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Health Care Cost Trends

The Impact of Wildfire-Related and Environmental Air Pollution on Morbidity

OCTOBER | 2025

SOA Research INSTITUTE
SOCIETAL PURPOSE

The Impact of Wildfire-Related Air Pollution on Morbidity

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Executive Summary

In recent years, wildfires have grown more frequent and intense across the United States as climate conditions become hotter and drier.[1] Contrary to common perception, wildfires are not just a West Coast phenomenon; they increasingly affect many regions across the United States.[2]

Wildfire smoke contains a complex mixture of chemical components, which undergo atmospheric reactions and condensation and form particulate matter that suspends the air. Among air pollutants, fine particulate matter with diameters of less than 2.5 micrometers in size (PM2.5) is of greatest concern due to its ability to penetrate deep into the lungs and enter the bloodstream, leading to systemic health effects.[3] Wildfire smoke also remains airborne for extended periods, allowing it to travel long distances via atmospheric currents such as jet streams, impacting air quality far from the wildfire source.[4]

This study sought to quantify the impact of PM2.5 exposure during the wildfire season and its lagged effects on the prevalence of four sets of disease conditions: circulatory conditions (CIR), mental and behavioral disorders (MBD), neoplasms (NEO), and respiratory conditions (RSP). Machine learning and statistical methods were applied to a combination of health care claims data, climate data, and community-level socioeconomic data for 2017–2023. Three major health insurance coverage types were included in the data: commercial, Medicare, and Medicaid.

The analysis considered two domains of risk drivers:

- Clinical risks and demographics, including measures of baseline health status, age, gender, and state of residence, and
- Environmental and socio-contextual factors, including measures of PM2.5 exposure during the wildfire season and its lagged effects, extreme heat and its lagged effects, seasonality, the COVID-19 pandemic, and social determinants of health (SDOH).

KEY FINDINGS

The study yields several important findings:

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[1] See “Climate Change Indicators: Wildfires,” EPA, last updated May 9, 2025, https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires.
[2] The National Interagency Fire Center tracks total number of wildfires and acres burned by state by year. See “National Fire News,” National Interagency Fire Center, June 21, 2025, https://www.nifc.gov/fire-information/nfn.
[3] See “Particulate Matter Basics,” EPA, last updated May 30, 2025, https://www.epa.gov/pm-pollution/particulate-matter-pm-basics.
[4] “Wildland Fire Activity and Modeled Impacts on O3 and PM2.5,” EPA, March 2022, https://www.epa.gov/system/files/documents/2022-03/epa_454_r_22_002.pdf.

- **Clinical risks and demographics explain the majority of condition prevalence rates.** Clinical risks and demographics factors explained approximately 68% to 92% of prevalence rates in the four sets of disease conditions studied. The remaining 8% to 32% was attributable to environmental and socio-contextual factors.
- **Within the environmental and socio-contextual domain, PM2.5 exposure is a leading driver of disease prevalence.** PM2.5 exposure during wildfires season and its lagged effects accounted for 11% to 26% of the environmental and socio-contextual domain (~1% to 4% of total prevalence). For RSP and MBD, the impact of PM2.5 exposure during wildfire season and its lagged effects exceeded that of SDOH.
- **The combined effects from exposure to PM2.5 and extreme heat are significant.** The combined effects of PM2.5 exposure during the wildfire season and its lagged effects, and extreme heat and its lagged effects accounted for 2.3% to 8.6% of disease prevalence, or 26% to 56% of the total environmental and socio-contextual influence. This magnitude rivaled and often exceeded that of the COVID-19 pandemic and its aftermath.
- **PM2.5 exposure is a material driver of MBD prevalence with the largest effects observed in the Medicaid population.** The combined effects of exposure from PM2.5 and extreme heat accounted for 6.7% to 7.8% of the total MBD prevalence rate, or 50–56% of the prevalence contribution from environmental and socio-contextual factors.
- **Exposure impacts are persistent and long term.** The effects of PM2.5 exposure during wildfire season extended for months and, in some cases, years after the exposure event, particularly for CIR and MBD.
- **There are variations in immediate versus lagged responses.** RSP exhibited immediate increases in prevalence following PM2.5 exposure during wildfire season. CIR and MBD displayed delayed responses, often peaking several months after exposure.
- **Health impacts are uneven.** Climate-related health effects were not experienced equally. Communities with limited health care access, higher social vulnerability, or preexisting chronic conditions tended to experience greater health burdens during wildfire and heat events, underscoring the importance of targeted, data-driven public health interventions.

IMPLICATIONS FOR THE HEALTH CARE AND INSURANCE INDUSTRIES

The findings of this study have important implications for health care systems, insurers, and policymakers.

Health insurers may consider integrating climate risks into actuarial models. Traditional risk assessments may underestimate the growing health care burden of climate change. Incorporating climate-adjusted predictive modeling could improve financial projections and premium pricing strategies.

Excess morbidity related to PM2.5 and extreme heat could place additional pressure on hospitals, emergency departments, and mental health services. Health care providers may consider approaches to meet demand surges during extreme climate events, such as using telemedicine, remote patient monitoring, and mobile health units to expand access in affected areas. It is equally important to consider coverage and delivery strategies after the wildfire peak seasons to address the delayed health impacts and health care needs from the impacted populations. In this process, data-driven prediction models similar to those in this study may be leveraged to support planning and enable quick responses.

Different populations and communities may require specific, targeted mitigation efforts, including increased health care access, air filtration subsidies, and community resilience programs to reduce exposure-related health disparities.

Policymakers and regulatory agencies may also evaluate whether existing frameworks for Medicare, Medicaid, and commercial health insurance sufficiently account for climate-related health impacts. Future updates could consider supporting infrastructure and interventions that promote health care system resilience in the face of environmental stressors.

LIMITATIONS AND FUTURE RESEARCH

While this study provides empirical insights into the health impacts of wildfire-related PM2.5 exposure, the complexity of the observed relationships and data limitations warrant cautious interpretation. Key limitations—such as challenges in exposure attribution and population representativeness—are discussed in Section 4.2. Further research is needed to expand the scope of health outcomes examined and to refine analytic methods for assessing long-term and cumulative effects, as outlined in Section 4.4.

CONCLUSION

Wildfire-related air pollution is not only an environmental issue—it increasingly affects public health and drives long-term increases in disease burden and health care utilization. By applying advanced analytics and fostering collaboration across sectors, health care organizations can enhance preparedness and resilience in the face of evolving climate-related health challenges.

Section 1: Background and Research Objectives

1.1 WILDFIRE-RELATED AIR POLLUTANTS

Wildfires have emerged as a growing environmental hazard in the United States. Trends over the past several decades show that wildfires in the United States are becoming larger and more frequent, with the total area burned annually more than doubling since 1984 and nine of the ten largest wildfire years occurring since 2000.[5] In 2024, for example, the National Interagency Fire Center reported 64,897 wildfires burning over 8.9 million acres, exceeding both the 5- and 10-year averages.[6] Seven of the 10 geographic regions experienced above-average wildfire activity.[7] The Southern Area reported the highest wildfire count, and the Northwest Area recorded the largest acreage burned.[8]

Wildfire smoke contains a complex mixture of chemical components, including gaseous pollutants such as carbon monoxide, hazardous air pollutants such as polycyclic aromatic hydrocarbons, volatile organic compounds, sulfur dioxide, nitrogen oxides, and water vapor. These pollutants contribute to both immediate and long-term health risks, with some acting as respiratory irritants and others classified as carcinogens. As these pollutants undergo atmospheric reactions and condensation, they form particulate matter, which consists of microscopic solid and liquid droplets suspended in the air. Particulate matter is categorized by size into PM10 (particulate matter ⩽10 micrometers or µm) and PM2.5 (particulate matter ⩽2.5 µm).

Among the particulate matter categories, PM2.5 is of greatest concern because of its ability to penetrate deep into the lungs and enter the bloodstream, leading to systemic health effects.[9] PM2.5 also remains airborne for extended periods, allowing it to travel long distances via atmospheric currents such as jet streams, impacting air quality far from the wildfire source.[10]

Larger particles, such as PM10, can also be found in wildfire smoke. However, PM10 particles are less likely to reach deep into the lungs; they primarily affect the upper airways, causing irritation.[11] Although both PM10 and PM2.5 can worsen conditions such as asthma, bronchitis, and cardiovascular disease,[12] PM2.5 is more concerning because it triggers systemic inflammation, increases the risk of heart attacks and strokes,[13] and may contribute to cognitive decline over time.[14]

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[5] "Climate Change Indicators: Wildfires". U.S. Environmental Protection Agency 2023, https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires.
[6] "Wildland Fire Summary and Statistics Annual Report 2024," National Interagency Coordination Center, January 2025, https://www.nifc.gov/sites/default/files/NICC/2-Predictive%20Services/Intelligence/Annual%20Reports/2024/annual_report_2024.pdf.
[7] "Wildland Fire Summary and Statistics Annual Report 2024," note 5 above.
[8] "Wildland Fire Summary and Statistics Annual Report 2024," note 5 above.
[9] See "Particulate Matter (PM) Basics," note 3 above.
[10] "Wildland Fire Activity and Modeled Impacts on O3 and PM2.5," EPA, March 2022, https://www.epa.gov/system/files/documents/2022-03/epa_454_r_22_002.pdf.
[11] See "Health and Environmental Effects of Particulate Matter (PM)," EPA, May 23, 2025, https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm.
[12] "Health and Environmental Effects of Particulate Matter (PM)," note 10 above.
[13] Stacey E. Alexeeff et al., "Long-Term PM2.5 Exposure and Risks of Ischemic Heart Disease and Stroke Events: Review and Meta-Analysis," *Journal of the American Heart Association* 10, no. 1 (2021): e016890, https://doi.org/10.1161/JAHA.120.016890.
[14] Giulia Grande et al., "Long-Term Exposure to PM2.5 and Cognitive Decline: A Longitudinal Population-Based Study," *Journal of Alzheimer's Disease* 81, no. 3 (2021): 1017–1026, https://doi.org/10.3233/JAD-200852.

1.2 MOBILITY AND DIFFICULTY IN ATTRIBUTION

PM2.5 from wildfires does not just affect the areas near the flames—it can travel hundreds or even thousands of miles, impacting regions far removed from the fire itself. For example, in June 2023, wildfire smoke from Canada led to dangerous air quality in cities across the eastern United States, increasing emergency visits for respiratory conditions.[15]

Determining exactly how much PM2.5 comes from wildfires versus other sources is a challenge:

- **Contribution of multiple pollution sources:** PM2.5 does not just come from wildfires—vehicle emissions, industrial pollution, and other sources add to the total burden.
- **Changes over time:** As wildfire smoke moves, its chemical makeup shifts because of interactions with sunlight and other pollutants, making it harder to trace back to its original source.
- **Measurement gaps:** Although air quality monitoring networks provide valuable data, they do not always have enough coverage, especially in rural areas. Satellite tracking helps but has its own limitations, such as interference from clouds or humidity.

To address these uncertainties, this study refers to "PM2.5 exposure during wildfire season" rather than attributing all seasonal air pollution directly to wildfires, acknowledging that PM2.5 comes from a mix of sources.

1.3 RESEARCH OBJECTIVES

This study models the impact of wildfire-related air pollution on the prevalence of selected medical conditions in the United States, using both traditional statistical methods and machine learning techniques. The key objectives include the following:

- How have PM2.5 exposures during past and recent wildfire seasons affected disease prevalence of circulatory conditions (CIR), mental and behavioral disorders (MBD), neoplasms (NEO), and respiratory conditions (RSP)?
- How do these effects differ by geography, insurance coverage type, and population status?

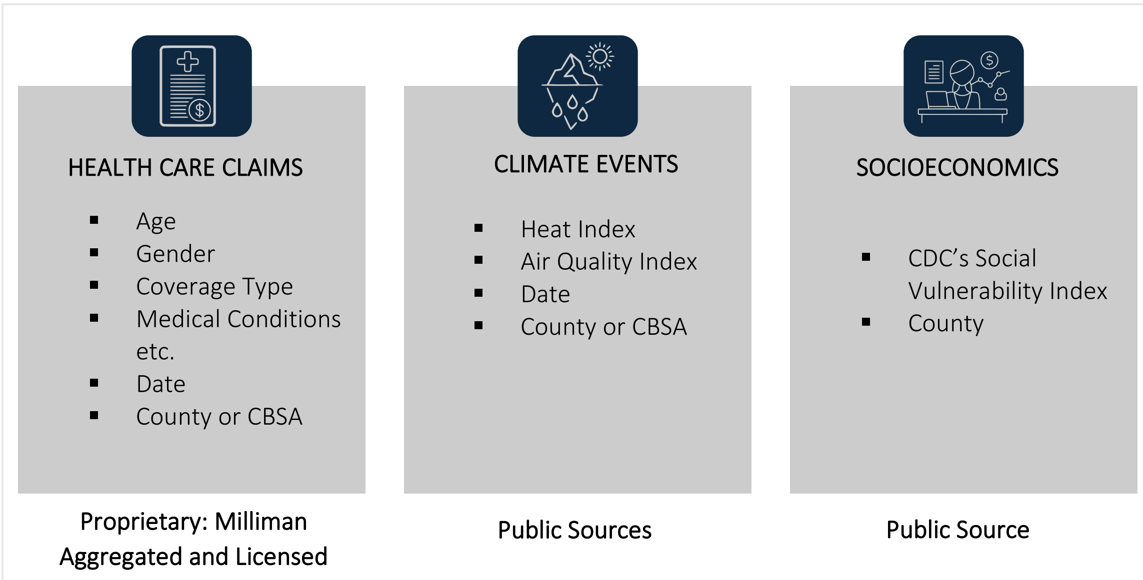
By addressing these questions, the report aims to provide insights for public health officials, insurers, and policymakers to better anticipate and potentially mitigate the health risks of wildfire-related air pollution.

[15] Haillie C. Meek et al., "Notes from the Field: Asthma-Associated Emergency Department Visits During a Wildfire Smoke Event—New York, June 2023," CDC Morbidity and Mortality Weekly Report 72, no. 34 (August 25, 2023): 933–935, https://doi.org/10.15585/mmwr.mm7234a5.

Section 2: Data

A meshed modeling dataset was created using daily temperature and relative humidity data, daily PM2.5 data, detailed individual-level health insurance claims data, and community-level socioeconomic data, linked by time and geography for a span of 2017 to 2023 (see Figure 1). Table A1 in Appendix A contains more descriptive statistics on the study populations.

Figure 1
DATA SOURCES



2.1 HEAT AND AIR QUALITY DATA

2.1.1 HEAT DATA

This study used publicly available daily surface weather data to estimate monthly heat intensity for each core-based statistical area (CBSA) during the summer months (May–September), when extreme heat is most likely to occur. Heat intensity was calculated based on deviations from historical temperature baselines, using apparent temperature—which accounts for both temperature and humidity—as the primary measure. For a detailed description of the data sources, calculation methods, and aggregation steps, see Appendix A.

2.1.2 PM2.5 DATA

This study utilized publicly available air quality data sourced from the U.S. Environmental Protection Agency (EPA) AirNow monitoring network. These data are comprehensive, covering the entire study period from 2017 to 2022. Reported daily values for 24-hour average PM2.5 concentration were extracted for all AirNow monitoring sites across the United States for each day in the study period. Monitoring site data were then aggregated to CBSAs to be merged with health care claims data. Finally, U.S. standard Air Quality Index (AQI) categories were assigned to standardize and quantify the number of days of each AQI designation per CBSA. AQI values and categories (good, moderate, unhealthy, etc.) can be derived from concentrations using standard EPA equations.

2.1.3 SEASONALITY

The frequency and intensity of wildfires are highly correlated with weather conditions. Prolonged periods of dry weather, high temperatures, and strong winds significantly increase the likelihood of wildfires and exacerbate their intensity. Research conducted by the EPA indicates that, over the past 20 years, the peak of wildfires has appeared in July.[16]

As discussed previously, wildfires are a major source of elevated concentrations of PM2.5, but from a measurement standpoint, differentiating between PM2.5 generated by local sources and that transported from wildfire-affected areas is a complex and often insurmountable task due to the lack of localized air pollution data, airflow modeling, and tracking capabilities. To address these challenges, a proximation methodology was used to categorize a 12-month period into three distinct wildfire-related seasons, so that PM2.5 concentrations may be associated with high wildfires season:

- Pre-season: February to May.
- High season: June to September.
- Post-season: October to January.

Using this four-month division also provides a consistent framework for calculating disease prevalence rates and assessing health impacts.

Wildfire seasonality patterns may vary by geography and year. An analysis of monthly unhealthy air quality days by census region and year was conducted. The results indicate that the above seasonal definition is broadly applicable across census regions and years. For detailed statistical results and visual representation, see Figure A1 in Appendix A.

2.1.4 REPRESENTING PM2.5 CONCENTRATION LEVEL AT THE CBSA LEVEL

Daily air quality data, including that of PM2.5 concentration levels, are reported by individual monitoring sites, and so these site-level data needed to be aggregated to the CBSA level to align geographically with the health care claims data for modeling. County population-weighted centroids from the U.S. Census Bureau were used to represent county geographies. These county centroids were then spatially related to the monitoring sites, typically within 25 kilometers. In instances with no sites within 25 kilometers, the next closest monitoring site was attributed to the centroid. Then inverse distance weighting was used to estimate for each county centroid the PM2.5 concentration value for each day in the study period. Finally, a Census-derived crosswalk file that maps counties to CBSAs using Federal Information Processing Series (FIPS) codes was used to calculate the daily average PM2.5 concentration across the CBSA.

2.2 HEALTH CARE CLAIMS DATA FOR CALCULATING DISEASE PREVALENCE RATES

To measure changes in disease prevalence rates at the population level, the Milliman Consolidated Health Cost Guidelines™ Sources Database Plus (CHSDPlus)[17] was used from 2017 to 2023. A few dozen national and regional health plans contribute their annual enrollment and claims detail to Milliman. Currently the

[16] See "Climate Change Indicators: Wildfires," EPA, May 9, 2025, https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires.
[17] See "Milliman Consolidated Health Cost Guidelines™ Sources Database (CHSD)," Milliman, https://us.milliman.com/en/health/life-sciences/data-assets.

CHSDPlus has data on more than 75 million total insured lives across all states and major lines of business, including commercial, Medicare Advantage and Part D, and Medicaid managed care.

2.2.1 ELIGIBILITY REQUIREMENT AND OTHER INCLUSION/EXCLUSION CRITERIA

For modeling purposes, members who had both medical and prescription drug coverage for at least 10 months within a calendar year were selected. Members were not required to have continuous enrollment year over year. This 10-month enrollment criterion was designed to ensure sufficient exposure to climate events and credible claims data for calculating disease prevalence rates. However, this approach introduces certain limitations:

- **Underrepresentation of deaths:** Individuals who pass away during the year are less likely to meet the 10-month criterion, resulting in a sample that may be healthier than the general population.

- **Underrepresentation of newborns:** Newborns often do not have 10 months of enrollment, which could skew the population sample, although the specific impact is unclear.

- **Medicaid-specific challenges:** Because of Medicaid's eligibility requirements, a substantial proportion of beneficiaries have enrollment durations of less than 10 months. Consequently, the enrollment criterion reduces the dataset size and introduces potential bias, although the exact effects on the resulting population are uncertain.

Model results were rebalanced through weighting in modeling to improve their representativeness in a later stage. It is still possible that the rebalancing may fail to fully address the above limitations.

In addition to the eligibility duration criterion, the following inclusion and exclusion criteria were also used:

- For the commercial population, members with both medical and pharmacy coverage were selected. For the Medicare population, members with Part A and Part B were selected regardless of Part D coverage.

- Additional members were excluded because of data quality concerns.

2.2.2 REPRESENTATIVENESS OF MODELING DATASET

The CHSDPlus has a good representation of the population covered under commercial health insurance. It includes all states, major plan types, and market segments. The Medicaid population is less well represented in the modeling dataset. Although all states are represented in the CHSDPlus, data from fee-for-service Medicaid states and populations are largely absent. This limited Medicaid sample was used in modeling for exploratory purposes, aimed at identifying potential impacts of climate events on this population and comparing these impacts to those observed in the commercial and Medicare populations.

2.2.3 MEDICAL CONDITIONS GROUPING

The Clinical Classifications Software Refined (CCSR)[18] diagnosis grouping logic was used to assign disease conditions at the individual level. The CCSR organizes more than 70,000 ICD-10-CM codes into

[18] See "Clinical Classifications Software Refined (CCSR)," Healthcare Cost & Utilization Project, Agency for Healthcare Research and Quality, November 13, 2024, https://hcup-us.ahrq.gov/toolssoftware/ccsr/ccs_refined.jsp.

approximately 530 clinically relevant categories. These categories allow researchers and analysts to study patterns of health care utilization, costs, and outcomes.

The following four clusters of medical conditions are modeled, as they have been found to have been impacted by poor air quality in the literature.[19] They encompass a mix of acute and chronic conditions, as well as severe and minor illnesses.

- **Diseases of the circulatory system (CIR), including acute myocardial infarction (heart attacks), hypertension, and heart failure:** Chronic exposure to fine particulate matter and other pollutants has been shown to exacerbate preexisting cardiovascular conditions, increasing the risk of severe outcomes such as cardiac arrest and cerebral infarction (strokes).
- **Mental, behavioral, and neurodevelopmental disorders (MBD):** Emerging research suggests that air pollution may influence mental and behavioral health, with potential links to conditions such as anxiety disorders, depressive disorders, and neurodevelopmental disorders. Elevated levels of air pollution have been associated with higher risks of cognitive decline and increased severity of conditions such as schizophrenia and bipolar disorder.
- **Neoplasms (NEO), including lung cancer, nasopharyngeal cancer, and laryngeal cancer:** Pollutants such as PM2.5 and airborne toxins can act as carcinogens, increasing the incidence of respiratory and other system-specific cancers.
- **Diseases of the respiratory system (RSP), including asthma, chronic obstructive pulmonary disease (COPD), and acute bronchitis:** Pollutants such as ozone and PM2.5 can trigger asthma attacks, worsen COPD symptoms and increase the risk of severe infections such as pneumonia. Long-term exposure is also associated with chronic conditions such as respiratory failure.

2.2.4 DISEASE PREVALENCE RATE

To ensure adequate sample size across multiple dimensions—coverage type, age/gender, geography, and season—analysis was conducted at the aggregate category level, focusing on the aforementioned broad groupings. Because of the seasonal nature of wildfires aggregate disease prevalence rates were calculated by season. The average prevalence rates are provided in Table A1 in the Appendix section. Note that the condition categories used here are very broad and include both uncomplicated and severe or even fatal ones. For example, essential hypertension is part of CIR, which impacts more than 71% of U.S. adults aged 60 and over.[20]

While calculating prevalence rates at the aggregate level by season would address the data sparsity issue and achieve computational efficiency in modeling, this approach sacrifices specificity and detailed insights into individual conditions.

[19] See notes 9 to 13.
[20] "Hypertension Prevalence, Awareness, Treatment, and Control Among Adults Age 18 and Older: United States, August 2021–August 2023," NCHS Data Brief No. 511, National Center for Health Statistics., October 2024, https://www.cdc.gov/nchs/products/databriefs/db511.htm.

2.3 SOCIAL VULNERABILITY DATA

Social vulnerability refers to demographic and socioeconomic factors—such as poverty, lack of access to transportation, and crowded housing—that increase a community's susceptibility to the impacts of hazards and stressors. These stressors can include natural disasters exacerbated by climate change, such as hurricanes, wildfires, or heatwaves, as well as human-caused incidents such as chemical spills or disease outbreaks such as COVID-19.

The CDC/ATSDR Social Vulnerability Index (SVI) is a tool designed to identify communities that may require additional support in preparing for, responding to, and recovering from disasters, including those intensified by climate risks.[21] The 2020 SVI uses 16 variables from the U.S. Census five-year American Community Survey, grouped into four themes representing critical dimensions of social vulnerability. These themes are integrated into a single measure, providing a comprehensive assessment of a community's ability to withstand and recover from climate-related and other hazards. The single SVI measure at the county level was used to control for the socioeconomic situations that an individual encounters when dealing with climate events and addressing health care needs.

2.4 MERGING OF DIFFERENT DATA SOURCES

The climate data and the health care claims data were merged by date and by county and then brought in the SVI data by county. Table A2 in the Appendix section provides a general description of the data samples by coverage type and by year.

Section 3: Methodology and Model Results

3.1 LITERATURE REVIEW

Recent years have witnessed an increasing amount of research on the impact of wildfire-related air pollution on morbidity and mortality. There has also been an increasing amount of research on climate change and its impact on the frequency, duration, and intensity of wildfires, especially in the western United States. To the best knowledge of the research team, very little research has been done using health insurance claims data. The research team conducted a literature review to better understand existing knowledge, with a focus on the following areas:

- Long-term trends of wildfires due to climate change.
- Interaction between wildfire-related air pollution and meteorological conditions.
- Identifying historical wildfire smoke event duration and geographic impact using ground and satellite-based air quality data.

[21] See "Social Vulnerability Index," ATSDR Place and Health—Geospatial Research, Analysis, and Services Program (GRASP), Department of Health and Human Services, July 22, 2024, https://www.atsdr.cdc.gov/place-health/php/svi/index.html.

- Impact of wildfire-related air pollution on morbidity and mortality.

The relevant papers in peer-reviewed journals are included in Appendix C.

3.2 COVID-19 PANDEMIC AND OTHER EXOGENOUS FACTORS

Between 2017 and 2023, health care in the United States saw great changes in health policy, such as the implementation of the Affordable Care Act and Medicaid expansion, as well as the opioid epidemic, the COVID-19 pandemic, and their aftermaths. These events have significantly impacted health care coverage, access, provision, and outcomes. It is conceivable that these changes may also interact with wildfire-related air pollution events; hence they needed to be controlled for in modeling and in extrapolating the model results to the general population. To approach this, year and season were included as features in the model, although it is possible that this may still oversimplify nuanced shifts in population distribution and health care provision.

3.3 CONSIDERATION OF CUMULATIVE AND LAGGED IMPACTS FROM CLIMATE EVENTS

Acute exposures to extreme heat and air pollution from wildfires often trigger immediate health effects, such as respiratory distress or cardiovascular events. However, these events can also have lagged impacts, where prolonged exposure to pollutants exacerbates chronic conditions or contributes to the development of new health issues over time. For instance, extended exposure to particulate matter from wildfires may accelerate the progression of asthma or COPD and increase long-term risks for cardiovascular disease. To account for the prolonged impact of wildfire-related air pollution, consider lagged effects of prior wildfire events. In modeling for this study, up to six seasonal lags (equivalent to 24 months) were included.

3.4 CHOICE OF MODEL AND ALGORITHM

The prevalence rates per 1,000 per season were predicted for four aggregate disease conditions (CIR, MBD, NEO, and RSP) by three major coverage types (commercial, Medicare, and Medicaid). This resulted in 12 distinct combinations for modeling.

3.4.1 GLM VS. XGBOOST

Two modeling approaches were explored: a traditional generalized linear model (GLM) and an XGBoost (XGB) algorithm, a popular machine learning technique. GLMs are rooted in traditional statistical frameworks, offering interpretable coefficients that quantify the direct impact of predictors on disease prevalence under well-defined assumptions. However, they require the relationships between variables to be specified by the researcher in advance, which can limit their ability to capture complex interactions. In contrast, XGBoost is a machine learning technique that does not rely on predefined functional forms and is well suited to uncovering intricate, nonlinear patterns within large, multidimensional datasets. By leveraging both GLM and XGBoost, the analysis highlights the trade-offs between interpretability and predictive performance, ultimately underscoring the value of machine learning techniques in uncovering complex patterns in health care data. Results from the XGBoost models are reported in this report because the predictive accuracy (validated through *k*-fold validation in the modeling process) was found to be significantly higher than GLMs. Additionally, XGBoost models produced deeper insights into the complex interactions between climate, health, and socioeconomic factors that GLM models are unable to unveil. Appendix A provides more technical details on the two modeling approaches and how they differ.

3.4.2 MODEL PERFORMANCE

To assess the performance of the models, R^2 values (see Table B3), a measure of how well each model explains the variance in disease prevalence rates, were compared. XGBoost demonstrated superior predictive accuracy across most disease categories and coverage types, reflecting its capacity to capture complex interactions and nonlinear relationships.

3.4.3 FEATURE IMPORTANCE

In the context of XGBoost, feature importance refers to the relative contribution of each predictor variable in determining model predictions. Features used in models were categorized into "clinical risk and demographics," which includes risk scores, age, gender, and state, and "environmental and socio-contextual factors," which includes PM2.5 and its lagged effects, heat and its lagged effects, the COVID-19 pandemic and its aftermath, SDOH, and wildfires seasonality as defined previously. Table 4 includes the feature importance by health insurance coverage and disease condition.

Table 4
FEATURE IMPORTANCE BY SHAP VALUE CONTRIBUTION

COMMERCIAL		CIR (%)	MBD (%)	NEO (%)	RSP (%)
Clinical risk and demographics		91.9	86.9	89.0	68.1
Environmental and socio-contextual factors	PM2.5	1.1	3.3	2.4	3.5
	Heat	1.2	4.0	2.3	5.0
	COVID	0.6	0.7	0.8	7.1
	SDOH	3.4	4.0	4.3	3.2
	Season	1.8	1.1	1.1	13.2
Share of PM2.5 in environmental and socio-contextual factors		13.8	25.1	22.2	11.1
Share of PM2.5 and heat in environmental and socio-contextual factors		28.1	56.0	43.3	26.6

MEDICARE		CIR (%)	MBD (%)	NEO (%)	RSP (%)
Clinical risk and demographics		86.8	87.6	87.2	76.3
Environmental and socio-contextual factors	PM2.5	2.2	3.1	3.2	3.8
	Heat	2.5	3.5	3.1	4.8
	COVID	1.3	0.5	0.6	4.1
	SDOH	3.7	3.9	4.4	3.7
	Season	3.6	1.4	1.5	7.4
Share of PM2.5 in environmental and socio-contextual factors		16.5	25.3	25.3	16.0
Share of PM2.5 and heat in environmental and socio-contextual factors		35.1	53.5	49.4	36.1

MEDICAID		CIR (%)	MBD (%)	NEO (%)	RSP (%)
Clinical risk and demographics		91.1	84.5	87.5	74.1
Environmental and socio-contextual factors	PM2.5	2.3	3.8	3.3	3.5
	Heat	2.0	4.0	3.3	4.5
	COVID	0.6	1.2	0.6	5.8
	SDOH	2.5	5.1	3.7	3.0
	Season	1.5	1.3	1.7	9.1
Share of PM2.5 in environmental and socio-contextual factors		26.2	24.3	26.2	13.4
Share of PM2.5 and heat in environmental and socio-contextual factors		48.4	50.2	52.2	30.7

It is worth noting the following:

- **Clinical risk and demographics:** Age, gender, health status, and state contribute most to disease prevalence across all models—ranging from approximately 68% to 92%. The remaining 8–32% of disease prevalence is attributable to environmental and socio-contextual factors.

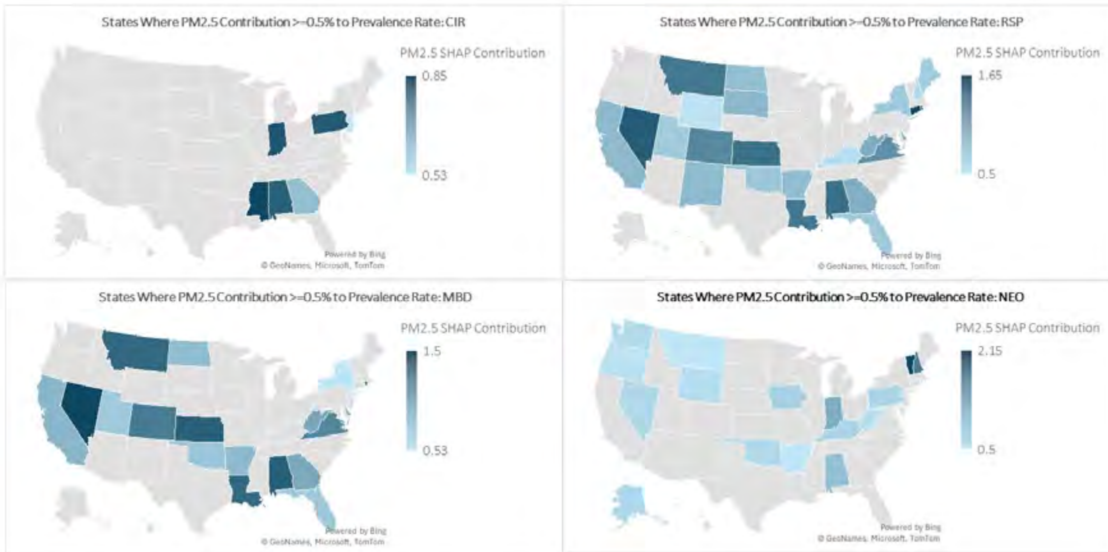
- **PM2.5 as a share of environmental and socio-contextual factors:** PM2.5 and its lagged effects are a significant factor among the environmental and socio-contextual factors, accounting for 11–26% in this category.
- **PM2.5 compared to SDOH:** SDOH consistently plays a slightly stronger role than PM2.5 in affecting disease prevalence of CIR, MBD, and NEO. For RSP, however, the relationship is reversed.
- **PM2.5 compared to COVID:** Except for RSP, the importance of PM2.5 air pollution is higher than the COVID-19 pandemic and its aftermath.
- **PM2.5 and heat combined impact as a share of environmental and socio-contextual factors:** PM2.5, heat, and their lagged effects accounted for 26–56% of environmental and socio-contextual factors' overall contribution to disease prevalence across all conditions and all coverage types. For MBD, this combined share was 50–56%. For NEO, it was 43–52%.

3.4.4 STATES MOST IMPACTED BY PM2.5 AIR POLLUTION

SHAP (SHapley Additive exPlanations) values from machine learning help explain how much each model feature – such as such as PM2.5 levels, or social vulnerability – contributes to the predicted outcome. A positive SHAP value means that the feature increased the predicted disease prevalence from the baseline, while a negative value means the feature decreased it. For instance, the prevalence rate of MBD for the South region is 421.4 per thousand for the Medicaid population during the wildfire season. A 1% SHAP value for PM2.5 air pollution may be interpreted as 4.214 per thousand MBD incidences are attributable to PM2.5 exposure, both during the current season's wildfires and from previous seasons.

To standardize the SHAP values for comparability across states, the percent contribution of PM2.5 was calculated by dividing the SHAP value for each state by the overall disease prevalence rate at the population level. This approach provides a relative measure of the effect of PM2.5 on disease prevalence, allowing for cross-state and cross-coverage comparisons. States where the SHAP value contributions are greater than or equal to 0.5%, i.e., PM2.5 air pollution contribution is at least 0.5% towards total disease prevalence rate, are shown in Figure 3 below. More details are included in Table B4 in the Appendix section.

Figure 3
PM2.5 SHAP VALUE CONTRIBUTION: TOP STATES MAP

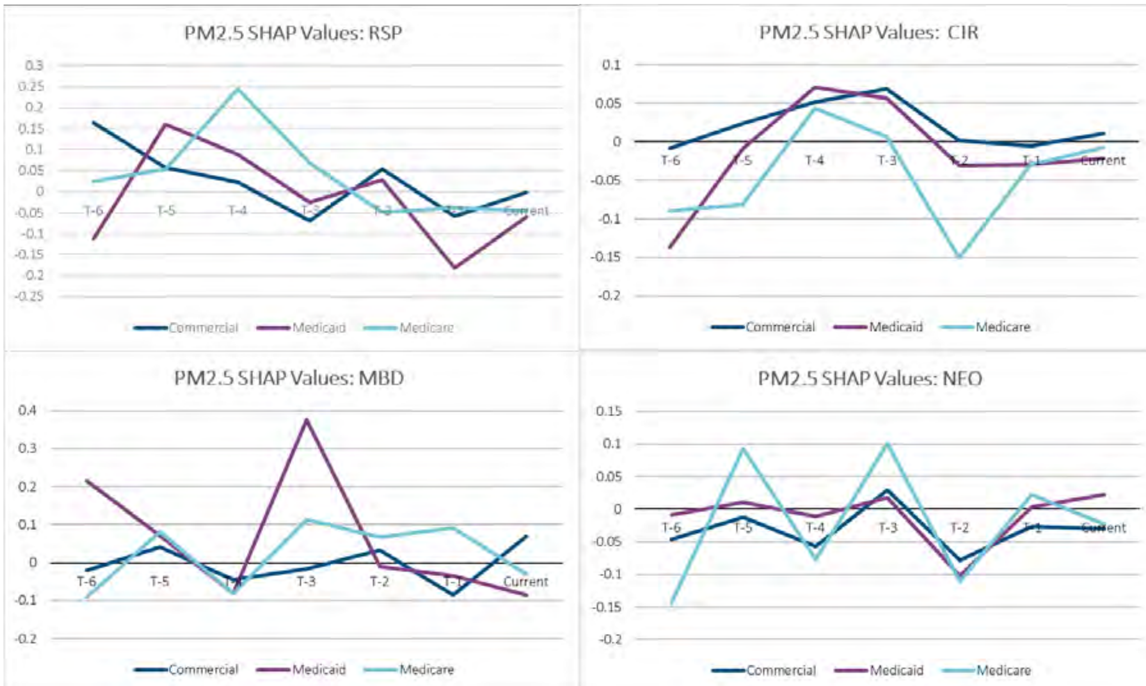


The four maps highlight the states where PM2.5 contributed at least 0.5% to disease prevalence for CIR, RSP, MBD and NEO conditions. They demonstrate that the geographic distribution of PM2.5-attributable burden varies by disease category. For example, CIR shows concentrated effects in the South and parts of the Midwest, whereas RSP and MBD exhibit broader geographic spread, including Western and Northeastern states. The intensity of PM2.5 SHAP contributions also varies, with the highest values in the MBD and NEO maps, where contributions in some states exceed 1.5% and 2.0%, respectively.

3.4.5 TEMPORAL PATTERNS

To assist in understanding the immediate, mid-to-longer-term impact of poor air quality on disease prevalence rates, the PM2.5 SHAP values across the current season and six lag periods (T-1 to T-6, or lag 1 to lag 6, where each lag represents four months) are plotted in Figure 2. The *x*-axis shows the lag period, with the current season on the furthermost right, and the *y*-axis shows the average SHAP value, which quantifies the average contribution of PM2.5 exposure at each period to predicted disease prevalence. A positive SHAP value indicates that PM2.5 exposure at that period increased the predicted prevalence of the condition, whereas a negative SHAP value suggests a decrease—perhaps because of delayed care-seeking behavior rather than as a protective effect.

Figure 2
PM2.5 SHAP VALUE TEMPORAL PATTERNS



It appears that the effects of PM2.5 exposure vary across time, disease categories, and coverage types. Specifically,

- **Immediate impact (no lag to one lag):** The strongest immediate effects of PM2.5 exposure appear in RSP for the commercial and Medicaid populations, with positive SHAP values indicating a rapid increase in prevalence, consistent with common medical knowledge that air pollution quickly exacerbates airway inflammation and acute respiratory distress. Medicaid MBD also display an early response, with positive SHAP values at lag 0 to 1. This may reflect acute stress responses, where spikes in air pollution correlate with increased anxiety, mood disturbances, or cognitive dysfunction. Given the higher prevalence of preexisting mental health conditions in Medicaid populations, this early effect could be driven by heightened physiological stress responses or increased vulnerability to environmental stressors.

- **Delayed effects (two or three lags):** At lags 2 to 3, CIR SHAP values rise across all coverage types, suggesting that PM2.5 contributes to long-term cardiovascular risks, likely because of systemic inflammation and oxidative stress. MBD also shows increasing SHAP values, consistent with existing empirical evidence that prolonged pollution exposure impacts neurological and psychiatric health.[22]

[22] S. Chen et al., "Air Pollution and Mental Health: Evidence from China," *AEA Papers and Proceedings* 114 (May 2024): 423–428. M. C. Power et al., "The Relation Between Past Exposure to Fine Particulate Air Pollution and Prevalent Anxiety: Observational Cohort Study," *BMJ* 350 (March 2015): h1111, https://doi.org/10.1136/bmj.h1111.

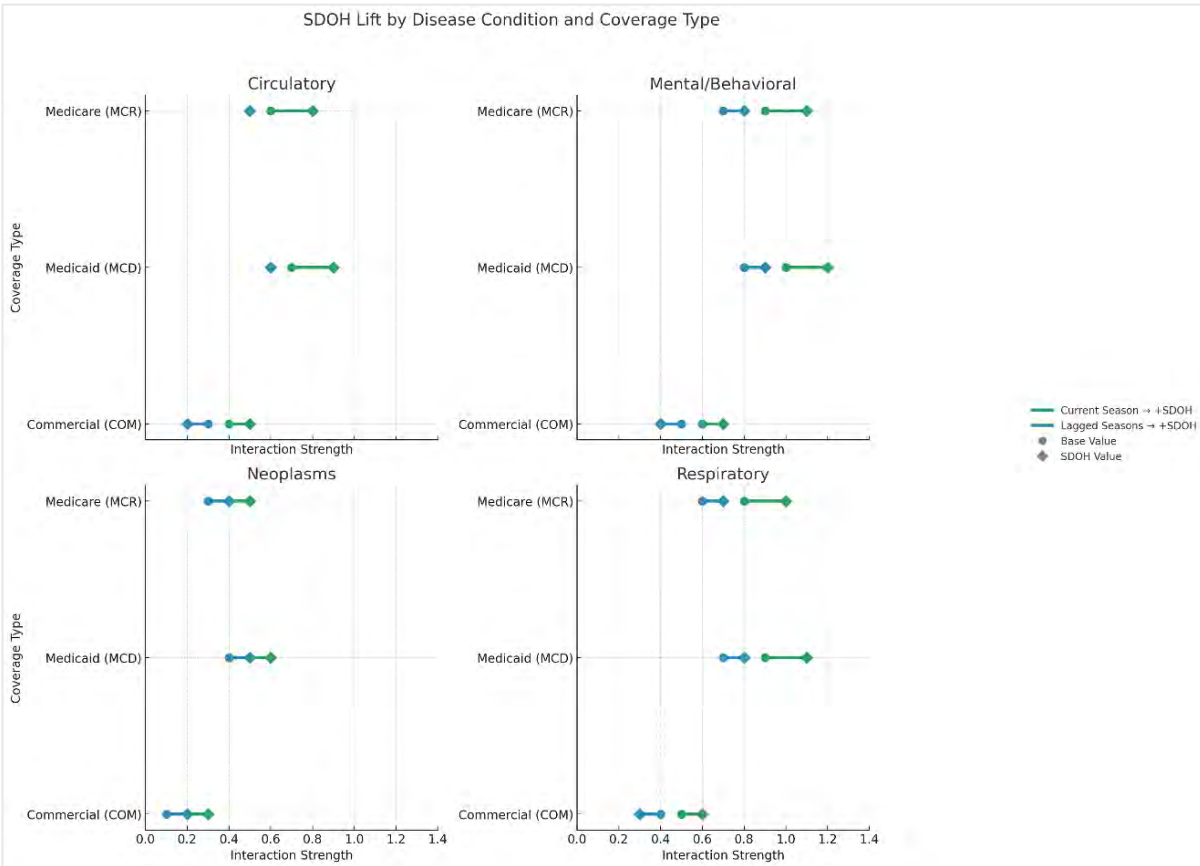
- **Longer-term cumulative effects (four to six lags):** By lags 4 to 6, Medicare populations show increasing SHAP values in CIR, MBD, and NEO, indicating cumulative effects of PM2.5 exposure. MBD in Medicare beneficiaries worsen over time, aligning with research linking air pollution to cognitive decline, dementia, and neurodegenerative diseases.[23] Unlike Medicaid, where the effects appear more immediate, Medicare's response is slower but persistent, reflecting gradual neurological deterioration rather than acute psychiatric episodes. For RSP, SHAP values fluctuate. Delayed exacerbations, compounded by interactions with respiratory infections or weather-related factors, likely contribute to nonlinear trends over time.
- **SHAP values that are negative across all time periods**: It is unlikely this indicates a protective effect of PM2.5, but rather may have reflected delays and avoidance of health care during high-pollution time periods.

[23] See note 12.

3.4.6 INTERACTIONS BETWEEN CLIMATE EVENTS AND OTHER DRIVERS OF DISEASE PREVALENCE RATES

The interactions between PM2.5 and SDOH are presented in Figure 3.

Figure 3
SDOH LIFT BY DISEASE CONDITION AND BY COVERAGE TYPE
INTERACTION STRENGTH BY COVERAGE TYPE (AVERAGE GAIN VALUES FROM XGBOOST MODELS)[24]



Note: Gain Value Unit = 1e10.

Figure 4 presents a set of dumbbell charts that visualize the strength of the interaction between PM2.5 and SDOH, measured by the Gain Value (on the order of 1e10). In XGBoost, gain refers to the improvement in model accuracy brought by a particular feature when it is used to split the data at a decision node. It quantifies the relative contribution of each feature to the model by measuring the average gain across all splits where the feature is used. Higher gain values indicate that the feature is more important for making accurate predictions.

In each chart, the model gain is compared: one with only the PM2.5 feature (represented by dots) and one where SDOH interact with these PM2.5 features, allowing for estimating the incremental Gain Value in XGBoost from including SDOH. Green segments reflect the gain or loss from adding SDOH to the current

[24] The absence (or near absence) of a blue line in the circulatory condition panel reflects that SDOH did not materially amplify the impact of lagged PM2.5 exposure in this model, as measured by incremental Gain Value.

season’s PM2.5 air pollution intensity, and blue segments reflect the gain or loss from adding SDOH to lagged-season pollution exposures. Longer lines indicate a stronger amplification effect from SDOH.

The analysis reveals that SDOH, which measures community level characteristics, can amplify the impact of immediate air pollution events across disease conditions and across all coverage types, with the strongest effects observed in Medicaid, followed by Medicare, and then commercially insured populations. This likely reflects population and community differences in access to health care and protective resources such as high-quality housing, air filtration systems, or timely medical care.

These findings illustrate that environmental risks are not experienced equally and suggest that individuals with fewer resources may face greater health consequences during high pollution periods. Public health and climate response strategies may benefit from prioritizing Medicaid and Medicare populations and include provisions to address both immediate and cumulative pollution exposures. Including SDOH in predictive models helps identify populations at higher risk and supports a more targeted and efficient risk mitigation strategy.

Section 4: Discussion

This study highlights the complex relationship between wildfire-related air pollution and health outcomes, particularly the role of PM2.5 exposure during wildfire seasons. As more frequent and severe wildfires occur, health care and insurance sectors will likely want to anticipate increasing burdens on morbidity and health care costs.

4.1 LESSONS LEARNED

The study results confirm that elevated PM2.5 levels during wildfire seasons correlate with increased respiratory, cardiovascular, neoplasms, and mental health conditions. The impact is not uniform across populations—Medicaid and Medicare enrollees experience the greatest additional health burden, suggesting that older adults and individuals with fewer health care resources may be more affected. The combination of preexisting health conditions, reduced access to health care, and environmental exposures likely contribute to these differences. These findings are consistent with academic research and industry experience, reinforcing the importance of considering public health interventions that target high-risk communities and integrate climate risks into health care planning.

From a methodological perspective, the study demonstrates the value of machine learning in improving risk prediction. Compared to traditional statistical models, machine learning techniques do not require much upfront knowledge about the underlying problem. The algorithms capture complex interactions between PM2.5, SDOH, and morbidity more comprehensively than traditional methods. However, these models come with challenges—although they provide strong predictive accuracy, their interpretability remains a concern. Actuaries and health care analysts may need to balance the advantages of machine learning with the need for clear, actionable insights.

The analysis underscores that SDOH plays a significant role in amplifying the health impacts of wildfire-driven air pollution. Communities with higher social vulnerability scores (e.g., lower income, reduced health care access, and higher environmental risk exposure) experience a disproportionately higher disease burden. These findings suggest that insurers, policymakers, and public health agencies could benefit from considering integrating climate risk factors into policy design and exploring targeted mitigation efforts such as air filtration subsidies, health care access expansion, and community-based intervention programs.

4.2 LIMITATIONS

A key challenge and limitation in this study was the difficulty in attributing PM2.5 levels specifically to wildfire smoke. Although wildfire seasons correlate strongly with increased PM2.5 exposure, other pollution sources such as traffic, industrial emissions, and secondary atmospheric reactions contribute to overall PM2.5 levels. Wildfire smoke can travel thousands of miles and undergo chemical transformations, making it harder to track its precise contribution to health impacts. To address this, the study adopted a seasonal exposure framework, which provides a practical approach for assessing health risks while acknowledging the inherent uncertainties in source attribution.

Although multiyear health care claims data and air quality records were used in the analysis, regional variations in air monitoring coverage affect data accuracy. Certain areas, particularly rural and underserved regions, may have limited air quality monitoring, introducing potential gaps in exposure estimation.

Another limitation is the lack of individual-level exposure data. The models rely on county- and regional-level PM2.5 measurements, assuming uniform exposure within these areas. However, individual exposure can vary widely based on housing conditions, indoor air filtration, occupational settings, and personal behavior. People working outdoors, for example, are likely to experience higher exposure than those spending most of their time indoors with air purification measures. Future studies incorporating personal exposure tracking or microlevel environmental sensors could improve the understanding of individual risk.

Additionally, the study is limited to insured populations. The study dataset primarily consists of commercial, Medicare, and Medicaid claims. Uninsured individuals who may face greater health risks because of delayed care or financial barriers were not represented in the study. As such, the study results may not fully capture the true burden of wildfire-related air pollution across the entire U.S. population.

Lastly, although the study focused on respiratory, cardiovascular, mental health, and neoplastic conditions, other health outcomes are likely to be influenced by wildfire smoke exposure that were not examined. Pregnancy-related complications, neurodevelopmental disorders, and cognitive decline are emerging areas of concern in air pollution research, and present opportunities to explore these impacts in greater detail in future studies.

4.3 INDUSTRY IMPLICATIONS

The health insurance industry is navigating an increasingly complex landscape. In recent years, insurers have contended with the implementation of health reforms to address coverage and affordability issues, the financial pressures of inflation, workforce burnout, and an aging population. The industry has also grappled with the adoption of data-driven business transformations, including generative artificial intelligence, as well as the long-term impacts of the opioid epidemic and the COVID-19 pandemic. Climate events and environmental hazards, such as PM2.5 air pollution and extreme heat, now introduce additional challenges that act as stressors to an already burdened health care system. These environmental risks could exacerbate existing uncertainties in health care utilization, premium pricing, and regulatory policies and may necessitate a fundamental shift in how insurers assess risk, design benefits, and engage with stakeholders.

From a financial and actuarial perspective, climate and environmental risks may introduce significant variability in cost projections and premium setting. Traditional actuarial models, which rely on projections based on historical claims data, may not fully account for the evolving health impacts of climate change. As air pollution and extreme heat events intensify, the prevalence and severity of respiratory and cardiovascular conditions, mental and behavioral disorders, and neoplasms—disease categories examined in this study—are likely to rise, driving higher claims costs and greater unpredictability. These risks are not evenly distributed. Geographic factors play a critical role, with urban heat islands and regions prone to wildfires and flooding facing disproportionate burdens. In addition, insurers with a strong presence in government-sponsored programs, such as Medicaid managed care and Medicare Advantage, may also face disproportionate exposure to climate-related risks because of their geographic and population concentration. Many Medicaid and Medicare plans operate in specific regions, making them particularly vulnerable to localized climate-driven health effects. Moreover, SDOH further amplify these differences, as populations with limited access to health care, inadequate housing, or preexisting conditions are more susceptible to climate-related health risks. Without strategic interventions, sustained cost increases could destabilize insurance markets.

Operationally, insurers may need to rethink how they engage with provider networks and policyholders in the face of climate-related disruptions. Natural disasters can disrupt health care delivery, strain emergency services, and create long-term care needs. Insurers may want to support providers in developing adaptation strategies, such as expanding telehealth services to ensure care continuity during extreme weather events and investing in community-based initiatives to address climate-sensitive conditions. As shown in this study, long-term exposure to environmental stressors is associated with a growing burden of chronic diseases, further straining insurance systems. To mitigate these impacts, insurers may consider incorporating climate risk factors into their actuarial models and develop preventive health interventions that reduce long-term health care costs associated with environmental exposures. Insurers may also want to look at their own workforces, systems, and operations to ensure they are designed to withstand climate stressors.

Regulatory frameworks may also evolve to reflect these emerging risks. Policymakers and regulators may consider working with insurers to develop climate-informed risk models that ensure equitable premium structures while maintaining financial sustainability. Investment in measures such as subsidies for air filtration systems, extreme temperature mitigation strategies, and targeted interventions for vulnerable populations may yield long-term cost savings by reducing preventable hospitalizations and emergency department visits. Public programs, including Medicare and Medicaid, may require policy adjustments to adequately cover climate-related health interventions and to prevent gaps in care access from widening.

To remain viable in this changing landscape, insurers may embrace innovative risk modeling approaches that integrate climate and environmental data into actuarial calculations. Predictive analytics and machine learning may be used in forecasting climate-driven health care utilization patterns and refining pricing strategies. Collaboration with public health organizations and governmental agencies could also be critical in developing comprehensive strategies to manage climate-driven health risks that integrate both health care and insurance perspectives. The increasing unpredictability of medical inflation suggests a growing importance for actuaries to explore new methods of quantifying uncertainty and develop appropriate contingency loadings. Illustrating the key uncertainties in premium setting and modeling policy response impacts to stakeholders at a granular level are likely to become more important. The aggregate actuarial models traditionally used for premium setting are unlikely to be sufficient to capture the complexity of future risks or highlight the main risk drivers and associated levels of variability.

Collaboration with academia could contribute to the understanding of the latest climate science and analytical approaches.

The intersection of climate risks and health insurance is no longer a theoretical concern but a tangible reality with significant financial, operational, and regulatory implications. The industry may need to act swiftly, leveraging data-driven insights and strategic partnerships to mitigate risks and avoid exacerbating existing disparities in health and financial security.

4.4 FUTURE RESEARCH

Building on this study, several areas warrant further exploration to enhance risk modeling and inform mitigation strategies.

Expanding the range of health conditions analyzed is a key area for future research. Although this study focused on four disease categories with well-documented links to air pollution, it established a methodological framework that may be applied to estimate the impact of PM2.5 exposure during wildfire seasons—and potentially other climate events—on a broader range of health conditions. Additionally, longer-term studies tracking cumulative exposure effects over multiple years could provide valuable insights into the long-term health consequences of wildfire-related air pollution.

Further refining machine learning models for actuarial and analytic applications is also an opportunity for future research. Although machine learning demonstrated strong predictive accuracy and captured complex interactions between air pollution, health, and socioeconomic factors, its interpretability and transparency remain challenging for decision-making and regulatory purposes. Exploring ways to improve explainability—such as through causal inference techniques or hybrid modeling approaches that combine machine learning with traditional statistical methods—would be beneficial.

From a public health policy and insurance operations perspective, integrating climate adaptation strategies into health care planning is an important consideration. Given the disproportionate impact of air pollution on vulnerable populations, insurers may want to incorporate climate-related health risks into morbidity and cost projections. Additionally, assessing the effectiveness of preventive measures—such as improved air filtration, targeted health care interventions, and telemedicine during wildfire events—could help reduce health care costs and improve outcomes.

Section 5: Acknowledgments

The research team's deepest gratitude goes to those without whose efforts this project could not have come to fruition: the volunteers who generously shared their wisdom, insights, advice, guidance, and arm's length review of this study prior to publication. Any opinions expressed may not reflect their opinions nor those of their employers. Any errors belong to the authors alone.

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Appendix A: Data and Descriptive Statistics

HEALTH DATA

In this study, extreme heat is represented by calculating average monthly heat intensity for each core-based statistical area (CBSA) during summer months (May–September because this is when extreme heat is most likely to occur). This process is shown for a subset of CBSAs in Figure 2 and involves the following steps for each CBSA:

1. Calculate average daily minimum apparent temperature.
2. Calculate monthly historical baseline.
3. Calculate daily heat intensity as daily minimum apparent temperature less relevant month's historical baseline.
4. Calculate average heat intensity for each month (May–September) in the study period.

Apparent temperature, also known as "feels-like" or the "heat index," combines temperature and humidity. When temperatures and humidity are both high, the body's ability to cool itself through sweating is reduced, making it feel hotter than the actual air temperature. Apparent temperature combines these factors into a measure of perceived temperature. Daily minimum apparent temperature is used here because negative health impacts have been shown to be associated with elevated nighttime temperatures and high humidity.[25]

Daily apparent temperature is derived by using the following equation:[26]

$$A = -1.3 + 0.92T + 2.2e,$$

where A is the apparent temperature (°C), T is air temperature (°C), and e is water vapor pressure (kilopascals).

To calculate daily apparent temperature for CBSAs, daily minimum temperature and vapor pressure raster datasets were obtained from Daymet Daily Surface Weather Data[27] for each study year (2017–2023). These data provide daily averages of minimum temperature and vapor pressure at a 1 km^2 resolution. Using the above equation, apparent temperature rasters were generated for each day in May–September for years 2017–2023. Daily apparent temperature was then aggregated to CBSAs by spatially averaging the apparent temperature values of all cells within each CBSA. Areas that are not included in any CBSA were grouped by state and considered as a single region.

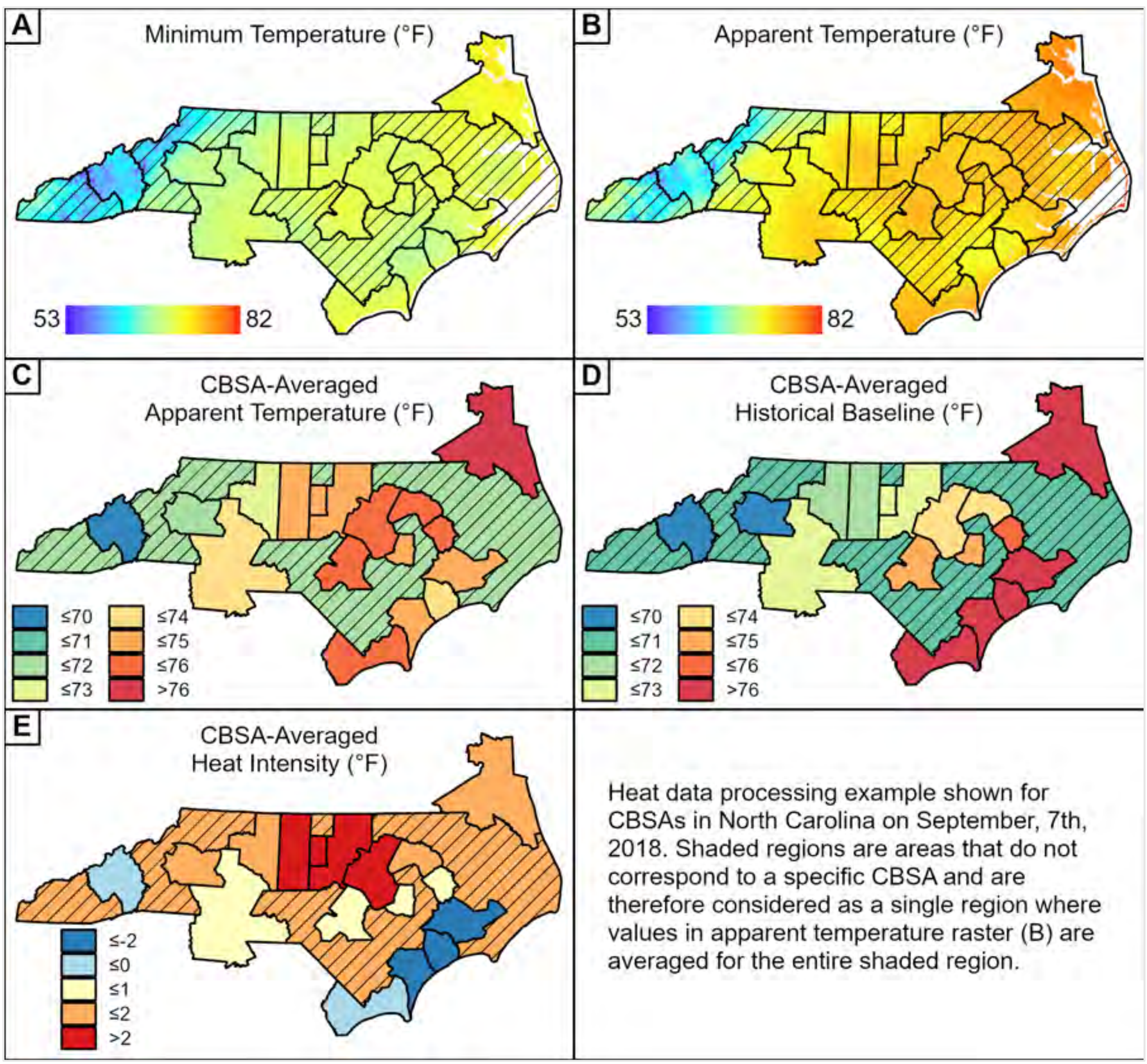
The methods were then repeated using daily data from 1980–2010 to obtain the historical baseline from which heat intensity is calculated. For each summer month, daily minimum apparent temperature values were calculated for each CBSA for all years between 1980 and 2010. This 30-year period was chosen to

[25] M. C. Sarofim et al., "Temperature-Related Death and Illness," in *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment* (Washington, DC: U.S. Global Change Research Program, 2016), 43–68. https://health2016.globalchange.gov.
[26] R. G. Steadman, "A Universal Scale of Apparent Temperature," *Journal of Applied Meteorology and Climatology* 23, no. 12 (1984): 1674–1687, https://doi.org/10.1175/1520-0450(1984)0232.0.CO;2.
[27] "Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 4 R1," ORNL DAAC, NASA, November 1, 2022, https://doi.org/10.3334/ORNLDAAC/2129.

represent the historical baseline value due to alignment with established climatological metrics.[28] Monthly historical baselines are defined as the 95th percentile of CBSA daily minimum apparent temperatures for each summer month during 1980–2010. Monthly baselines were chosen rather than a single baseline encompassing all summer months to avoid artificially exaggerating and minimizing heat intensity during cooler months (May and September) and warmer months (June–August), respectively.

Daily heat intensity for each CBSA during the study period was determined by calculating the difference between daily minimum apparent temperature and the associated historical baseline. Finally, monthly averaged heat intensity values for each CBSA were calculated by averaging all positive heat intensity values for each summer month in 2016–2023.

Figure A1
HEAT INTENSITY DEFINITION



[28] "U.S. Climate Normals," National Centers for Environmental Information, NOAA, 2023, https://www.ncei.noaa.gov/products/land-based-station/us-climate-normals.

Figure A2
MONTHLY AIR QUALITY INDICATOR BY YEAR AND BY CENSUS REGION

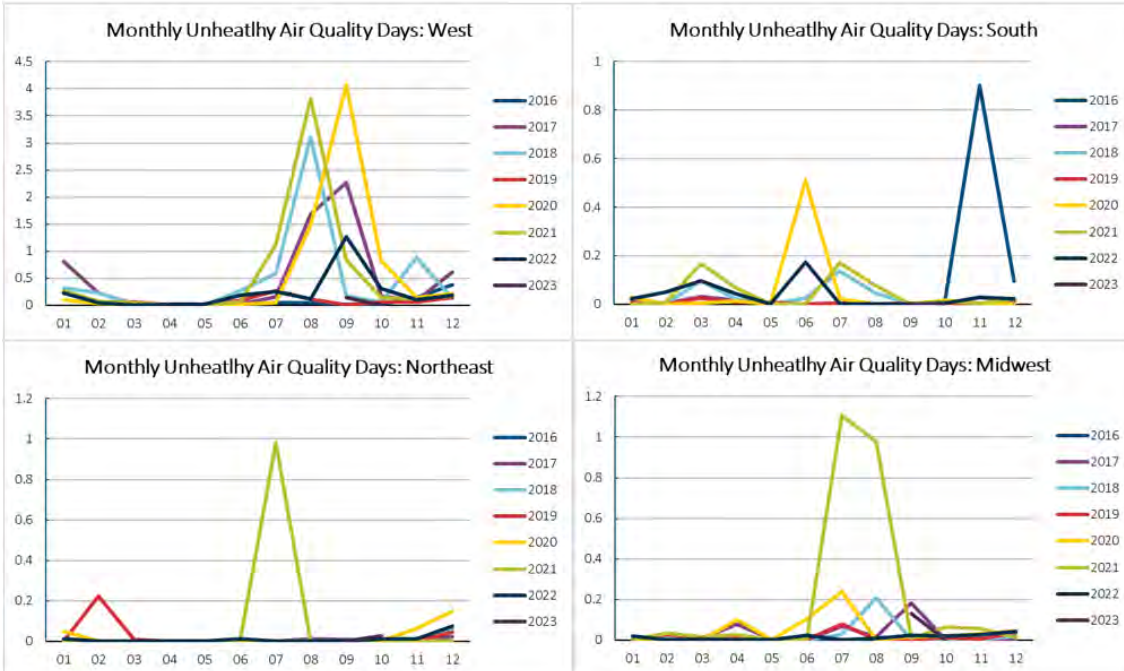


Table A3

DISEASE CONDITION PREVALENCE RATES BY CENSUS REGION (PER 1,000 MEMBERS, PER FOUR MONTHS, DATA FROM 2017 TO 2023)

Northeast

	Pre-season			High season			Post-season		
Condition category	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid
CIR	401.4	734.2	434.5	381.7	704.3	419.7	391.9	725.7	428.6
MBD	281.0	427.6	440.3	273.2	415.8	427.6	280.0	430.3	434.1
RSP	343.7	461.1	402.1	271.4	413.4	346.1	349.4	461.3	412.9
NEO	180.6	273.9	107.1	183.3	275.4	106.0	181.5	276.2	105.3

South

	Pre-season			High season			Post-season		
Condition category	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid
CIR	431.9	759.6	461.7	416.3	729.9	443.7	423.0	746.8	453.5
MBD	265.7	370.7	431.0	259.5	358.7	421.4	263.3	367.4	428.9
RSP	382.3	460.5	403.5	315.5	411.9	355.2	405.3	464.0	422.7
NEO	161.4	266.8	91.2	165.0	264.9	89.5	161.1	267.1	86.6

West

	Pre-season			High season			Post-season		
Condition category	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid
CIR	362.9	672.9	395.9	347.1	644.9	384.0	353.5	665.9	392.4
MBD	258.2	351.0	433.9	252.9	339.6	417.7	258.5	350.8	428.3
RSP	322.1	410.2	359.6	258.4	364.2	301.6	322.1	411.3	364.9
NEO	165.1	279.8	95.4	168.6	279.3	97.6	166.2	281.2	92.9

Midwest

	Pre-season			High season			Post-season		
Condition category	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid	Commercial	Medicare	Medicaid
CIR	374.2	723.9	442.9	360.5	699.5	427.3	370.1	717.3	435.7
MBD	285.5	399.8	481.7	277.9	387.9	471.7	285.3	401.9	481.8
RSP	348.1	458.0	417.5	277.3	410.9	360.5	357.8	458.3	430.3
NEO	151.1	245.1	89.2	156.9	248.3	90.9	154.4	248.2	87.1

Table A4

MODEL DEVELOPMENT SAMPLE DESCRIPTIVE STATISTICS

Unique member count

Coverage type	2017	2018	2019	2020	2021	2022
Commercial	39,811,207	20,277,903	20,293,795	16,629,155	17,304,863	17,070,948
Medicare	7,186,108	4,215,666	4,649,268	3,026,225	2,983,034	3,012,006
Medicaid	3,974,067	2,289,685	3,324,803	3,427,110	4,239,319	4,839,278

% female

Coverage type	2017	2018	2019	2020	2021	2022
Commercial	50.3	50.3	50.2	50.0	50.0	49.9
Medicare	50.9	50.9	50.7	50.9	50.9	50.9
Medicaid	53.1	53.1	52.9	52.9	52.7	52.2

Average age (years)

Coverage type	2017	2018	2019	2020	2021	2022
Commercial	43.6	42.7	42.3	41.8	41.6	41.3
Medicare	60.0	59.0	58.2	59.1	59.3	59.6
Medicaid	37.0	37.4	37.7	39.2	39.4	40.0

Appendix B: Generalized Linear Models and XGBoost Algorithms

The generalized linear model (GLM) is a parametric approach that assumes a specific functional relationship between predictors and the dependent variable. One of its advantages is the interpretability of its coefficients, which directly represent the marginal effect of a one-unit change in a predictor variable on the disease prevalence rate; e.g., one extra bad air quality day may cause *X* increase/decrease per 1,000 of respiratory conditions. This level of interpretability is useful especially for health care payers. However, GLMs rely heavily on prior knowledge about variable relationships (such as how preexisting health status or socioeconomics interact with climate events), model structure (such as linear or log linear), and assumptions such as normality or distribution-specific error terms.

XGBoost, a gradient-boosted decision tree algorithm, is a machine learning model that does not require predefined assumptions about variable relationships. This flexibility makes it particularly suitable for research where underlying relationships are complex or not well understood such as the impact of wildfire-related air pollution on health. Unlike GLMs, XGB provides feature importance metrics such as FScore (frequency of a feature's usage) and Gain (contribution to model improvement), as well as SHAP (SHapley Additive exPlanations) values, which quantify the contribution of each feature to a specific prediction. Although SHAP values offer insights into feature influence, they do not directly represent marginal effects in the same way as GLM coefficients.

XGBoost was favored over other machine learning algorithms because of its robustness and ability to handle large and complex datasets efficiently. It also incorporates regularization techniques to mitigate overfitting, making it a reliable choice for our research objectives. The combination of superior predictive accuracy and advanced interpretability tools such as SHAP values positioned XGB as the optimal algorithm for modeling disease prevalence rates in this study.

In machine learning algorithms, a feature refers to an individual measurable property or characteristic used as input for the model. Features are often derived from raw data through processes such as transformation, encoding, or scaling and are selected for their predictive power or relevance to the outcome variable. In our XGB model, unhealthy air quality days serve as a feature for predicting respiratory disease rates. The algorithm accounts for nonlinear interactions between unhealthy air quality days and other features, such as demographics, health status, and socioeconomic factors. XGBoost does not require explicit upfront specification of relationships, meaning that no prior assumptions about variable interactions are necessary. Instead, the algorithm autonomously identifies and captures complex relationships within the data, making it well suited for uncovering intricate patterns in multidimensional datasets. The complexity of these interactions is significant; for instance, XGB can evaluate hundreds or thousands of potential interactions among features, a scale of complexity that would be computationally intensive to approximate using GLM.

In contrast, a predictor or explanatory variable in GLMs is a variable explicitly hypothesized to have a specific, linear, or nonlinear relationship with the dependent variable, often grounded in theory or prior knowledge. Using the same example, unhealthy air quality days could serve as an explanatory variable in a GLM, where its impact on respiratory disease rates is quantified through a coefficient that represents the marginal effect of each additional day of unhealthy air quality. Although features in machine learning may be abstract or engineered without prior assumptions about their relationships to the target variable, explanatory variables in GLM are selected and modeled based on their anticipated direct impact, offering interpretable insights into their contribution to the outcome.

Tables B1 and B2 list the features used in the XGBoost models and the explanatory variables used in the GLM model.

Table B1
FEATURES INCLUDED IN XGBOOST MODELS

Features
Age group
Indicator for 2020
Gender
Risk score percentile (avg ~1)
Social Vulnerability Index
Seasonality of wildfires: pre-season (Feb.–May), high season (Jun.–Sep.), post-season (Oct.–Jan.)
State
High heat intensity days (current season)
High heat intensity days (lagged: 1 season ago)
High heat intensity days (lagged: 2 seasons ago)
High heat intensity days (lagged: 3 seasons ago)
High heat intensity days (lagged: 4 seasons ago)
High heat intensity days (lagged: 5 seasons ago)
High heat intensity days (lagged: 6 seasons ago)
Unhealthy/worse air quality days (current season)
Unhealthy/worse air quality days (lagged: 1 season ago)
Unhealthy/worse air quality days (lagged: 2 seasons ago)
Unhealthy/worse air quality days (lagged: 3 seasons ago)
Unhealthy/worse air quality days (lagged: 4 seasons ago)
Unhealthy/worse air quality days (lagged: 5 seasons ago)
Unhealthy/worse air quality days (lagged: 6 seasons ago)

Table B2

VARIABLES INCLUDED IN GLM MODELS

Variables
Age group
Indicator for 2020
Gender
Risk score percentile (avg ~1)
Social Vulnerability Index
Seasonality of wildfires: pre-season (Feb.–May), high season (Jun.–Sep.), post-season (Oct.–Jan.)
State
High heat intensity days (current season)
High heat intensity days (lagged: 1 season ago)
High heat intensity days (lagged: 2 seasons ago)
High heat intensity days (lagged: 3 seasons ago)
High heat intensity days (lagged: 4 seasons ago)
High heat intensity days (lagged: 5 seasons ago)
High heat intensity days (lagged: 6 seasons ago)
Unhealthy/worse air quality days (current season)
Unhealthy/worse air quality days (lagged: 1 season ago)
Unhealthy/worse air quality days (lagged: 2 seasons ago)
Unhealthy/worse air quality days (lagged: 3 seasons ago)
Unhealthy/worse air quality days (lagged: 4 seasons ago)
Unhealthy/worse air quality days (lagged: 5 seasons ago)
Unhealthy/worse air quality days (lagged: 6 seasons ago)
Risk score interaction with high heat intensity days (current season)
Risk score interaction with high heat intensity days (lagged: 1 season ago)
Risk score interaction with high heat intensity days (lagged: 2 seasons ago)
Risk score interaction with high heat intensity days (lagged: 3 seasons ago)
Risk score interaction with high heat intensity days (lagged: 4 seasons ago)
Risk score interaction with high heat intensity days (lagged: 5 seasons ago)
Risk score interaction with high heat intensity days (lagged: 6 seasons ago)
Risk score and SVI interaction with high heat intensity days (current season)
Risk score and SVI interaction with high heat intensity days (lagged: 1 season ago)
Risk score and SVI interaction with high heat intensity days (lagged: 2 seasons ago)
Risk score and SVI interaction with high heat intensity days (lagged: 3 seasons ago)
Risk score and SVI interaction with high heat intensity days (lagged: 4 seasons ago)
Risk score and SVI interaction with high heat intensity days (lagged: 5 seasons ago)
Risk score and SVI interaction with high heat intensity days (lagged: 6 seasons ago)
Risk score interaction with unhealthy/worse air quality days (current season)
Risk score interaction with unhealthy/worse air quality days (lagged: 1 season ago)
Risk score interaction with unhealthy/worse air quality days (lagged: 2 seasons ago)
Risk score interaction with unhealthy/worse air quality days (lagged: 3 seasons ago)
Risk score interaction with unhealthy/worse air quality days (lagged: 4 seasons ago)
Risk score interaction with unhealthy/worse air quality days (lagged: 5 seasons ago)
Risk score interaction with unhealthy/worse air quality days (lagged: 6 seasons ago)
Risk score and SVI interaction with unhealthy/worse air quality days (current season)
Risk score and SVI interaction with unhealthy/worse air quality days (lagged: 1 season ago)
Risk score and SVI interaction with unhealthy/worse air quality days (lagged: 2 seasons ago)
Risk score and SVI interaction with unhealthy/worse air quality days (lagged: 3 seasons ago)
Risk score and SVI interaction with unhealthy/worse air quality days (lagged: 4 seasons ago)
Risk score and SVI interaction with unhealthy/worse air quality days (lagged: 5 seasons ago)
Risk score and SVI interaction with unhealthy/worse air quality days (lagged: 6 seasons ago)

It is theoretically possible to approximate how machine learning algorithms use features in a GLM by explicitly specifying interaction terms and nonlinear transformations. For example, the interactions between unhealthy air quality days and demographics or socioeconomic variables could be modeled through interaction terms or polynomial expansions in a GLM. However, the effort to approximate the complexity identified by XGB would be substantial. Each potential interaction and transformation would need to be manually defined, requiring domain expertise and significant computational resources. In practice, this could involve specifying thousands of interaction terms to capture the equivalent relationships automatically learned by XGB, highlighting the efficiency and scalability of machine learning models compared to traditional GLMs.

Table B3

MODEL R^2

XGBoost model R^2 (validated by *k*-fold validation)

Condition category	Commercial	Medicare	Medicaid
CIR	63.6%	41.6%	59.4%
MBD	43.4	34.6	43.3
NEO	45.2	36.4	32.6
RSP	34.3	41.6	31.8

GLM model R^2

Condition category	Commercial	Medicare	Medicaid
CIR	55.9%	27.5%	49.1%
MBD	22.2	15.4	20.5
NEO	23.6	18.9	14.1
RSP	19.1	20.0	17.9

Table B4

TOP 10 STATES BY SHAP VALUE AS A PERCENTAGE OF DISEASE PREVALENCE RATE

CIR (%)					
Commercial		Medicare		Medicaid	
AL	0.24	CA	0.11	AL	0.80
CA	0.26	CT	0.07	CT	0.37
CT	0.23	FL	0.02	GA	0.61
DE	0.24	MA	0.05	IA	0.27
MD	0.21	MN	0.02	IL	0.43
MS	0.37	NH	0.03	IN	0.82
OH	0.29	NM	0.17	KY	0.42
RI	0.28	NY	0.12	MS	0.85
SC	0.22	SD	0.05	NJ	0.53
WV	0.24	VA	0.09	PA	0.81
RSP (%)					
Commercial		Medicare		Medicaid	
AZ	0.27	AZ	0.33	AL	0.39
CA	0.50	CT	0.35	CA	0.42
MT	0.19	ME	0.33	CT	1.65
NH	0.34	NH	0.58	KY	0.55

NM	0.53	NM	0.81	LA	0.21
NY	0.14	NY	0.70	ME	0.67
SD	0.30	RI	0.54	MO	0.15
TX	0.14	SD	0.83	OK	0.21
VT	0.19	VA	0.63	TN	0.15
WY	0.52	VT	0.49	VT	0.43
MBD (%)					
Commercial		Medicare		Medicaid	
AL	1.03	CA	0.36	AL	1.35
AR	0.80	FL	0.70	CO	1.18
CA	0.82	KS	0.34	DE	0.86
GA	0.90	LA	0.68	KS	1.35
KS	0.89	MA	0.45	LA	1.29
LA	0.93	NH	0.40	MT	1.30
NV	0.69	NY	0.53	ND	0.78
OK	0.73	RI	1.34	NV	1.50
UT	0.70	SD	0.49	VA	1.12
WV	0.70	VA	0.65	WV	0.91
NEO (%)					
Commercial		Medicare		Medicaid	
AL	0.89	GA	0.49	AK	0.64
AR	0.50	ID	0.44	DE	0.41
GA	0.46	KS	0.49	IA	0.71
IL	0.44	KY	0.50	IN	1.08
IN	0.83	LA	0.43	NH	1.59
KS	0.49	ME	0.47	VA	0.45
KY	0.69	MT	0.50	VT	2.15
OK	0.63	NV	0.64	WA	0.61
PA	0.68	OR	0.54	WV	0.58
TN	0.48	UT	0.48	WY	0.58

Appendix C: Selected Bibliography

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