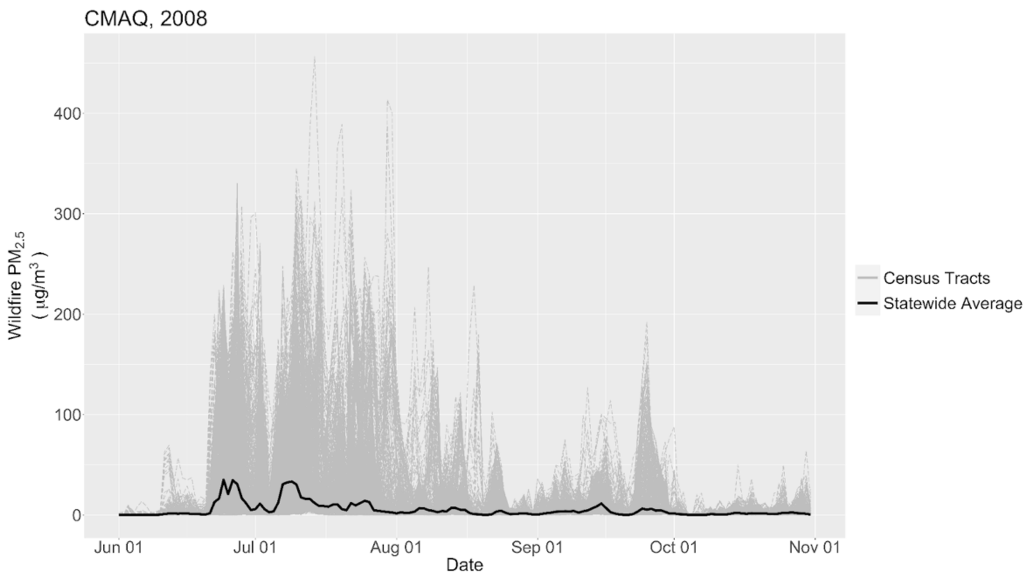


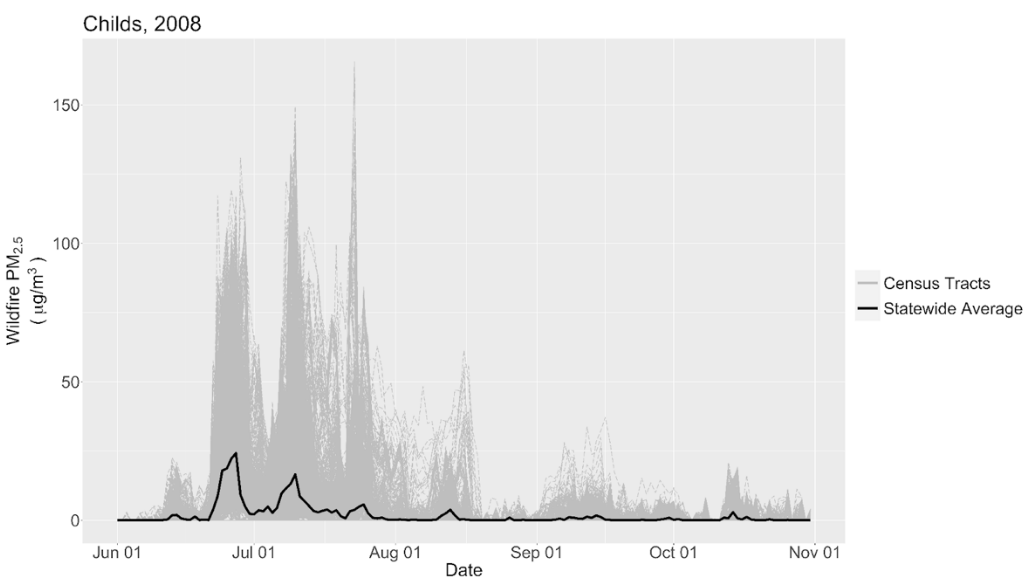
Figure 4. Temporal distribution of the 2008-2018 monthly average smoke $PM_{2.5}$ (µg/m^3) across California census tracts for each dataset.

The daily temporal analysis was focused on 2008 due to the large wildland fire activity, particularly in Northern California, during that year, with over 6,000 fires burning over 1,500,000 acres across the state (CAL FIRE, 2020). During the fire season of 2008, daily smoke $PM_{2.5}$ concentrations varied temporally within and between datasets (Figure 5). For all datasets, daily concentrations across census tracts were highest during July and August, compared to other fire season months, which coincides with the timing of several large wildland fires (Figure 5). Additionally, the statewide average smoke $PM_{2.5}$ concentration for all datasets remained relatively low compared to daily concentrations from individual census tracts, suggesting that averaging estimates statewide can mask high concentrations observed in several census tracts. The magnitude and temporal distribution of concentrations from Childs and Casey were similar, with some higher concentrations observed for Casey in late June and mid-October compared to

Childs (Figure 5B-C). Though the temporal distribution of concentrations from CMAQ was relatively similar to the other two datasets, the magnitude largely differed, with high concentrations reaching over 400 μg/m^3 in some census tracts (Figure 5A).



A.



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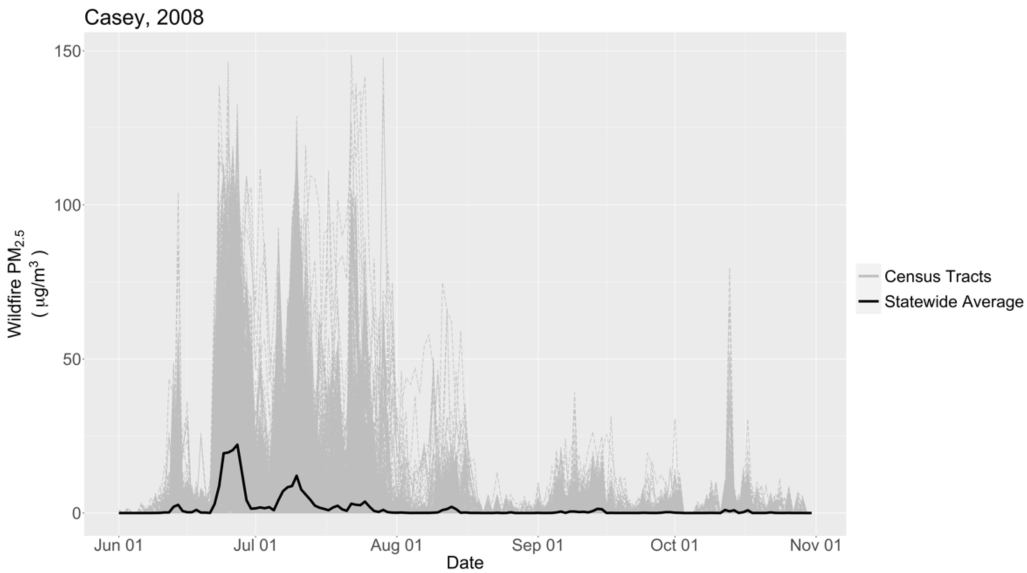
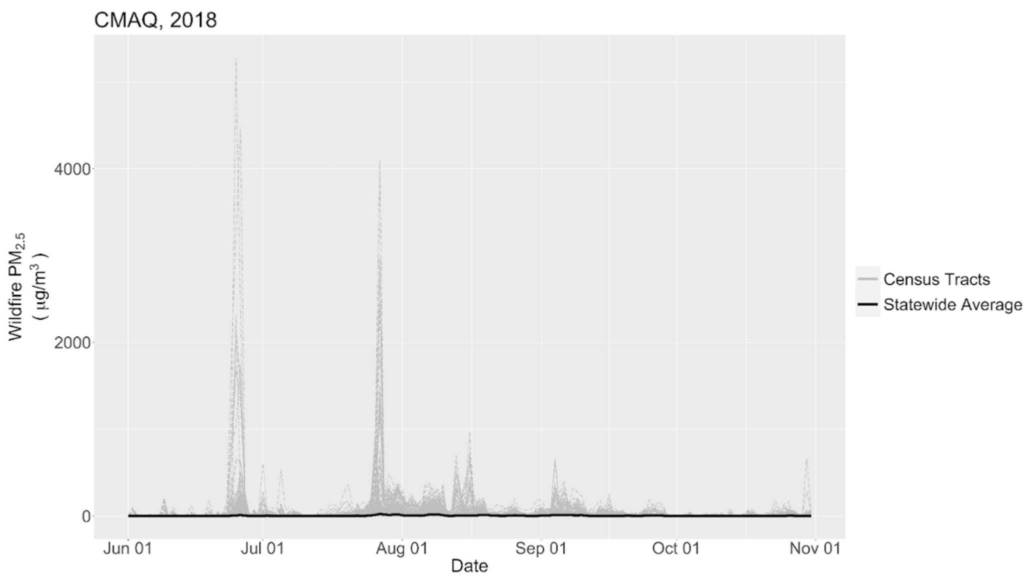


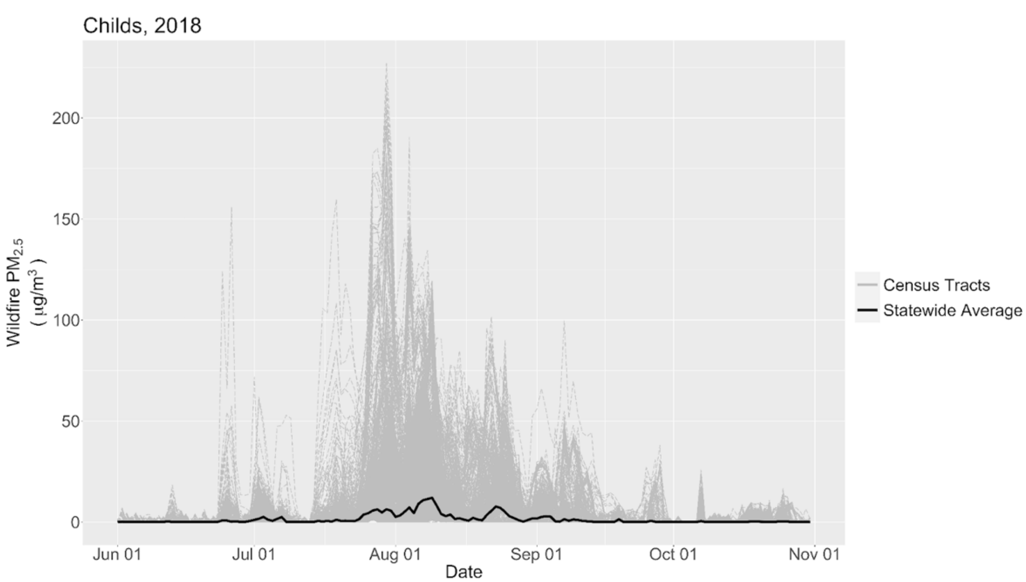
C.

Figure 5. Temporal distribution of daily smoke $PM_{2.5}$ (µg/m^3) for all California census tracts and the daily statewide average smoke $PM_{2.5}$ (µg/m^3) for each dataset, during the fire season (June to October) of 2008. Note change in scale on y-axis.

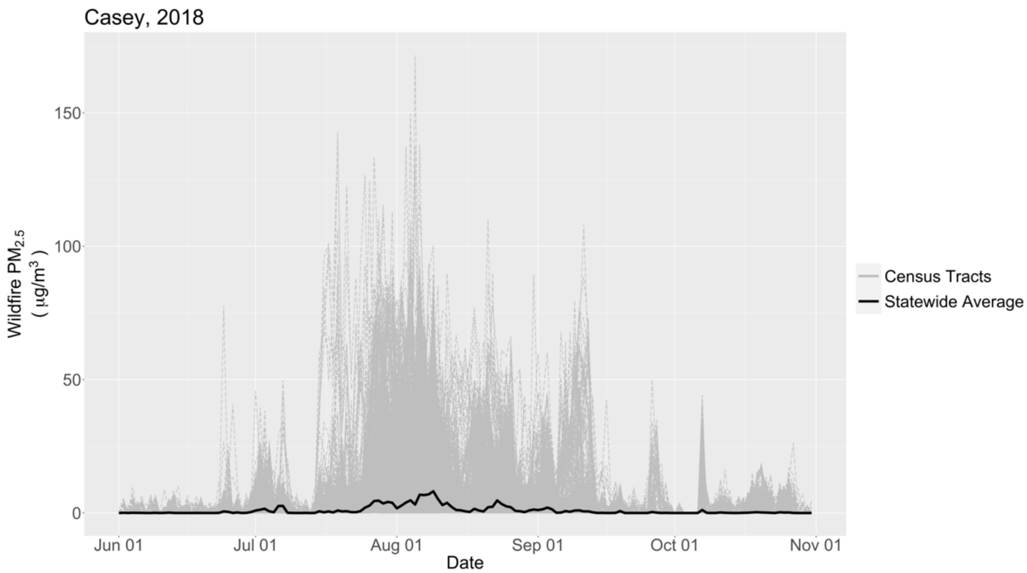
Similarly, the daily temporal analysis was also focused on 2018 since California experienced large wildland fire activity during this year, with close to 8,000 fires burning nearly 2,000,000 acres statewide (CAL FIRE, 2020). Daily smoke $PM_{2.5}$ concentrations also varied temporally within and between datasets during the fire season of 2018 (Figure 6). Similar to 2008, the statewide average smoke $PM_{2.5}$ concentration for all datasets was low compared to daily concentrations from individual census tracts. For Childs and Casey, the magnitude and temporal distribution of concentrations were relatively similar, and concentrations were highest during August and September, when wildland fire activity was greatest. Minor differences between the two included higher concentrations reaching over 200 µg/m^3 during late July and early August in some census tracts for Childs and higher concentrations during September and early October in some census tracts for Casey (Figure 6B-C). Both the magnitude and temporal distribution of concentrations for CMAQ largely differed from the other two. Extremely high concentrations reaching over 4000 μg/m^3 in some census tracts were observed in late June and late July, which is approximately 20 times larger than the highest concentrations from Childs and Casey (Figure 6A). These high concentrations masked the variation in the temporal distribution of the statewide average and other census tracts.



A.



B.



C.

Figure 6. Temporal distribution of daily smoke $PM_{2.5}$ (µg/m^3) for all California census tracts and the daily statewide average smoke $PM_{2.5}$ (µg/m^3) for each dataset, during the fire season (June to October) of 2018. Note change in scale on y-axis.

Health impact assessment

Literature review

The updated literature review yielded 26 articles that passed the first inclusion criterion, with most articles based in the US and eight articles based in California, specifically (Table S3). The articles evaluated wildland fire smoke effects across a range of respiratory health outcomes among elderly populations, including asthma, COPD, bronchitis, pneumonia, respiratory tract infections, and more.

Most articles assessed wildland fire smoke exposure through $PM_{2.5}$ as the primary pollutant, though some articles did examine PM_{10} or smoke plumes. $PM_{2.5}$ concentrations were obtained from a range of approaches, including both monitoring data and various chemical transport models, such as CMAQ, the Weather Research and Forecasting with Chemistry model (WRF-Chem), and the Goddard Earth Observing System model (GEOS-Chem) (Gan et al., 2017;

Heaney et al., 2022; Stowell et al., 2019). Other approaches included kriging of monitoring data and geographically weighted regression that combines monitoring and satellite data and simulated estimations from chemical transport models (Gan et al., 2017; Le et al., 2014). The wide range of smoke exposure estimation methods across articles highlights the possibility of variation in health risk and impact estimates based on the method used. To evaluate associations between smoke exposure and health outcomes, the articles defined smoke $PM_{2.5}$ in several ways. Many articles developed a binary indicator to compare outcomes on smoke days versus non-smoke days, with smoke days defined by $PM_{2.5}$ concentrations exceeding a certain threshold, which varied across articles. Some articles determined different exposure periods, such as pre-, post-, and during wildland fire periods, to compare risk of outcomes across periods. Several articles investigated the effects of smoke $PM_{2.5}$ exposure on outcomes through concentration response functions, estimating risk per increment of exposure. Lag periods, of both single days and moving averages, were also considered across many articles.

Increased risk of all respiratory (or respiratory disease), asthma, bronchitis, and pneumonia outcomes with exposure to wildland fire smoke among elderly populations was consistent across most articles, with the largest effects observed for asthma. Some articles did find decreased risk at certain lags and within certain age groupings among the elderly population; however, at other lags and other age groupings, increased risk was observed (Doubleday et al., 2023; Hahn et al., 2021; Kollanus et al., 2016; Le et al., 2014; Tinling et al., 2016). Despite a general consensus of increased risk for bronchitis and pneumonia effects, less than half of the total articles assessed these outcomes, which could be due to several reasons including incomplete or inadequate health data or low prevalence of these outcomes among the elderly in certain areas. Results for COPD among the elderly were more inconsistent, with some articles observing increased risk and others finding decreased risk. Inconsistencies could be due to methodological differences, such as in the exposure assessment or statistical analysis, or due to regional differences in wildland fire activity or COPD prevalence. Future studies should consider focusing on COPD, bronchitis, pneumonia, and other less commonly studied respiratory outcomes, such as upper respiratory infections, to strengthen the evidence base for these outcomes.

Overall, evidence from the literature suggests an increased risk of respiratory morbidity among elderly populations from wildland fire smoke exposure, with stronger evidence for certain respiratory outcomes. However, the evidence could be further strengthened as some articles did not find a statistically significant positive association. The results of the literature review highlight the elderly as a highly susceptible group that shoulders increased respiratory health burdens from wildland fire smoke exposure.

Selection of elderly-specific dose-response value

In selecting an elderly-specific dose-response value, 21 articles of the total 26 articles did not satisfy the second set of inclusion criteria and were subsequently excluded. This yielded five articles to potentially select dose-response values from. Table 4 provides a summary of the study information from the five articles.

Table 4. Selected articles from the updated literature review to potentially extract elderly-specific dose-response values from.

Author	*Article Title*	*Study Year*	*Study Area*	*Age Range*	*Exposure Characterization*	*Health Outcomes*	*Medical Care Type*
(Delfino et al., 2009)	The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003	2003	Southern California, USA	65-99	2-day moving average $PM_{2.5}$ concentration for (1) a continuous concentration response function of 10 μg/m^3 change, and for (2) pre-, during, and post-wildland fire periods	All respiratory*; asthma*; COPD; acute bronchitis and bronchiolitis*; pneumonia*	HA
(Duncan et al., 2023)	Acute Health Effects of Wildfire Smoke Exposure During a Compound Event: A Case-Crossover Study of the 2016 Great Smoky Mountain Wildfires	2016	North Carolina, USA	55+	Daily 24-hour mean $PM_{2.5}$ concentration for a continuous concentration response function of 5 μg/m^3 change for wildland fire smoke days (defined as days with $PM_{2.5}$ concentrations >20.4 μg/m^3)	All respiratory*; asthma*; COPD*; bronchitis*; emphysema*	ER/ER
(Hahn et al., 2021)	Wildfire Smoke Is Associated With an Increased Risk of Cardiorespiratory Emergency	2015-2019	Alaska, USA	65+	Daily 24-hour average smoke $PM_{2.5}$ concentration for a continuous concentration response function of 10 μg/m^3 change	All respiratory; asthma*; COPD; bronchitis; pneumonia	ED/ER

	Department Visits in Alaska						
(Reid, Jerrett, et al., 2016)	Differential respiratory health effects from the 2008 northern California wildfires; a spatiotemporal approach	2008	Northern California, USA	65+	2-day moving average (prior to admissions and does not include admission date) from daily 24-hour average $PM_{2.5}$ concentration for a continuous concentration response function of 5 μg/m^3 change	All respiratory*; asthma*; COPD; pneumonia	ED/ER; HA
(Thilakaratne et al., 2023)	Wildfires and the Changing Landscape of Air Pollution-related Health Burden in California	2008-2016	California, USA	65+	Daily 24-hour mean $PM_{2.5}$ concentration on all days and wildland fire smoke days for a continuous concentration response function of 10 μg/m^3 change	Respiratory*; asthma*; COPD	ED/ER; HA

*Notes: * denotes at least one statistically significant dose-response values found for the specified health outcome. COPD = chronic obstructive pulmonary disease; ED = emergency department; ER = emergency room; HA = hospitalization*

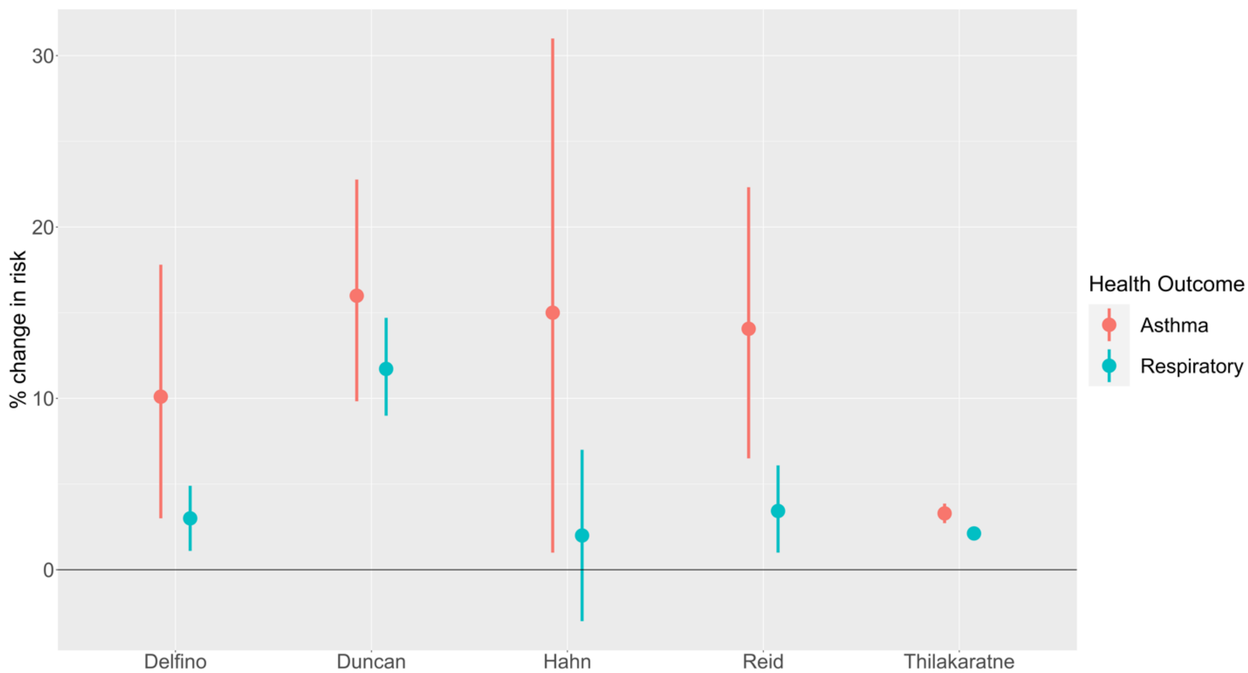


Figure 7. Distribution of elderly-specific dose-response values for respiratory and asthma outcomes from selected articles, presented as a percentage change in risk and 95% CI per 10 µg/m^3 change of smoke $PM_{2.5}$ exposure.

Notes: Dose-response values for lag 0 were selected if multiple lags were provided. Dose-response values for ED/ER visits were selected for all articles, aside from Delfino et al., in which only dose-response values for hospitalizations were provided. Dose-response values from Duncan et al. only apply to smoke $PM_{2.5}$ *above 20.4 µg/m*^{3}.

Of the five articles, I prioritized articles based in California, which included Delfino et al., Reid et al., and Thilakaratne et al. While Reid et al. and Thilakaratne et al. examined both respiratory hospitalizations and ED/ER visits (Reid, Jerrett, et al., 2016; Thilakaratne et al., 2023), Delfino et al. only focused on respiratory hospitalizations (Delfino et al., 2009). ED/ER visits generally occur more often than hospitalizations (National Center for Health Statistics, n.d., 2021); consequently, omitting ED/ER visits could inadvertently underestimate the magnitude of health impacts. Additionally, Delfino et al. assessed smoke exposure in 2003 (Delfino et al., 2009), which falls outside of the study period for this study. For these reasons, I removed Delfino et al. from consideration.

Of the two remaining articles, Thilakaratne et al. assessed smoke exposure and health impacts across California between 2008 and 2016 (Thilakaratne et al., 2023). Reid et al. focused their analysis on only Northern California during 2008 (Reid, Jerrett, et al., 2016). Since the study by Thilakaratne et al. spanned a longer time frame across the entire state, and thus provided estimates that would better align with the study area and period of this study, I selected elderly-specific dose response values from Thilakaratne et al. for the main analysis. However, I considered elderly-specific dose-response values from Reid et al. in a sensitivity analysis.

Elderly-specific dose-response values for respiratory and asthma hospitalizations and ED/ER visits were extracted from Thilakaratne et al. and Reid et al. (Table 5). All elderly-specific dose-response values were statistically significant, with the exception of the respiratory hospitalization estimate from Reid et al., which was near statistical significance.

Table 5. Extracted elderly-specific dose-response values for selected respiratory outcomes from smoke $PM_{2.5}$ exposure from Thilakaratne et al. and Reid et al.

BenMAP-CE Health Endpoint	***BenMAP-CE ICD-9 Codes***	***Article Author***	***Article ICD-9 Codes***	***Article Increment Change in $PM_{2.5}$***	***Article Dose-Response Type***	***Article Dose-Response Values***
ER visits, Respiratory	491-493, 460-466, 477.0-477.9, 480-486, 496, 786.07, 786.09	Thilakaratne et al.	493, 491-492, 496, 480-486, 786	10 µg/m^3	% change in risk	2.12 (95% CI: 1.82, 2.41)
		Reid et al.	493, 496, 491–492, 480–486	5 µg/m^3	RR	1.017 (95% CI: 1.005, 1.030)
ER visits, Asthma	493	Thilakaratne et al.	493	10 µg/m^3	% change in risk	3.29 (95% CI: 2.72, 3.86)
		Reid et al.	493	5 µg/m^3	RR	1.068 (95% CI: 1.032, 1.106)
HA, Respiratory illness-1	466, 480-486, 490-493	Thilakaratne et al.	493, 491-492, 496, 480-486, 786	10 µg/m^3	% change in risk	1.27 (95% CI: 1.06, 1.48)
		Reid et al.	493, 496, 491–492, 480–486	5 µg/m^3	RR	1.014 (95% CI: 0.999, 1.030)
HA, Asthma	493	Thilakaratne et al.	493	10 µg/m^3	% change in risk	1.57 (95% CI: 1.10, 2.05)
		Reid et al.	493	5 µg/m^3	RR	1.067 (95% CI: 1.021, 1.116)

Notes: ER = emergency room; HA = hospitalization; ICD = International Classification of Disease; $PM_{2.5}$ = fine particulate matter; RR = relative risk; CI = confidence interval

Estimation of health impacts

Using annual smoke estimates from the CMAQ, Childs, and Casey datasets, smoke $PM_{2.5}$ exposure contributed to 5,482, 1,965, and 1,337 respiratory hospitalizations and ED/ER visits among elderly populations between 2008 and 2018, respectively (Table 6). As for asthma, 867, 310, and 210 asthma hospitalizations and ED/ER visits among the elderly are attributable to smoke $PM_{2.5}$ exposure between 2008 and 2018 using smoke estimates from CMAQ, Childs, and Casey, respectively (Table 6). For both respiratory and asthma outcomes, health impacts estimated using smoke concentrations from Childs and Casey were closer in magnitude and smaller compared to health impacts estimated using smoke concentrations from CMAQ. These results align with my observations from the smoke exposure comparisons, in which smoke estimates from Childs and Casey were similar and smaller in magnitude than those from CMAQ.

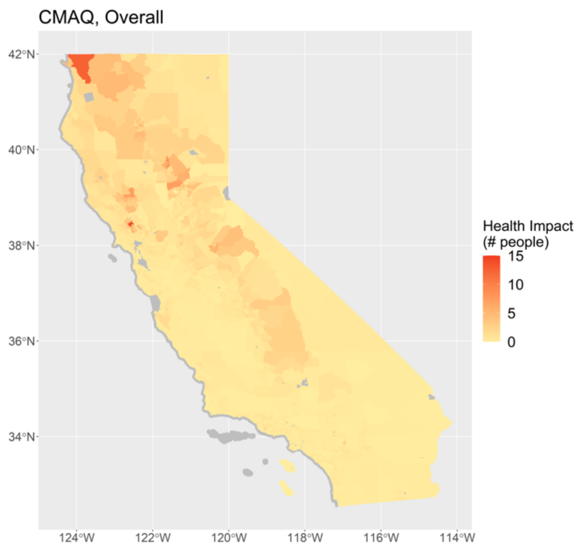
The sensitivity analysis using dose-response values from Reid et al. found larger health impact estimates but still retained similar patterns across the datasets as the main analysis. Health impact estimates for both respiratory and asthma outcomes were more similar when using Childs and Casey smoke estimates, and they were larger when using CMAQ smoke estimates (Table 6). The overall larger health impact estimates observed in the sensitivity analysis could likely be explained by the larger dose-response values from Reid et al. compared to those from Thilakaratne et al., who found more conservative effects. Notably, the lower CI of respiratory hospitalization estimates for Reid et al. were negative, likely because the lower CI of the RR values from Reid et al. were less than 1.

Spatial heterogeneity was observed in the respiratory ED/ER health impacts among elderly populations attributable to smoke $PM_{2.5}$ across California census tracts within and between datasets (Figure 8). Larger health impacts were concentrated in Northern California census tracts, with moderate health impacts concentrated in some Central California census tracts (Figure 8). The distribution of health impacts was consistent with the spatial distribution of smoke exposures, implying that larger health impacts were observed in similar regions where smoke exposures were observed. Variations in health impacts were more easily observed for CMAQ, given the larger health impacts estimated from this dataset.

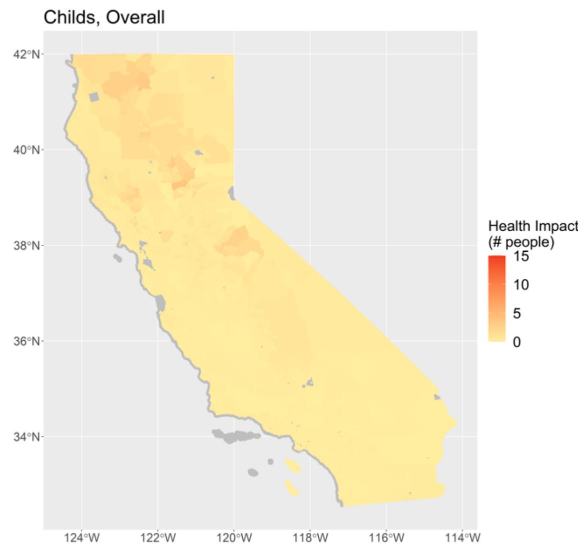
As for trends in health impact estimates over time, larger respiratory and asthma health impacts were observed during high fire years (e.g., 2008, 2017, and 2018), regardless of the dataset (Figure 9). During high fire years, the differences in health impact estimates were larger between the datasets, particularly between CMAQ with Childs and Casey, compared to low fire years (e.g., 2010-2012) where the differences were smaller (Figure 9). The rank order of the top three years with the largest health impacts were identical between Childs and Casey, with 2018 as the year with the most health impacts across all outcomes, followed by 2008 and 2017. The rank order for CMAQ differed slightly, with 2017 ranked as the highest for asthma ED/ER visits and hospitalizations, 2018 ranked as the highest for respiratory hospitalizations, and 2017 and 2018 tied as the highest for respiratory ED/ER visits (Figure 9). Trends in the estimates over time for all health outcomes in the sensitivity analysis were similar to trends observed in the main analysis; however, the CI for the estimates were wider, notably for CMAQ, when using dose-response values from Reid et al. compared to Thilakaratne et al.

Table 6. Respiratory health impact estimates and 95% CI among elderly populations attributable to smoke $PM_{2.5}$ ($\mu g/m^3$) across all California census tracts for the overall study period (2008-2018).

	Respiratory			Asthma		
	ED/ER	HA	Total	ED/ER	HA	Total
Thilakaratne et al.						
CMAQ	4,102	1,380	5,482	707	160	867
	(3,526–4,657)	(1,148–1,604)	(4,674–6,261)	(584–825)	(111–207)	(695–1,032)
Childs	1,482	483	1,965	255	55	310
	(1,273–1,682)	(402–561)	(1,675–2,243)	(211–298)	(38–71)	(249–369)
Casey	1,009	328	1,337	173	37	210
	(867–1,146)	(273–382)	(1,140–1,528)	(143–202)	(26–48)	(169–250)
Reid et al.						
CMAQ	6,572	3,031	9,603	2,814	1,305	4,119
	(1,674–11,236)	(-386–6,278)	(1,288–17,514)	(1,316–4,221)	(394–2,158)	(1,710–6,379)
Childs	2,378	1,062	3,440	1,027	453	1,480
	(603–4,079)	(-135–2,208)	(468–6,287)	(476–1,551)	(136–755)	(612–2,306)
Casey	1,620	723	2,343	698	305	1,003
	(411–2,779)	(-91–1,503)	(320–4,282)	(323–1,055)	(91–509)	(414–1,564)



A.



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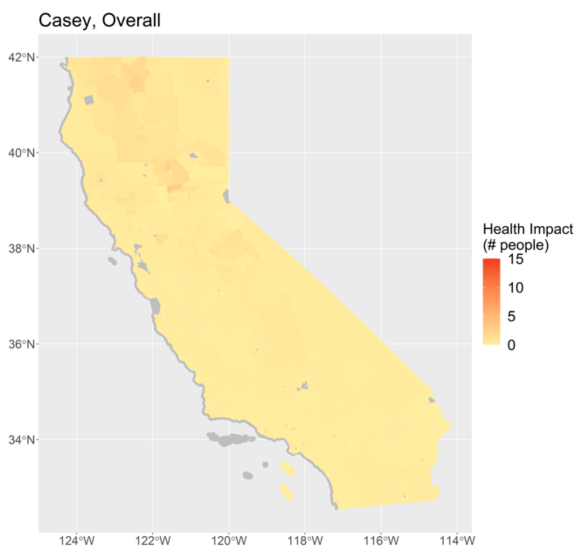


C.

Figure 8. Spatial distribution of respiratory ED/ER health impacts among elderly populations attributable to smoke $PM_{2.5}$ ($\mu g/m^3$) at the census tract-level in California for each dataset for the overall study period (2008-2018), using dose-response values from Thilakaratne et al.

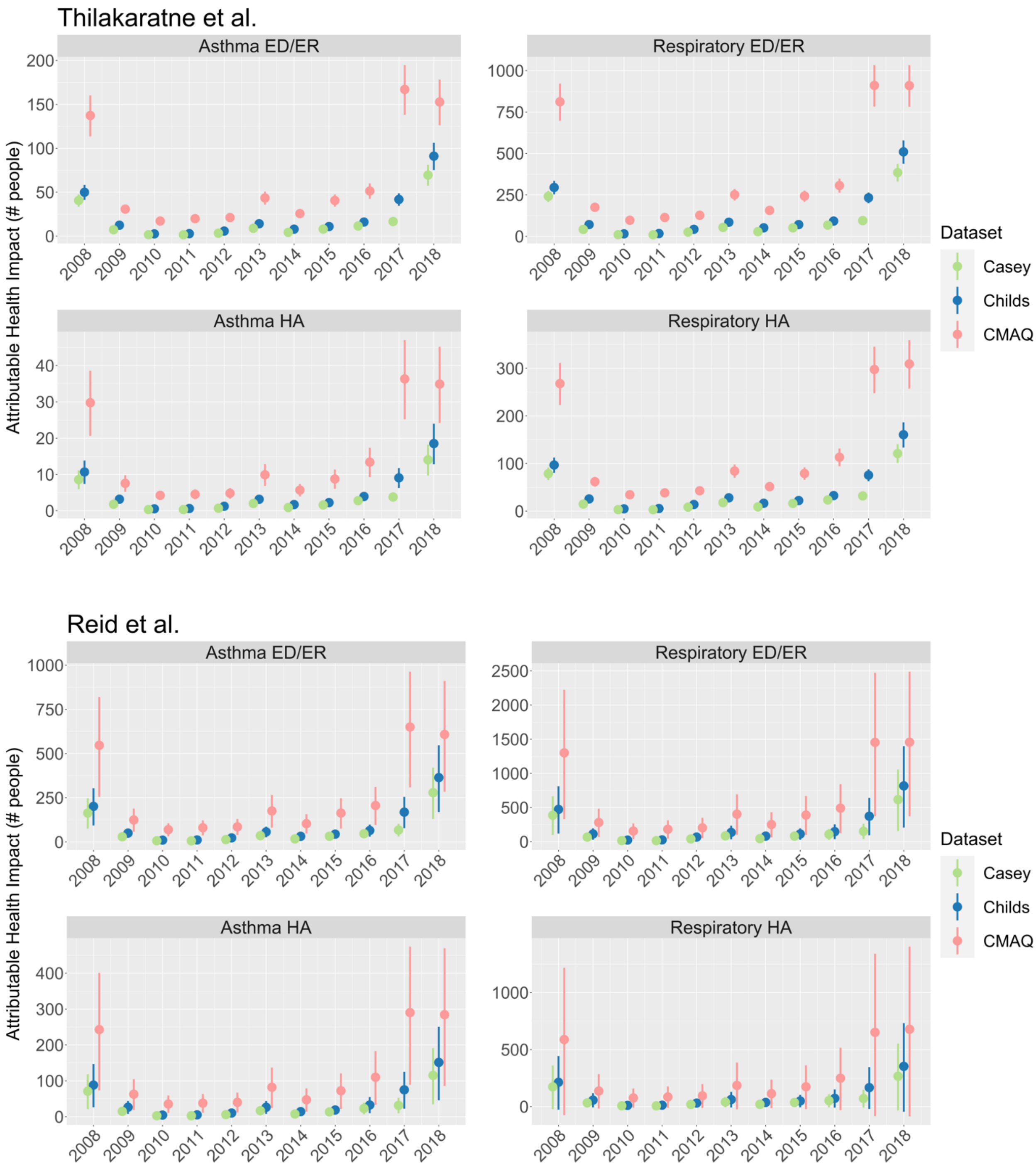


Figure 9. Respiratory health impact estimates and 95% CI among elderly populations attributable to smoke $PM_{2.5}$ ($\mu g/m^3$) across all California census tracts, stratified by year.

DISCUSSION

This study compared smoke $PM_{2.5}$ estimates between three different smoke datasets using various statistical, spatial, and temporal analysis techniques to understand the variation in smoke estimates across datasets. Then, I quantified respiratory health burdens attributable to smoke $PM_{2.5}$ exposure among elderly populations in California using smoke $PM_{2.5}$ estimates from the three datasets and compared these burdens to assess the variation in health impact estimates across datasets. I observed three main findings. First, larger correlations, smaller differences in spatial distributions, and similar temporal trends were observed between the Childs and Casey datasets, suggesting greater agreement between the two compared to CMAQ, which is expected since these two rely on similar input datasets. Smoke estimates from CMAQ were much larger in magnitude compared to Childs and Casey, with daily concentrations in some census tracts surpassing 400 $\mu g/m^3$ in 2008 and 4000 $\mu g/m^3$ in 2018. These extremely large smoke estimates are likely unrealistic and overpredictions of the CMAQ model, which the authors discussed tends to occur with atypical fire events, e.g. with megafires that occurred during 2008 and 2018, in their model performance evaluation (Wilkins et al., 2018). Modest differences did exist between Childs and Casey, including statistically significance differences observed across most climate regions during most years and differences in spatial distributions during some years, but these differences were smaller compared to differences observed with CMAQ.

Second, across all smoke datasets, approximately 1,300 to 5,400 respiratory hospitalizations and ED/ER visits and approximately 200 to 860 asthma hospitalizations and ED/ER visits among the elderly are attributable to smoke $PM_{2.5}$ in California from 2008 to 2018. The magnitude of health impacts was lower for asthma outcomes, which is expected since asthma represents only one of several respiratory outcomes. Fann et al. quantified respiratory hospitalizations for all ages attributable to smoke $PM_{2.5}$ in the US from 2008 to 2012 (Fann et al., 2018). Though the authors did not estimate health impacts in California specifically, they did emphasize that California, along with other Western US states, was particularly affected by severe wildland fires during this period. Fann et al. estimated 32,600 respiratory hospitalizations attributable to smoke $PM_{2.5}$ using dose-response values from Delfino et al. (Fann et al., 2018). Given that the elderly population represented around 13% of the total US population during this period (US Department of Health and Human Services, 2013), approximately 4,200 respiratory hospitalizations among the elderly would have been attributable across the nation between 2008 to 2012, compared to this study's estimate of approximately 300-1,400 respiratory hospitalizations in California between 2008 to 2018. These results underscore the elderly population as a highly susceptible group burdened by adverse respiratory health impacts as a result of wildland fire smoke exposure.

Third, health impact estimates differed based on the specific smoke dataset used. Attributable respiratory hospitalizations and ED/ER visits using smoke estimates from Childs and Casey were both around a magnitude of 1,000, while attributable respiratory hospitalizations and ED/ER visits using smoke estimates from CMAQ were around a magnitude of 5,000. These results mirrored patterns observed from the smoke exposure comparisons, with more agreement in both smoke and health impact estimates from Childs and Casey compared to CMAQ, which yielded larger estimates. Additionally, the sensitivity analysis estimated larger respiratory health impacts, which ranged from approximately 2,300 to 9,600, highlighting the dependency of estimates on the dose-response value selected as well.

Similarities in both smoke and health impact estimates between Childs and Casey are likely due to both groups' use of similar exposure estimation methods. Both groups employed machine learning techniques to predict smoke $PM_{2.5}$ concentrations, basing their models on $PM_{2.5}$ monitoring data from the US EPA and incorporating similar explanatory variables, such as smoke plume data from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS), aerosol optical depth measurements from Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-Angle Implementation of Atmospheric Correction (MAIAC) data, and land cover data from the National Land Cover Database (NLCD) (Aguilera et al., 2023; Childs et al., 2022). As such, the Childs and Casey datasets are not entirely independent, which explains the expected higher agreement observed between the two. Additionally, smoke estimates from Childs and Casey were provided at the census-tract level, while estimates from CMAQ were calculated at a 12-km grid, a much larger spatial resolution. Similarities in Childs and Casey's native spatial resolutions, compared to CMAQ, could have also contributed to the observed patterns across smoke and health impact estimates.

The dependency of health impact estimates on the smoke dataset used has over-arching implications for epidemiological studies or health impact assessments that select one dataset over another. Health impact or risk estimates quantified using a certain smoke dataset may differ with estimates derived from analyses conducted with a different dataset. Though the magnitude of discrepancies in this study was on the order of a few thousand, the potential for larger discrepancies in estimates from other health outcomes and within other vulnerable groups should not be overlooked. Since estimates were also dependent on the dose-response value selected from the literature, differences observed from using different dose-response values also contribute to an additional uncertainty factor when assessing health impacts. Approaches to potentially address this uncertainty could include using dose-response values from meta-analyses that pull effect estimates from multiple studies into a single dose-response, or pooling the health impact estimates calculated using dose-response values from different studies within BenMAP-CE. Additionally, the use of a near statistically significant dose-response for respiratory hospitalizations in the sensitivity analysis generated negative health impacts for the lower CI, which cannot feasibly occur in real-world situations and thus, undermines our confidence in these results.

Despite the discrepancies in the magnitude of the estimates, the trends in health impacts over time remained consistent across datasets, with larger health impacts observed during high fire years. Of these high fire years, the largest health impacts were observed in 2018, followed by 2008 and 2017, for smoke estimates from Childs and Casey, with slight differences in the rank order for CMAQ. These results suggest that though the magnitude of health impacts may be influenced by particular datasets, the trends in health impacts over time are robust regardless of the dataset. Moreover, years with increased fire activity clearly contribute to more respiratory health burdens.

The implications of differences in health impact estimates can extend beyond the scope of empirical studies and influence policy as well. Government agencies, policymakers, community organizations, and various stakeholders may utilize findings from empirical studies to inform decision-making and policy development (D’Evelyn et al., 2022; Strydom et al., 2010). Additionally, researchers could motivate change in policy through their research (D’Evelyn et al., 2022). Different health impact and risk estimates can influence major public health policies and guidelines that use these estimates as a basis of evidence. However, confirming the accuracy of a health impact estimate or smoke dataset over another remains challenging. To minimize potential discrepancies in health impact estimates, researchers could explore exposure estimates from multiple smoke datasets as sensitivity analyses. Beyond this, researchers may need to carefully consider the implications of selecting certain datasets over others.

The estimated respiratory health impacts attributable to smoke exposure among elderly populations in California highlight the health burdens that wildland fires can impose on highly susceptible populations. These estimates only consider elderly individuals admitted under a respiratory-related hospitalization or ED/ER visit, which likely underestimates the true health burden if more elderly individuals experienced respiratory symptoms but decided not to seek out healthcare. Healthcare avoidance among the elderly could be due to various underlying reasons, such as high health insurance costs, negative feelings about the healthcare system, distrust of doctors, or fear of having a serious illness (Leyva et al., 2020). Generally, the results of this study were consistent with other studies that estimated increased risk of respiratory health outcomes due to smoke exposure among the elderly (Barros et al., 2023; Chen et al., 2023; Delfino et al., 2009). These health burdens could be further heightened as the elderly are often not prepared for disasters and may not be aware of or have access to resources when disasters appear (Carlson et al., 2024).

Increasing knowledge of and access to necessary resources during wildland fire events is critical to reducing health burdens among the elderly. Since many elderly individuals tend to be socially isolated or live alone (Cudjoe et al., 2020) and may suffer from pre-existing health complications, governments and community organizations could implement programs to check up on the elderly during wildland fire events and assist them with evacuations as needed (Carlson et al., 2024). Additional strategies include supporting transportation needs among the elderly, who may have limited mobility or scarce access to reliable transportation, through ride-sharing programs (Rhoades et al., 2021) and equipping the elderly with resources needed to call for emergency assistance. Efforts to partner with senior centers and organizations that work closely with the elderly may be helpful to increase knowledge of resources among this population (Carlson et al., 2024). Many elderly individuals may be unfamiliar with or choose to not use the internet (van Deursen & Helsper, 2015), so ensuring that smoke notices and evacuation alerts are distributed through channels that would reach this population is also crucial.

The novelty of this study lies in its comparison of smoke and health impact estimates across various datasets. Few studies have compared different smoke exposure estimation methods, particularly in California, and this is the first study to examine differences in the attributable respiratory health burden from smoke $PM_{2.5}$ among elderly populations across different smoke datasets. By highlighting these differences, this study emphasized the influence that selecting one smoke dataset over another can have in health impact assessments or epidemiological studies, with overarching implications for policy development. Moreover, this study synthesized and summarized the current knowledge on respiratory health effects from smoke $PM_{2.5}$ exposure among the elderly, underscoring this population as a vulnerable group. Actionable strategies are needed to reduce the risk of respiratory health issues attributable to wildland fire smoke among the elderly.

This study has several limitations. First, transforming CMAQ smoke estimates from 12-km grid cells to census tract-level boundaries could have potentially resulted in exposure misclassifications. Due to the coarse spatial resolution of a 12-km grid, smaller census tracts could have been assigned smoke estimates that did not accurately reflect their exposure. Second, the strength of exposure to smoke $PM_{2.5}$ is stronger in areas where more people reside; however, this study did not take into account variations in population within census tracts in the smoke comparisons analysis, which could have contributed to underestimates in exposure for highly populated regions. Third, access to spatially resolved health data across multiple years of the study period was limited, so I relied on 2014 county-level incidence data preloaded in BenMAP-CE. Doing so does not consider changes in incidence rates over time, which could have resulted in overestimates or underestimates of the true health impacts. Additionally, applying county-level incidence rates to census tracts could have introduced misclassification errors. Fourth, the study did not consider disparities in health impacts across different vulnerable groups among the elderly, in which evidence suggests higher risk of respiratory morbidity from smoke $PM_{2.5}$ for women, Black, and lower SES groups compared to men, white, and higher SES groups (Liu, Wilson, Mickley, Ebisu, et al., 2017).

Future research could explore deeper analyses of the comparisons between smoke $PM_{2.5}$ datasets, such as focusing on case studies of specific fire events or comparing spatial and temporal differences in specific regions. The health impact assessment could be expanded by assessing other health outcomes, such as cardiovascular health outcomes, which has mixed but suggestive evidence of increased risk from smoke $PM_{2.5}$ exposure (Cascio, 2018; Reid, Brauer, et al., 2016). Since cardiovascular health burdens remain high among elderly populations (Qu et al., 2024), exploring cardiovascular health impacts attributable to smoke $PM_{2.5}$ exposure among this population and potential differences in health impacts across different datasets may be of interest. Additionally, evaluating disparities in health impacts across various socio-demographic indicators among the elderly can highlight potential environmental justice concerns that should be addressed. Elderly populations are only one of several vulnerable groups that are impacted by smoke $PM_{2.5}$ so future research could also look into health impacts among other highly susceptible groups, such as pediatric or unhoused populations. Lastly, completing an economic valuation of the health impacts is a crucial next step of this study.

CONCLUSION

Differences in smoke estimates between the CMAQ, Childs, and Casey datasets contributed to differences in health impact estimates of respiratory hospitalizations and ED/ER visits among elderly populations in California, which were more apparent between CMAQ with both Childs and Casey. Discrepancies in health impact estimates have overarching implications for wildland fire policies that rely on these estimates. Discrepancies aside, regardless of the dataset used, thousands of respiratory hospitalizations and ED/ER visits among the elderly are attributable to smoke $PM_{2.5}$ in California, highlighting the need to focus on vulnerable groups such as the elderly in an effort to reduce health risks from wildland fire smoke.

APPENDIX

Supplemental Figures and Tables

Table S1. P-values from the Kruskal-Wallis and Dunn tests of differences in annual smoke $PM_{2.5}$ ($\mu g/m^3$) between datasets across all California census tracts for the overall study period (2008-2018) and stratified by year.

	Kruskal-Wallis	Dunn		
		CMAQ, Childs	CMAQ, Casey	Childs, Casey
Year				
Overall	<0.05	0	0	<0.05
2008	<0.05	0	0	<0.05
2009	<0.05	0	0	0
2010	<0.05	0	0	<0.05
2011	<0.05	0	0	<0.05
2012	<0.05	0	0	0
2013	<0.05	0	0	<0.05
2014	<0.05	0	0	<0.05
2015	<0.05	0	0	<0.05
2016	<0.05	0	0	<0.05
2017	<0.05	0	0	0
2018	<0.05	0	0	<0.05

Table S2. P-values from the Dunn test of differences in annual smoke $PM_{2.5}$ ($\mu g/m^3$) between datasets across all California census tracts grouped by climate regions for the overall study period (2008-2018) and stratified by year.

	North Coast	Sierra Nevada Mountains	Sacramento Valley	San Francisco Bay Area	San Joaquin Valley	Central Coast	Los Angeles	Inland Desert	San Diego
Year									
Overall									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	0	<0.05	0	<0.05	0
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
2008									
CMAQ, Childs	<0.05	<0.05	<0.05	0	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	<0.05	<0.05	0	<0.05	0
Childs, Casey	0.62	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	**1**	<0.05
2009									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	0	<0.05	0	<0.05	0
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
2010									
CMAQ, Childs	<0.05	<0.05	<0.05	0	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	0	<0.05	0	<0.05	0
Childs, Casey	**0.075**	**0.054**	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
2011									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	0	0	0	<0.05	0	<0.05	0
Childs, Casey	<0.05	**0.24**	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
2012									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	0	<0.05	0	<0.05	0
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05

2013									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	0	0	0	<0.05	0	<0.05	<0.05
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
2014									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	0	<0.05	0	<0.05	0
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
2015									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	<0.05	<0.05	0	<0.05	0
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
2016									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	0	<0.05	<0.05	0	<0.05	0
Childs, Casey	**0.34**	**0.27**	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
2017									
CMAQ, Childs	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	0	0	0	<0.05	0	<0.05	0
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
2018									
CMAQ, Childs	<0.05	<0.05	<0.05	**1**	<0.05	<0.05	0	<0.05	<0.05
CMAQ, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05
Childs, Casey	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0	<0.05	<0.05

Notes: Bold denotes p-values >0.05.

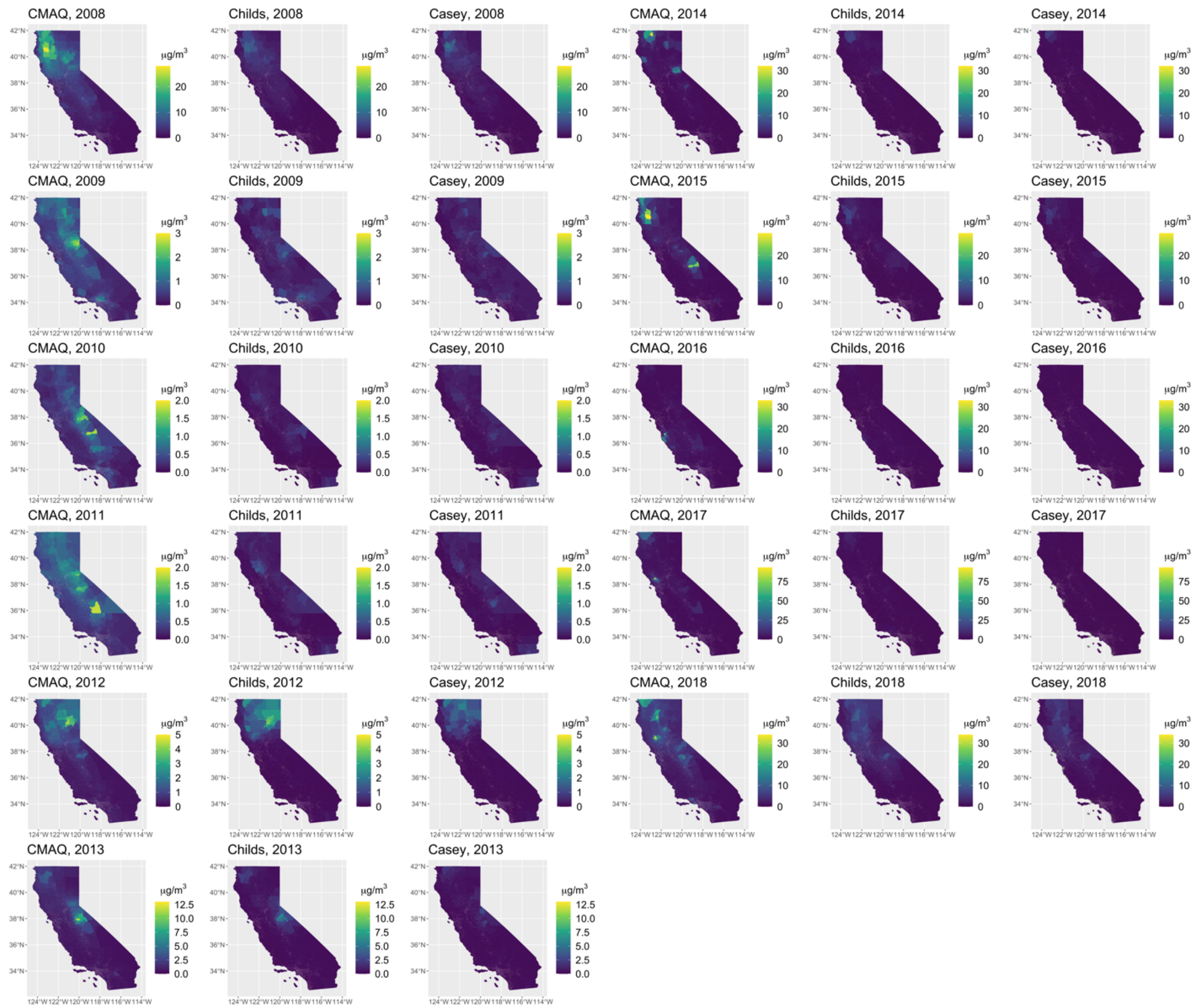


Figure S1. Spatial distribution of annual average smoke $PM_{2.5}$ ($\mu g/m^3$) at the census tract-level in California for each dataset, stratified by year.

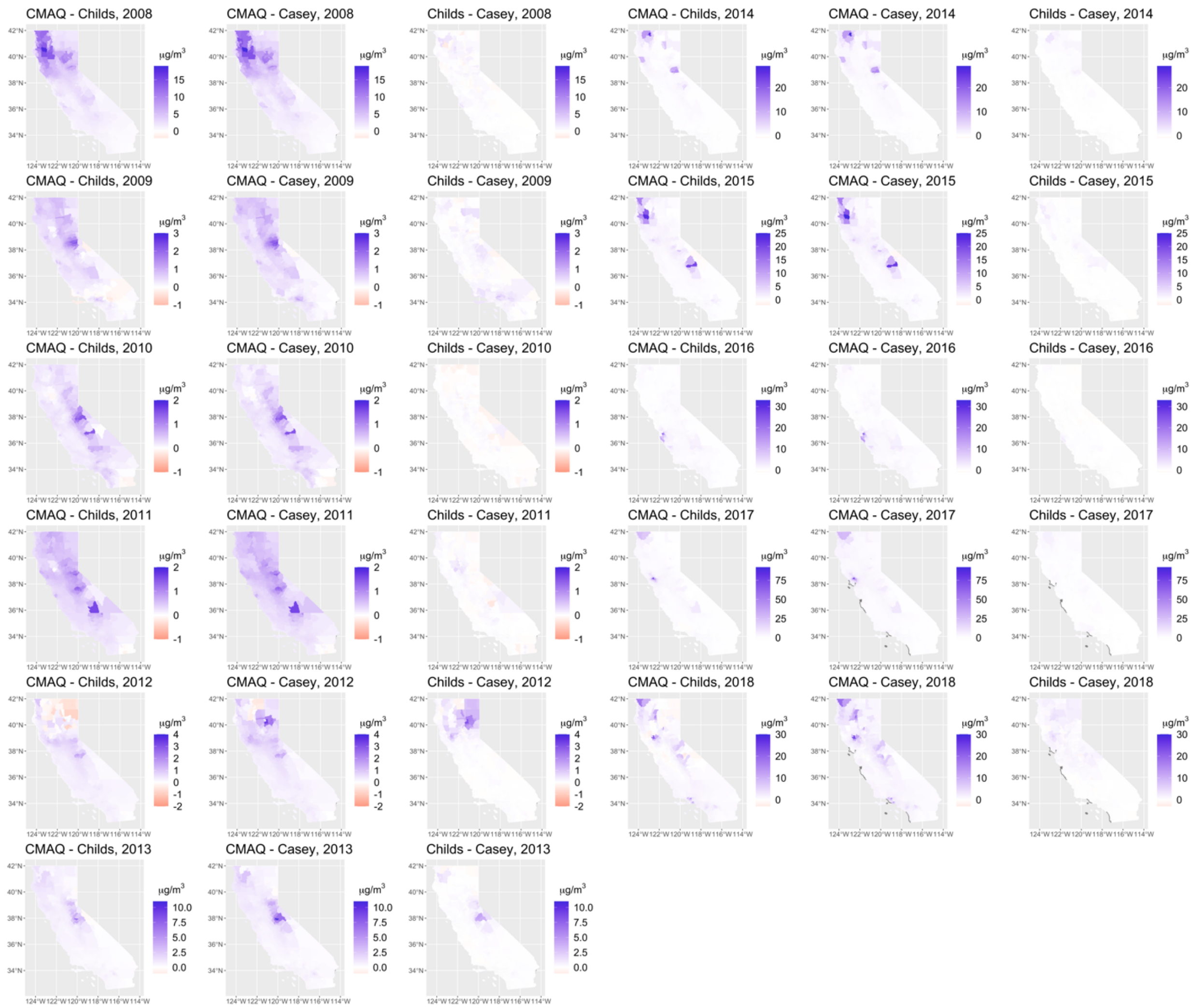
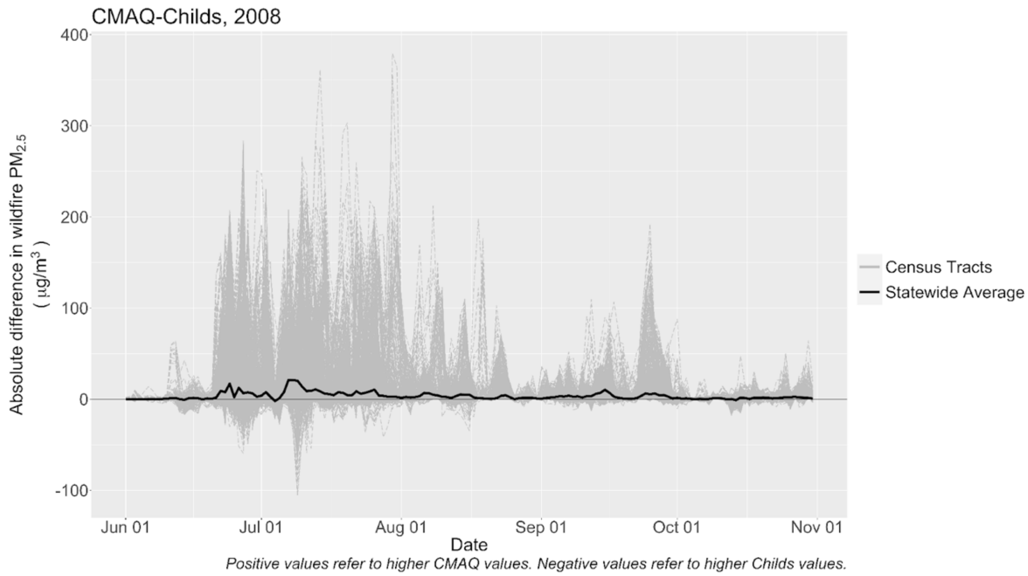
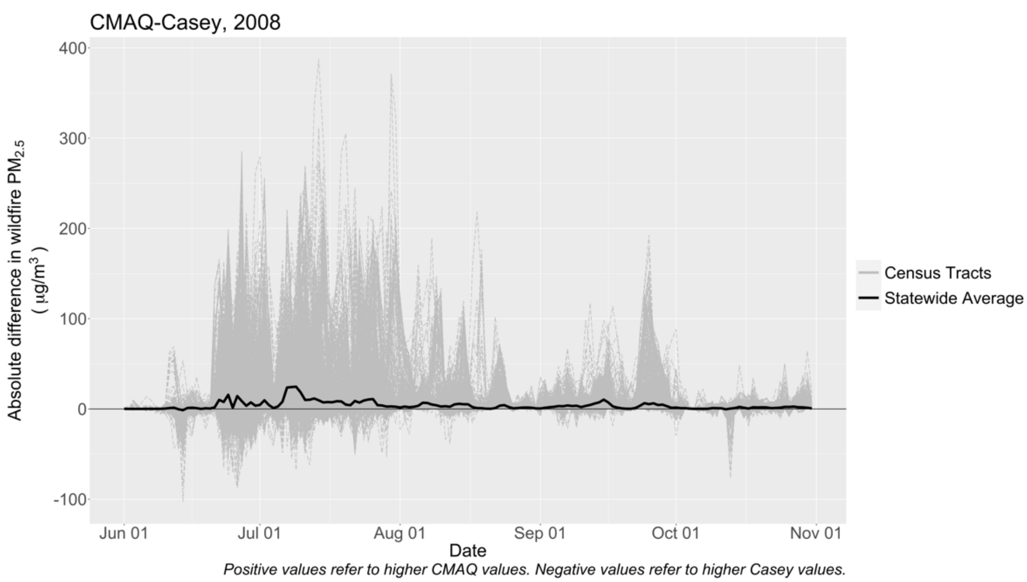


Figure S2. Spatial distribution of the differences in annual average smoke $PM_{2.5}$ ($\mu g/m^3$) at the census tract-level in California for each dataset, stratified by year.

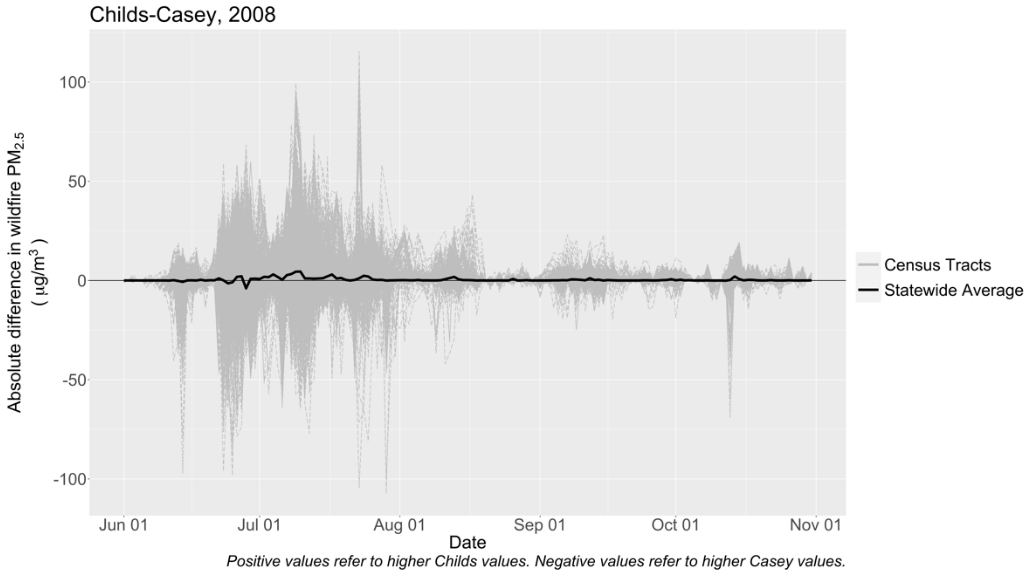
Notes: Blue refers to higher values for the former dataset, and red refers to higher values for the latter dataset.


CMAQ-Childs, 2008
Absolute difference in wildfire $PM_{2.5}$ (μg/m^3)
400
300
200
100
0
-100
Jun 01
Jul 01
Aug 01
Sep 01
Oct 01
Nov 01
Date
Census Tracts
Statewide Average
Positive values refer to higher CMAQ values. Negative values refer to higher Childs values.

A.


CMAQ-Casey, 2008
Absolute difference in wildfire $PM_{2.5}$ (μg/m^3)
400
300
200
100
0
-100
Jun 01
Jul 01
Aug 01
Sep 01
Oct 01
Nov 01
Date
Census Tracts
Statewide Average
Positive values refer to higher CMAQ values. Negative values refer to higher Casey values.

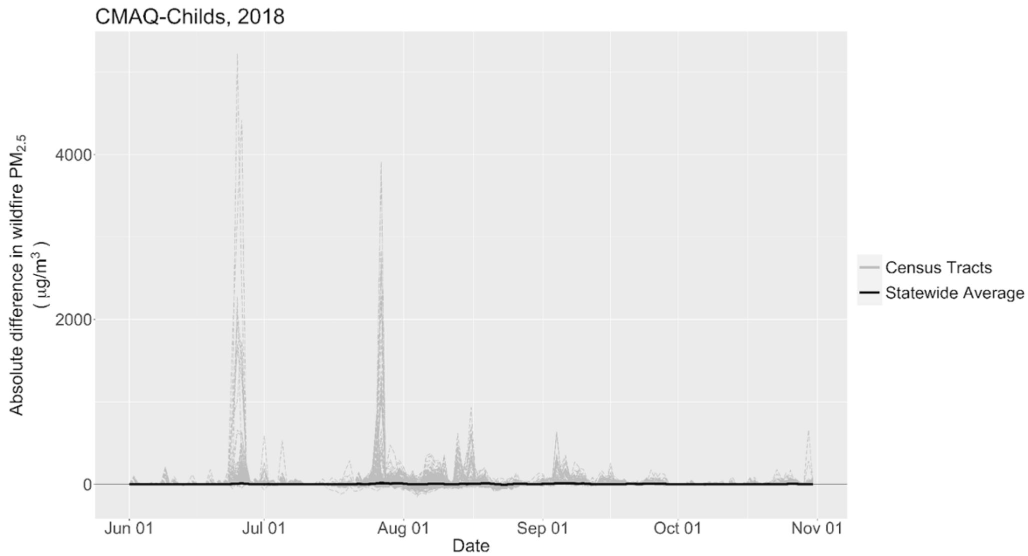
B.



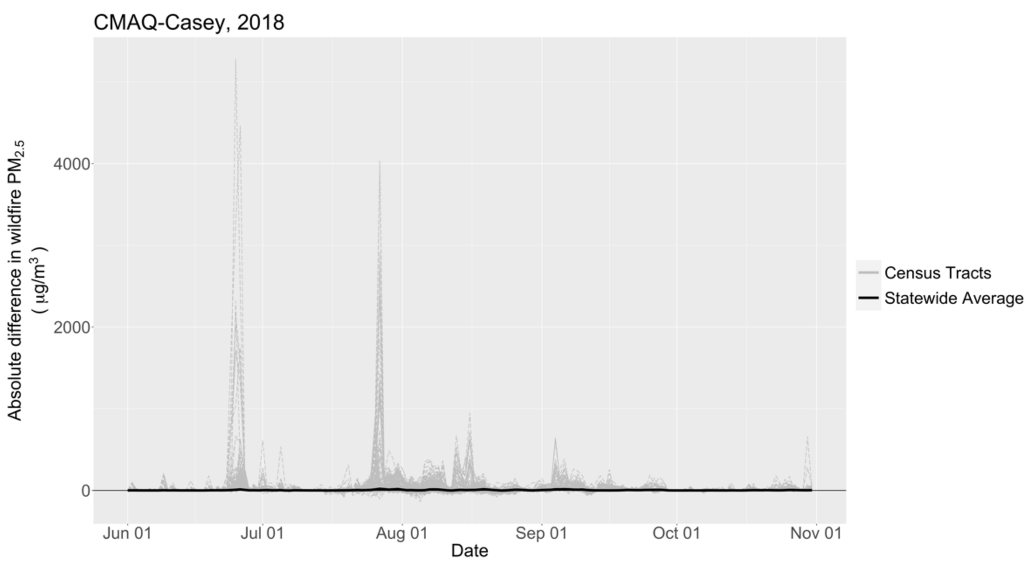
C.

Figure S3. Temporal distribution of the differences in daily smoke $PM_{2.5}$ ($\mu g/m^3$) for all California census tracts and the daily statewide average smoke $PM_{2.5}$ ($\mu g/m^3$) for each dataset, during the fire season (June to October) of 2008. Note change in scale on y-axis.

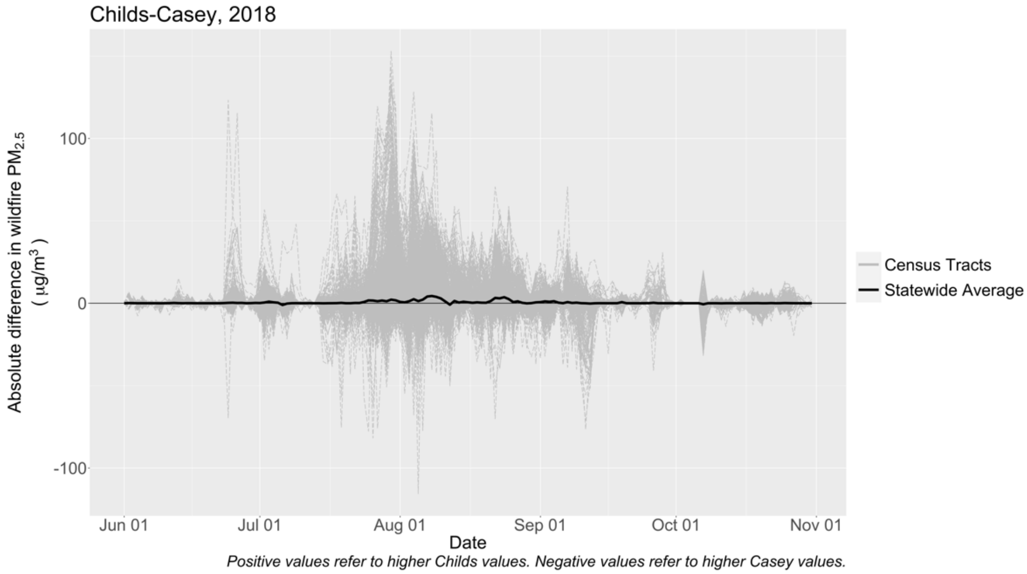
Note: Positive values refer to higher values for the former dataset, and negative values refer to higher values for the latter dataset.



A. *Positive values refer to higher CMAQ values. Negative values refer to higher Childs values.*



B. *Positive values refer to higher CMAQ values. Negative values refer to higher Casey values.*



C.

Figure S4. Temporal distribution of the differences in daily smoke $PM_{2.5}$ ($\mu g/m^3$) for all California census tracts and the daily statewide average smoke $PM_{2.5}$ ($\mu g/m^3$) for each dataset, during the fire season (June to October) of 2018. Note change in scale on y-axis.

Note: Positive values refer to higher values for the former dataset, and negative values refer to higher values for the latter dataset.

Table S3. Selected articles from the updated literature review on the respiratory health effects of wildland fire smoke exposure among elderly populations.

Author	***Article Title***	***Study Area***	***Respiratory Health Outcomes among Elderly***
(Alman et al., 2016)	The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: a case crossover study	Colorado, USA	Respiratory disease; asthma and wheeze
(Barros et al., 2023)	Continent-based systematic review of the short-term health impacts of wildfire emissions	USA	All respiratory
(Borchers Arriagada et al., 2019)	Association between fire smoke fine particulate matter and asthma-related outcomes: systematic review and meta-analysis	USA/Australia	Asthma
(Chen et al., 2023)	Emergency department visits associated with wildfire smoke events in California, 2016-2019	California, USA	All respiratory; asthma; pneumonia; acute upper respiratory infections; chronic lower respiratory disease
(DeFlorio-Barker et al., 2019)	Cardiopulmonary effects of fine particulate matter exposure among older adults, during wildfire and non-wildfire periods, in the United States 2008–2010	USA	Respiratory; asthma, bronchitis, or wheezing
(Delfino et al., 2009)	The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003	Southern California, USA	All respiratory; asthma; COPD; acute bronchitis and bronchiolitis; pneumonia
(Doubleday et al., 2023)	Wildfire smoke exposure and emergency department visits in Washington State	Washington, USA	All respiratory; asthma

(Duncan et al., 2023)	Acute Health Effects of Wildfire Smoke Exposure During a Compound Event: A Case-Crossover Study of the 2016 Great Smoky Mountain Wildfires	North Carolina, USA	All respiratory; asthma; COPD; bronchitis; emphysema
(Gan et al., 2017)	Comparison of wildfire smoke estimation methods and associations with cardiopulmonary-related hospital admissions	Washington, USA	All respiratory; asthma; COPD; acute bronchitis; pneumonia
(Gan et al., 2020)	The association between wildfire smoke exposure and asthma-specific medical care utilization in Oregon during the 2013 wildfire season	Oregon, USA	Asthma
(Hahn et al., 2021)	Wildfire Smoke Is Associated With an Increased Risk of Cardiorespiratory Emergency Department Visits in Alaska	Alaska, USA	All respiratory; asthma; COPD; bronchitis; pneumonia
(Heaney et al., 2022)	Impacts of Fine Particulate Matter From Wildfire Smoke on Respiratory and Cardiovascular Health in California	California, USA	All respiratory; asthma; COPD; acute respiratory infections
(Johnston et al., 2014)	Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996-2007: A case-crossover analysis	Sydney, Australia	All respiratory; asthma; COPD; pneumonia/acute bronchitis
(Kollanus et al., 2016)	Effects of long-range transported air pollution from vegetation fires on daily mortality and hospital admissions in the Helsinki metropolitan area, Finland	Helsinki, Finland	All respiratory
(Kondo et al., 2019)	Meta-Analysis of Heterogeneity in the Effects	Multiple	All respiratory

	of Wildfire Smoke Exposure on Respiratory Health in North America		
(Le et al., 2014)	Canadian forest fires and effects of long-range transboundary air pollution on hospitalizations among the elderly	Northeast and Mid-Atlantic USA	Respiratory; asthma; COPD; respiratory tract infection
(Liu, Wilson, Mickley, Dominici, et al., 2017)	Wildfire-specific Fine Particulate Matter and Risk of Hospital Admissions in Urban and Rural Counties	Western USA	Respiratory
(Liu, Wilson, Mickley, Ebisu, et al., 2017)	Who Among the Elderly Is Most Vulnerable to Exposure to and Health Risks of Fine Particulate Matter From Wildfire Smoke?	Western USA	Respiratory
(Morgan et al., 2010)	Effects of bushfire smoke on daily mortality and hospital admissions in Sydney, Australia	Sydney, Australia	Respiratory; COPD; pneumonia and acute bronchitis
(Rappold et al., 2011)	Peat Bog Wildfire Smoke Exposure in Rural North Carolina Is Associated with Cardiopulmonary Emergency Department Visits Assessed through Syndromic Surveillance	North Carolina, USA	All respiratory; asthma; COPD; pneumonia and acute bronchitis; upper respiratory infection; respiratory/other chest symptoms
(Reid, Jerrett, et al., 2016)	Differential respiratory health effects from the 2008 northern California wildfires; a spatiotemporal approach	Northern California, USA	All respiratory; asthma; COPD; pneumonia
(Resnick et al., 2015)	Health outcomes associated with smoke exposure in Albuquerque, New Mexico, during the 2011 Wallow fire	New Mexico, USA	All respiratory; asthma; other diseases of the respiratory system
(Stowell et al., 2019)	Associations of wildfire smoke PM2. 5 exposure with cardiorespiratory events in Colorado 2011–2014	Colorado, USA	Respiratory disease; asthma; COPD; bronchitis; upper respiratory infection

(Thilakaratne et al., 2023)	Wildfires and the Changing Landscape of Air Pollution-related Health Burden in California	California, USA	Respiratory; asthma; COPD;
(Tinling et al., 2016)	Repeating cardiopulmonary health effects in rural North Carolina population during a second large peat wildfire	North Carolina, USA	All respiratory; chronic pulmonary conditions; upper respiratory infection; respiratory/other chest symptoms
(Wettstein et al., 2018)	Cardiovascular and cerebrovascular emergency department visits associated with wildfire smoke exposure in California in 2015	California, USA	All respiratory

REFERENCES

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, *113*(42), 11770–11775. https://doi.org/10.1073/pnas.1607171113

Aguilera, R., Corringham, T., Gershunov, A., & Benmarhnia, T. (2021). Wildfire smoke impacts respiratory health more than fine particles from other sources: Observational evidence from Southern California. *Nature Communications*, *12*(1), Article 1. https://doi.org/10.1038/s41467-021-21708-0

Aguilera, R., Luo, N., Basu, R., Wu, J., Clemesha, R., Gershunov, A., & Benmarhnia, T. (2023). A novel ensemble-based statistical approach to estimate daily wildfire-specific PM2.5 in California (2006–2020). *Environment International*, *171*, 107719. https://doi.org/10.1016/j.envint.2022.107719

Alman, B. L., Pfister, G., Hao, H., Stowell, J., Hu, X., Liu, Y., & Strickland, M. J. (2016). The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: A case crossover study. *Environmental Health*, *15*(1), 64. https://doi.org/10.1186/s12940-016-0146-8

Barros, B., Oliveira, M., & Morais, S. (2023). Continent-based systematic review of the short-term health impacts of wildfire emissions. *Journal of Toxicology and Environmental Health, Part B*, *26*(7), 387–415. https://doi.org/10.1080/10937404.2023.2236548

Borchers Arriagada, N., Horsley, J. A., Palmer, A. J., Morgan, G. G., Tham, R., & Johnston, F. H. (2019). Association between fire smoke fine particulate matter and asthma-related outcomes: Systematic review and meta-analysis. *Environmental Research*, *179*, 108777. https://doi.org/10.1016/j.envres.2019.108777

CAL FIRE. (2020). *California Wildfires and Acres for all Jurisdictions*. https://web.archive.org/web/20221228012125/https://www.fire.ca.gov/media/11397/fires-acres-all-agencies-thru-2018.pdf

California Natural Resources Agency. (n.d.). *Ca. 4th Climate Change Assessment Regions (CaNAD83)*. Retrieved April 10, 2024, from https://gis.data.cnra.ca.gov/maps/CAnature::ca-4th-climate-change-assessment-regions-canad83

Calkin, D. E., Thompson, M. P., & Finney, M. A. (2015). Negative consequences of positive feedbacks in US wildfire management. *Forest Ecosystems*, *2*(1), 9. https://doi.org/10.1186/s40663-015-0033-8

Carlson, B., Kohon, J. N., Carder, P. C., Himes, D., Toda, E., & Tanaka, K. (2024). Climate Change Policies and Older Adults: An Analysis of States' Climate Adaptation Plans. *The Gerontologist*, *64*(3), gnad077. https://doi.org/10.1093/geront/gnad077

Cascio, W. E. (2018). Wildland fire smoke and human health. *Science of The Total Environment*, *624*, 586–595. https://doi.org/10.1016/j.scitotenv.2017.12.086

Casey, J., Benmarhnia, T., & Aguilera, R. (2024). *Daily census tract-level wildfire fine particulate matter concentrations for California, 2006-2020* [dataset]. [object Object]. https://doi.org/10.7910/DVN/CICODO

Chen, A. I., Ebisu, K., Benmarhnia, T., & Basu, R. (2023). Emergency department visits associated with wildfire smoke events in California, 2016–2019. *Environmental Research*, *238*, 117154. https://doi.org/10.1016/j.envres.2023.117154

Childs, M. L., Li, J., Wen, J., Heft-Neal, S., Driscoll, A., Wang, S., Gould, C. F., Qiu, M., Burney, J., & Burke, M. (2022). Daily Local-Level Estimates of Ambient Wildfire Smoke

PM2.5 for the Contiguous US. *Environmental Science & Technology*, *56*(19), 13607–13621. https://doi.org/10.1021/acs.est.2c02934

Connolly, R., Marlier, M. E., Garcia-Gonzales, D. A., Wilkins, J., Su, J., Bekker, C., Jung, J., Bonilla, E., Burnett, R. T., Zhu, Y., & Jerrett, M. (2024). Mortality attributable to PM2.5 from wildland fires in California from 2008 to 2018. *Science Advances*, *10*(23), eadl1252. https://doi.org/10.1126/sciadv.adl1252

Cudjoe, T. K. M., Roth, D. L., Szanton, S. L., Wolff, J. L., Boyd, C. M., & Thorpe, R. J., Jr. (2020). The Epidemiology of Social Isolation: National Health and Aging Trends Study. *The Journals of Gerontology: Series B*, *75*(1), 107–113. https://doi.org/10.1093/geronb/gby037

DeFlorio-Barker, S., Crooks, J., Reyes, J., & Rappold, A. G. (2019). Cardiopulmonary Effects of Fine Particulate Matter Exposure among Older Adults, during Wildfire and Non-Wildfire Periods, in the United States 2008–2010. *Environmental Health Perspectives*, *127*(3), 037006. https://doi.org/10.1289/EHP3860

Delfino, R. J., Brummel, S., Wu, J., Stern, H., Ostro, B., Lipsett, M., Winer, A., Street, D. H., Zhang, L., Tjoa, T., & Gillen, D. L. (2009). The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003. *Occupational and Environmental Medicine*, *66*(3), 189–197. https://doi.org/10.1136/oem.2008.041376

Dennison, P. E., Brewer, S. C., Arnold, J. D., & Moritz, M. A. (2014). Large wildfire trends in the western United States, 1984–2011. *Geophysical Research Letters*, *41*(8), 2928–2933. https://doi.org/10.1002/2014GL059576

D'Evelyn, S. M., Jung, J., Alvarado, E., Baumgartner, J., Caligiuri, P., Hagmann, R. K., Henderson, S. B., Hessburg, P. F., Hopkins, S., Kasner, E. J., Krawchuk, M. A., Krenz, J. E., Lydersen, J. M., Marlier, M. E., Masuda, Y. J., Metlen, K., Mittelstaedt, G., Prichard, S. J., Schollaert, C. L., … Spector, J. T. (2022). Wildfire, Smoke Exposure, Human Health, and Environmental Justice Need to be Integrated into Forest Restoration and Management. *Current Environmental Health Reports*, *9*(3), 366–385. https://doi.org/10.1007/s40572-022-00355-7

Dinno, A. (2015). Nonparametric Pairwise Multiple Comparisons in Independent Groups using Dunn's Test. *The Stata Journal: Promoting Communications on Statistics and Stata*, *15*(1), 292–300. https://doi.org/10.1177/1536867X1501500117

Doubleday, A., Sheppard, L., Austin, E., & Isaksen, T. B. (2023). Wildfire smoke exposure and emergency department visits in Washington State. *Environmental Research: Health*, *1*(2), 025006. https://doi.org/10.1088/2752-5309/acd3a1

Duncan, S., Reed, C., Spurlock, T., Sugg, M. M., & Runkle, J. D. (2023). Acute Health Effects of Wildfire Smoke Exposure During a Compound Event: A Case-Crossover Study of the 2016 Great Smoky Mountain Wildfires. *GeoHealth*, *7*(10), e2023GH000860. https://doi.org/10.1029/2023GH000860

Fann, N., Alman, B., Broome, R. A., Morgan, G. G., Johnston, F. H., Pouliot, G., & Rappold, A. G. (2018). The health impacts and economic value of wildland fire episodes in the U.S.: 2008–2012. *Science of The Total Environment*, *610–611*, 802–809. https://doi.org/10.1016/j.scitotenv.2017.08.024

Feng, S., Gao, D., Liao, F., Zhou, F., & Wang, X. (2016). The health effects of ambient PM2.5 and potential mechanisms. *Ecotoxicology and Environmental Safety*, *128*, 67–74. https://doi.org/10.1016/j.ecoenv.2016.01.030

Gan, R. W., Ford, B., Lassman, W., Pfister, G., Vaidyanathan, A., Fischer, E., Volckens, J., Pierce, J. R., & Magzamen, S. (2017). Comparison of wildfire smoke estimation methods and associations with cardiopulmonary-related hospital admissions. *GeoHealth*, *1*(3), 122–136. https://doi.org/10.1002/2017GH000073

Gan, R. W., Liu, J., Ford, B., O'Dell, K., Vaidyanathan, A., Wilson, A., Volckens, J., Pfister, G., Fischer, E. V., Pierce, J. R., & Magzamen, S. (2020). The association between wildfire smoke exposure and asthma-specific medical care utilization in Oregon during the 2013 wildfire season. *Journal of Exposure Science & Environmental Epidemiology*, *30*(4), 618–628. https://doi.org/10.1038/s41370-020-0210-x

Hahn, M. B., Kuiper, G., O'Dell, K., Fischer, E. V., & Magzamen, S. (2021). Wildfire Smoke Is Associated With an Increased Risk of Cardiorespiratory Emergency Department Visits in Alaska. *GeoHealth*, *5*(5), e2020GH000349. https://doi.org/10.1029/2020GH000349

Heaney, A., Stowell, J. D., Liu, J. C., Basu, R., Marlier, M., & Kinney, P. (2022). Impacts of Fine Particulate Matter From Wildfire Smoke on Respiratory and Cardiovascular Health in California. *GeoHealth*, *6*(6), e2021GH000578. https://doi.org/10.1029/2021GH000578

Heilman, W. E., Liu, Y., Urbanski, S., Kovalev, V., & Mickler, R. (2014). Wildland fire emissions, carbon, and climate: Plume rise, atmospheric transport, and chemistry processes. *Forest Ecology and Management*, *317*, 70–79. https://doi.org/10.1016/j.foreco.2013.02.001

Johnston, F. H., Purdie, S., Jalaludin, B., Martin, K. L., Henderson, S. B., & Morgan, G. G. (2014). Air pollution events from forest fires and emergency department attendances in Sydney, Australia 1996–2007: A case-crossover analysis. *Environmental Health*, *13*(1), 105. https://doi.org/10.1186/1476-069X-13-105

Keane, R. E., Ryan, K. C., Veblen, T. T., Allen, C. D., Logan, J., & Hawkes, B. (2002). *Cascading Effects of Fire Exclusion in Rocky Mountain Ecosystems: A Literature Review*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Kollanus, V., Tiittanen, P., Niemi, J. V., & Lanki, T. (2016). Effects of long-range transported air pollution from vegetation fires on daily mortality and hospital admissions in the Helsinki metropolitan area, Finland. *Environmental Research*, *151*, 351–358. https://doi.org/10.1016/j.envres.2016.08.003

Koman, P. D., Billmire, M., Baker, K. R., de Majo, R., Anderson, F. J., Hoshiko, S., Thelen, B. J., & French, N. H. F. (2019). Mapping Modeled Exposure of Wildland Fire Smoke for Human Health Studies in California. *Atmosphere*, *10*(6), Article 6. https://doi.org/10.3390/atmos10060308

Kondo, M. C., De Roos, A. J., White, L. S., Heilman, W. E., Mockrin, M. H., Gross-Davis, C. A., & Burstyn, I. (2019). Meta-Analysis of Heterogeneity in the Effects of Wildfire Smoke Exposure on Respiratory Health in North America. *International Journal of Environmental Research and Public Health*, *16*(6), Article 6. https://doi.org/10.3390/ijerph16060960

Le, G. E., Breysse, P. N., McDermott, A., Eftim, S. E., Geyh, A., Berman, J. D., & Curriero, F. C. (2014). Canadian Forest Fires and the Effects of Long-Range Transboundary Air

Pollution on Hospitalizations among the Elderly. *ISPRS International Journal of Geo-Information*, *3*(2), Article 2. https://doi.org/10.3390/ijgi3020713

Leyva, B., Taber, J. M., & Trivedi, A. N. (2020). Medical Care Avoidance Among Older Adults. *Journal of Applied Gerontology*, *39*(1), 74–85. https://doi.org/10.1177/0733464817747415

Li, S., & Banerjee, T. (2021). Spatial and temporal pattern of wildfires in California from 2000 to 2019. *Scientific Reports*, *11*(1), 8779. https://doi.org/10.1038/s41598-021-88131-9

Liu, J. C., Pereira, G., Uhl, S. A., Bravo, M. A., & Bell, M. L. (2015). A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research*, *136*, 120–132. https://doi.org/10.1016/j.envres.2014.10.015

Liu, J. C., Wilson, A., Mickley, L. J., Dominici, F., Ebisu, K., Wang, Y., Sulprizio, M. P., Peng, R. D., Yue, X., Son, J.-Y., Anderson, G. B., & Bell, M. L. (2017). Wildfire-specific Fine Particulate Matter and Risk of Hospital Admissions in Urban and Rural Counties. *Epidemiology*, *28*(1), 77. https://doi.org/10.1097/EDE.0000000000000556

Liu, J. C., Wilson, A., Mickley, L. J., Ebisu, K., Sulprizio, M. P., Wang, Y., Peng, R. D., Yue, X., Dominici, F., & Bell, M. L. (2017). Who Among the Elderly Is Most Vulnerable to Exposure to and Health Risks of Fine Particulate Matter From Wildfire Smoke? *American Journal of Epidemiology*, *186*(6), 730–735. https://doi.org/10.1093/aje/kwx141

Masri, S., Scaduto, E., Jin, Y., & Wu, J. (2021). Disproportionate Impacts of Wildfires among Elderly and Low-Income Communities in California from 2000–2020. *International Journal of Environmental Research and Public Health*, *18*(8), Article 8. https://doi.org/10.3390/ijerph18083921

McKight, P. E., & Najab, J. (2010). Kruskal-Wallis Test. In *The Corsini Encyclopedia of Psychology* (pp. 1–1). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470479216.corpsy0491

Morgan, G., Sheppeard, V., Khalaj, B., Ayyar, A., Lincoln, D., Jalaludin, B., Beard, J., Corbett, S., & Lumley, T. (2010). Effects of Bushfire Smoke on Daily Mortality and Hospital Admissions in Sydney, Australia. *Epidemiology*, *21*(1), 47. https://doi.org/10.1097/EDE.0b013e3181c15d5a

National Center for Health Statistics. (n.d.). *Health, United States 2020–2021*. https://www.cdc.gov/nchs/data/hus/2020-2021/HospAdmis.pdf

National Center for Health Statistics. (2021). *National Hospital Ambulatory Medical Care Survey: 2021 Emergency Department Summary Tables*. https://www.cdc.gov/nchs/data/nhamcs/web_tables/2021-nhamcs-ed-web-tables-508.pdf

Palinkas, L. A. (2020). The California Wildfires. In L. A. Palinkas (Ed.), *Global Climate Change, Population Displacement, and Public Health: The Next Wave of Migration* (pp. 53–67). Springer International Publishing. https://doi.org/10.1007/978-3-030-41890-8_4

Pope, C. A., & Dockery, D. W. (2006). Health Effects of Fine Particulate Air Pollution: Lines that Connect. *Journal of the Air & Waste Management Association*, *56*(6), 709–742. https://doi.org/10.1080/10473289.2006.10464485

Qu, C., Liao, S., Zhang, J., Cao, H., Zhang, H., Zhang, N., Yan, L., Cui, G., Luo, P., Zhang, Q., & Cheng, Q. (2024). Burden of cardiovascular disease among elderly: Based on the Global Burden of Disease Study 2019. *European Heart Journal - Quality of Care and Clinical Outcomes*, *10*(2), 143–153. https://doi.org/10.1093/ehjqcco/qcad033

Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., Butsic, V., Hawbaker, T. J., Martinuzzi, S., Syphard, A. D., & Stewart, S. I. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences*, *115*(13), 3314–3319. https://doi.org/10.1073/pnas.1718850115

Rappold, A. G., Stone, S. L., Cascio, W. E., Neas, L. M., Kilaru, V. J., Carraway, M. S., Szykman, J. J., Ising, A., Cleve, W. E., Meredith, J. T., Vaughan-Batten, H., Deyneka, L., & Devlin, R. B. (2011). Peat Bog Wildfire Smoke Exposure in Rural North Carolina Is Associated with Cardiopulmonary Emergency Department Visits Assessed through Syndromic Surveillance. *Environmental Health Perspectives*, *119*(10), 1415–1420. https://doi.org/10.1289/ehp.1003206

Reid, C. E., Brauer, M., Johnston, F. H., Jerrett, M., Balmes, J. R., & Elliott, C. T. (2016). Critical Review of Health Impacts of Wildfire Smoke Exposure. *Environmental Health Perspectives*, *124*(9), 1334–1343. https://doi.org/10.1289/ehp.1409277

Reid, C. E., Jerrett, M., Tager, I. B., Petersen, M. L., Mann, J. K., & Balmes, J. R. (2016). Differential respiratory health effects from the 2008 northern California wildfires: A spatiotemporal approach. *Environmental Research*, *150*, 227–235. https://doi.org/10.1016/j.envres.2016.06.012

Resnick, A., Woods, B., Krapfl, H., & Toth, B. (2015). Health Outcomes Associated With Smoke Exposure in Albuquerque, New Mexico, During the 2011 Wallow Fire. *Journal of Public Health Management and Practice*, *21*(Supplement 2), S55–S61. https://doi.org/10.1097/PHH.0000000000000160

Rhoades, J., Gruber, J., & Horton, B. (2021). Enhancing Vulnerable Groups' Resilience to Climate Change: Lessons Learned from a Case Study with Older Adults. *Journal of Community Engagement and Scholarship*, *13*(2). https://doi.org/10.54656/OCCQ6889

State of California. (n.d.). *Regional Reports—California Climate Assessment*. California's Fourth Climate Change Assessment. Retrieved June 4, 2024, from https://climateassessment.ca.gov/regions/

Stowell, J. D., Geng, G., Saikawa, E., Chang, H. H., Fu, J., Yang, C.-E., Zhu, Q., Liu, Y., & Strickland, M. J. (2019). Associations of wildfire smoke PM2.5 exposure with cardiorespiratory events in Colorado 2011–2014. *Environment International*, *133*, 105151. https://doi.org/10.1016/j.envint.2019.105151

Strydom, W. F., Funke, N., Nienaber, S., Nortje, K., & Steyn, M. (2010). Evidence-based policymaking: A review : review article. *South African Journal of Science*, *106*(5), 1–8. https://doi.org/10.10520/EJC97042

Sullivan, D. C., Larkin, N. K., Raffuse, S. M., Solomon, R., Pryden, D. A., Strand, T., Craig, K. J., Reid, S. B., Wheeler, N. J. M., & Chinkin, L. R. (2008, June 5). *Development and Applications of Systems for Modeling Emissions and Smoke from Fires: The BlueSky Smoke Modeling Framework and SMARTFIRE*. https://www3.epa.gov/ttnchie1/conference/ei17/session12/raffuse_pres.pdf

Thilakaratne, R., Hoshiko, S., Rosenberg, A., Hayashi, T., Buckman, J. R., & Rappold, A. G. (2023). Wildfires and the Changing Landscape of Air Pollution–related Health Burden in California. *American Journal of Respiratory and Critical Care Medicine*, *207*(7), 887–898. https://doi.org/10.1164/rccm.202207-1324OC

Tinling, M. A., West, J. J., Cascio, W. E., Kilaru, V., & Rappold, A. G. (2016). Repeating cardiopulmonary health effects in rural North Carolina population during a second large peat wildfire. *Environmental Health*, *15*(1), 12. https://doi.org/10.1186/s12940-016-0093-4

US Census Bureau. (n.d.). *TIGER/Line Shapefiles*. Census.Gov. Retrieved April 11, 2024, from https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html

US Department of Health and Human Services. (2013). *A Profile of Older Americans: 2013*. https://acl.gov/sites/default/files/Aging%20and%20Disability%20in%20America/2013_Profile.pdf

US EPA. (2014, December 5). *BenMAP Community Edition* [Data and Tools]. https://www.epa.gov/benmap/benmap-community-edition

US EPA. (2019, August 13). *Why Wildfire Smoke is a Health Concern* [Overviews and Factsheets]. Wildfire Smoke and Your Patients' Health. https://www.epa.gov/wildfire-smoke-course/why-wildfire-smoke-health-concern

US EPA. (2021). *Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE) (1.5)* [Computer software]. https://www.epa.gov/benmap

US EPA. (2023). *Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE) User's Manual*. https://www.epa.gov/sites/default/files/2015-04/documents/benmap-ce_user_manual_march_2015.pdf

van Deursen, A. J., & Helsper, E. J. (2015). A nuanced understanding of Internet use and non-use among the elderly. *European Journal of Communication*, *30*(2), 171–187. https://doi.org/10.1177/0267323115578059

Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity. *Science*, *313*(5789), 940–943. https://doi.org/10.1126/science.1128834

Wettstein, Z. S., Hoshiko, S., Fahimi, J., Harrison, R. J., Cascio, W. E., & Rappold, A. G. (2018). Cardiovascular and Cerebrovascular Emergency Department Visits Associated With Wildfire Smoke Exposure in California in 2015. *Journal of the American Heart Association*, *7*(8), e007492. https://doi.org/10.1161/JAHA.117.007492

Wilkins, J. L., Pouliot, G., Foley, K., Appel, W., & Pierce, T. (2018). The impact of US wildland fires on ozone and particulate matter: A comparison of measurements and CMAQ model predictions from 2008 to 2012. *International Journal of Wildland Fire*, *27*(10), 684–698. https://doi.org/10.1071/WF18053

Yao, J., Brauer, M., Raffuse, S., & Henderson, S. B. (2018). Machine Learning Approach To Estimate Hourly Exposure to Fine Particulate Matter for Urban, Rural, and Remote Populations during Wildfire Seasons. *Environmental Science & Technology*, *52*(22), 13239–13249. https://doi.org/10.1021/acs.est.8b01921

Youssouf, H., Liousse, C., Roblou, L., Assamoi, E. M., Salonen, R. O., Maesano, C., Banerjee, S., & Annesi-Maesano, I. (2014). Quantifying wildfires exposure for investigating health-related effects. *Atmospheric Environment*, *97*, 239–251. https://doi.org/10.1016/j.atmosenv.2014.07.041