

Supplementary Information:

Socially vulnerable communities face disproportionate exposure and susceptibility to U.S. wildfire and prescribed burn smoke.

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Supplementary Methods

Supplementary Methods: AP4 & AP4T Integrated Assessment Models

The AP4 integrated assessment model connects emissions to monetized damages in the United States (U.S.) for the following five criteria air pollutants: ammonia (NH₃), nitrogen oxides (NO_x), primary particulate matter (primary PM_{2.5}), sulfur dioxide (SO₂), and volatile organic compounds (VOCs). AP4 is the fourth installment of the Air Pollution Emissions Experiments and Policy analysis model (APEEP) [1]. For information on APEEP, see its technical appendix [2]. AP4 is closely related to its direct predecessor, AP3 [3], [4], [5].

AP4T is an extension of the AP4 model. Specifically, AP4T is a stand-alone model, but it is dependent on AP4, using many of its input and much of its structure. AP4T is built to expand the modeling capabilities of the AP4 model to consider the marginal impacts of emissions at the census tract level. AP4T enables a higher resolution for distributional impact analyses, which is particularly important for environmental justice.¹ AP4 (and its predecessors in the APEEP series) operates at the county level for impact reception. The primary goal of AP4T is to expand the dimensionality of the receptors—i.e., downscale from the county to the tract level. The resulting model enables downwind air pollution impact analyses, originally limited to 3,108 counties, for 72,538 tracts.

This file contains an abbreviated overview of AP4 and AP4T (with a particular focus on AP4T's usage in this study); however, an extended exposition can be found in the AP4 & AP4T Technical Appendix (referred to henceforth as “the technical appendix”). The technical appendix can be accessed at <https://nickmuller.tepper.cmu.edu/APModel.aspx> [7].

Supplementary Methods 1: Reduced-complexity air quality modeling

To discuss the reduced-complexity modeling framework of AP4T, the model used for this research, it is necessary to discuss AP4 as well. In this reduced-complexity modeling-focused Supplementary Methods, we discuss both AP4 and AP4T as is necessary to explain our methods.

AP4's input emissions & binning structure

AP4 models NH₃, NO_x, primary PM_{2.5}, SO₂, and VOCs. AP4 uses all emissions provided by the Environmental Protection Agency's (EPA's) National Emissions Inventory (NEI) to estimate baseline concentrations of ambient PM_{2.5} in every contiguous U.S. (CONUS) county [8]. We use the 2017 NEI to compute a unique baseline against which we assess marginal emissions. The baseline accounts for ambient PM_{2.5} levels resulting from nationwide emissions.

¹ The resolution of air quality models matters when looking at distributional impacts. For example, previous work has shown that exposure disparities by race/ethnicity are higher when considering how impacts vary within more granular geographic boundaries [6].

Atmospheric dispersion behaves differently based on the height of pollutant discharge. Therefore, the model treats ground-level sources differently than point sources. Further, AP4 treats electric generating unit (EGU) point sources differently than non-EGU point sources. This results in three bins defined by height of discharge: ground-level emissions are released as such, non-EGU emissions are released from the emission-weighted average effective height across stacks within the county, and EGU emissions are released from the emission-weighted average effective height across stacks at the facility. Effective height is stack height plus plume rise [9]. We calculate plume rise according to Seinfeld & Pandis (2016) [10].

Importantly, emissions from ground-level and non-EGU point sources are modeled as discharging from the population-weighted centroid of the county where the emissions occur. On the other hand, emissions from EGU point sources are modeled as discharging from the coordinates of the facility at which the emissions occur. Supplementary Table 3 summarizes AP4-modeled emissions by bin and pollutant.

AP4T's input emissions & binning structure adaptation

The emissions data for AP4T are the same as those for AP4 [8]. However, the binning structure adapts. We model emissions either from specific coordinates (in the case of all pollutants from EGUs), individual tracts (in the case of primary $\text{PM}_{2.5}$ and VOCs from wildland fires), or population-weighted county centroids (for everything else).

Modeling EGUs from specific coordinates is no different from AP4. Modeling other emissions from the population-weighted county centroids is also no different from AP4 (or its predecessors). The assumption is that economic activity and the resulting emissions are spatially correlated with population. The county centroid method (1) is based on the procedure of AP3 [3], [4], [5] and AP4, which achieve desired air quality modeling performance standards [11], [12], and (2) keeps AP4T's operations manageable. This latter point is a driving factor in several decisions for AP4T. A substantial benefit of AP4 is its reduced-complexity modeling framework—i.e., its simplicity (at least compared to chemical transport models). For AP4T, we balance modeling detail with maintaining computational efficiency and data accessibility.

The unique choice for AP4T's source binning is to model primary $\text{PM}_{2.5}$ and VOC emissions from wildland fires (i.e., wildfires and prescribed burns) from individual tracts. There are four reasons for this modeling choice:

1. **Emission source of focus:** In this research, we use the AP4T model to evaluate the damages from wildland fire smoke. Adding specific modeling detail for the source of interest helps ensure accuracy.
2. **Wildland fire locations:** Wildland fires do not tend to occur in more urban areas but rather in more rural areas (i.e., wildlands). Hence, they typically occur far from their county's population-weighted centroid. Take Siskiyou County, California, for example. Siskiyou's wildfires burnt nearly 150 thousand acres in June, July, and August of 2017 [13]. Siskiyou's wildfires emitted more than 100,000 metric tons of primary $\text{PM}_{2.5}$ during 2017,

the most of any CONUS county [8]. Siskiyou is more than 6,000 square miles [14],² and its three biggest wildfires (98% of its burned acreage) occurred in the western part of the county [13], far from its population-weighted county centroid (see Supplementary Fig. 20).

3. **Atmospheric chemistry:** We only model primary PM_{2.5} and VOCs specially because they settle as ambient PM_{2.5} independently and more rapidly—i.e., they have less of an opportunity to spread and “smooth out.” Robinson et al. (2019), looking at how well land-use regression modeling explained spatial variation in particulate subspecies, found that primary PM_{2.5} and secondary organic aerosols (from VOCs) had notably higher R² values than secondary inorganic species (from NH₃, NO_x, and SO₂) [15]. NH₃, NO_x, and SO₂ react to form secondary PM_{2.5} (mostly in the presence of one another) and have more of an opportunity to spread before doing so and settling in the air as PM_{2.5}.³ This justifies modeling their release from the county centroid simply because their exact release point is less important.
4. **Fire emission magnitudes by pollutant type:** As shown in Supplementary Table 3, the most substantial pollutant resulting from wildland fires is primary PM_{2.5}. This is both considering wildland fires’ contribution to national emissions and primary PM_{2.5}’s contribution to total fire emission tonnage. Regarding the former, wildland fires accounted for 41% of national primary PM_{2.5} emissions in 2017. VOCs are next, where wildland fires accounted for just less than 15% of the national total. Contrarily, fires accounted for 9.7% of NH₃, 8.0% of SO₂, and 3.5% of NO_x. Regarding the latter, primary PM_{2.5} accounted for approximately 24% of total tonnage from wildland fires. Focusing on primary PM_{2.5}’s contribution to the other bins—which does not exceed 8%—emphasizes this magnitude. VOCs are the dominant contributor to wildland fire emission tonnage, but VOCs are also substantial for other bins (i.e., non-fire ground and non-EGU point sources). On the contrary, NO_x and SO₂ are much smaller contributors to total wildland fire emission tonnage than to other bins’ total emission tonnage.

By treating wildland fire emissions uniquely as being released from individual tracts, we effectively add a fourth bin in AP4T compared to AP4—i.e., a wildland fire source bin. We remove wildland fires’ primary PM_{2.5} and VOCs from the county-level ground source bin of AP4 and place them in a tract-level wildland fire source bin for AP4T. We emphasize that NH₃, NO_x, and SO₂ from wildland fires are still modeled from the county-level ground source bin.

National Emissions Inventory’s procedure for estimating wildland fire emissions

While many of the NEI’s point sources, like heavy manufacturing or fossil fuel-fired power plants, are directly monitored, most ground-level sources (including wildland fires) require a more

² For perspective, the mean across the U.S. is approximately 1,000 square miles [14].

³ See the “Interpollutant atmospheric chemistry for secondary PM_{2.5} formation” section in this Supplementary Methods for more information. We note the SO₂ can constitute PM_{2.5} with or without NH₃; NH₃ will not without reacting with either SO₂ or NO_x, and NO_x will not without reacting with NH₃.

complicated procedure to estimate emissions. The NEI estimates wildland fire emissions using fire activity data collected from state, local, and tribal (S/L/T) agencies as well as from national agencies and organizations. These raw burned area datasets are compiled and then reconciled using other data sources—e.g., satellite data from the National Oceanic and Atmospheric Administration’s (NOAA’s) Hazard Mapping System (HMS)—via a geographic information system-based algorithm, SMARTFIRE [16]. Then, it uses a fuel (here, wildland vegetation) consumption-to-emissions model to derive emission factors, BlueSky [17]. Using SMARTFIRE and BlueSky together yields emissions by pollutant type at the county level, reported by the NEI [8].⁴

Distributing fire emissions to the tract level

The NEI only reports fire emissions at the county level [8].⁵ We consider burned area boundary data to distribute fire emissions from the county to the tract level. The percentage of total burned area within a county accounted for by each tract dictates the percentage of primary PM_{2.5} and VOC fire emissions attributed to that tract. We determine burned area boundaries using MTBS wildfire and prescribed burn shapefiles for 2017 [18]. Where the type of fire (i.e., wildfire or prescribed burn) is unknown, we attribute the burned area to wildfires, assuming it is more likely for prescribed burn activity to be identified, tracked, and reported by the responsible party. We find the burned area by tract by overlapping the MTBS spatial data with shapefiles from the U.S. Census Bureau [14].

Supplementary Fig. 20 shows Siskiyou County, California’s census tracts [14] and burned area boundaries [18]. Also shown in the map is Siskiyou’s population-weighted county centroid and its tracts’ geometric centroids. Our distribution procedure allocates all of Siskiyou’s primary PM_{2.5} and VOC fire emissions to the two westernmost tracts (i.e., where all the burned areas are located). We note that the westernmost burned area boundary spreads into Siskiyou’s neighboring California county and the northernmost burned area boundary spreads over the northern state border into Oregon. These areas are not accounted for in Siskiyou’s fire emissions distribution but rather in that for their neighboring counties.

While this procedure covers most of 2017’s wildland fire emissions, some counties with fire emissions data in the NEI do not have any burned area tracked via MTBS. For these counties, we consider the area of “wildlands” in each tract for county-to-tract fire emissions distribution. Specifically, the percentage of total county wildlands accounted for by each tract dictates the percentage of emissions attributed to that tract. We determine wildland areas by tract using the National Neighborhood Data Archive (NaNDA) from researchers at the University of Michigan [19]. We define wildlands as deciduous forest, evergreen forest, mixed forest, shrub/scrub, and herbaceous land area.

⁴ For more information, see the Technical Support Document (TSD) for the NEI (note: Figure 7-4 of the TSD is particularly informative) [8].

⁵ This refers to the publicly available, readily downloadable data [8]. NEI TSD documentation and the EPA’s process for estimating emissions suggests data may be available at a higher spatial resolution (e.g., the tract level) upon request.

There are limitations to our wildland fire emissions distribution process. First, emissions can vary as a function of the amount and type of fuel—i.e., what was burned rather than how much area was burned [20], [21]. In Siskiyou County, California, the tract in the northwest has more burned area than the tract in the southwest; however, the southwest could have released more emissions based on what was burned. Our burned area boundary methodology is ignorant to fuel type variation within counties. Second, wildland percentage does not necessarily correlate with fire activity. For example, Siskiyou’s southeasternmost tract has the greatest amount of wildland across the county, but Supplementary Fig. 20 demonstrates the tract contained no burned area in 2017. While the two tracts with burned area are the next two with the most wildland, this would misallocate substantial fire emissions to the southeasternmost tract. Still, the wildland percentage methodology is better than modeling all wildland fire primary PM_{2.5} and VOC emissions from the population-weighted county centroid (far from most wildlands in Siskiyou) and is only used when burned area boundary data from MTBS are not reported. Most wildland fire emissions come from counties covered by MTBS—e.g., only 6% of primary PM_{2.5} emissions from wildfires come from counties without MTBS burned area boundary data reported [8], [18].

Source-receptor matrices

AP4 uses source-receptor (SR) matrices to estimate resolved concentrations of speciated pollution in every CONUS county from all sources of emissions. The SR matrices use Gaussian plumes, which model three-dimensional atmospheric dispersion or pollutant transport from the discharge point [10], [22], [23], [24].

The following equations demonstrate the SR matrix modeling process of AP4. First, emissions (e) from each source county or EGU (s) are loaded in as vectors (E) by pollutant (p) and bin height (h), as shown in Supplementary Equation 1:

Supplementary Equation 1. AP4’s emissions inventories.

$$E_{p,h} = \begin{bmatrix} e_1 \\ \vdots \\ e_s \end{bmatrix}$$

AP4’s SR matrices, depicted in Supplementary Equation 2, model the transport (χ) of a ton of pollution from each source to each receptor county (r), again by pollutant and bin height. The SR matrices represent an average of atmospheric conditions relevant to pollutant transport from the source:

Supplementary Equation 2. AP4’s source-receptor matrices.

$$SR_{p,h} = \begin{bmatrix} \chi_{1,1} & \cdots & \chi_{1,r} \\ \vdots & \ddots & \vdots \\ \chi_{s,1} & \cdots & \chi_{s,r} \end{bmatrix}$$

Multiplying the emissions vectors by the corresponding SR matrices, shown in Supplementary Equation 3, provides annual average speciated concentrations (C) of ambient pollution, by pollutant and bin height, in each CONUS county resulting from all sources' emissions:

Supplementary Equation 3. AP4's speciated concentration estimates.

$$C_{p,h} = (E_{p,h})^T \times (SR_{p,h})$$

The concentrations are subsequently aggregated across the different bin heights for total annual average speciated ambient pollution in every county resulting from NH_3 , NO_x , primary $\text{PM}_{2.5}$, SO_2 , and VOC emissions.

Gaussian plume modeling

AP4 models pollutant transport considering a representation of annually averaged atmospheric conditions. Three-dimensional transport (yielding $\chi_{s,r}$ in Supplementary Equation 2) of one metric ton of emissions per year (Q) from each source (s) to annual concentrations of $\text{PM}_{2.5}$ in each downwind receptor (r) is modeled according to Turner (1994) [24], depicted by Supplementary Equation 4. Please see the technical appendix for the data sources providing the meteorological inputs to Supplementary Equation 4:

Supplementary Equation 4. AP4's Gaussian plume-based three-dimensional dispersion modeling.

$$\chi_{s,r} = \sum_{\text{Stb}} \sum_{\text{Spd}} \left(\frac{2Q_s f_s f_p}{\sqrt{2\pi} \sigma_z u \frac{2\pi x}{36}} \exp \left(-0.5 \left(\frac{H_s}{\sigma_z} \right)^2 \right) \right)$$

Supplementary Equation 4 is used to compute concentrations from a source to a receptor for 12 wind speed classes, 36 wind directions, and relevant Pasquill stability categories. Wind speed classes and wind direction sectors are modeled via a representative speed and direction [24]. Wind speeds (u) are divided into 12 wind classes (Spd): the first 11 classes are defined from 0 to 11 m/s in increments of 1 m/s (i.e., 0 to 1 m/s, 1 to 2 m/s, ..., 10 to 11 m/s), and the 12th class is any speed greater than 11 m/s. The wind directions are divided into 36 sectors, each accounting for 10° of a wind rose. The Pasquill-Gifford vertical dispersion parameter (σ_z) accounts for the plume spread—and dilution of pollutant concentrations—considering stability conditions (Stb) and distance downwind (x). Pasquill stability categories are dependent on surface wind speed, cloud cover, and solar radiance [22].

Average concentrations are determined by weighting the results for each wind speed class, wind rose sector, and stability category combination by frequency of occurrence at the source (f_s). Other variables for Supplementary Equation 4 include the effective height of the source (H_s) and

a unitless factor accounting for deposition and chemistry processes (f_p), which depend on the pollutant. The factors consider timescales that are first-order loss rates that occur via deposition or chemistry (please see the technical appendix for details). The results of Supplementary Equation 4 are speciated concentrations of NH_3 , nitrate (NO_3^-), primary $\text{PM}_{2.5}$, sulfate (SO_4^{2-}), and organic aerosols (from VOCs).

Interpollutant atmospheric chemistry for secondary $\text{PM}_{2.5}$ formation

AP4 augments its atmospheric transport modeling with a representation of interpollutant chemistry applied once speciated concentrations are estimated in receptor locations. The total ambient $\text{PM}_{2.5}$ modeled by AP4 combines directly emitted $\text{PM}_{2.5}$, organic aerosols from VOC emissions, ammonium sulfate ($(\text{NH}_4)_2\text{SO}_4$) from NH_3 and SO_2 emissions, and ammonium nitrate (NH_4NO_3) from NH_3 and NO_x emissions.

Importantly, the formation of each $(\text{NH}_4)_2\text{SO}_4$ and NH_4NO_3 is dependent on the equilibrium between NH_3 , sulfuric acid (H_2SO_4 from SO_2), and nitric acid (HNO_3 from NO_x) in the ambient air [25], [26], [27].⁶ NH_3 preferentially reacts with H_2SO_4 to form $(\text{NH}_4)_2\text{SO}_4$.⁷ Then, the leftover NH_3 reacts with HNO_3 , forming NH_4NO_3 .⁸ This results in either a nitrate-limited regime, where NH_3 is in surplus, or an ammonium-limited regime, where HNO_3 is in surplus. The regime in which a receptor county resides affects the extent to which marginal emissions of NH_3 and NO_x form NH_4NO_3 because free NH_3 (i.e., not reacting with H_2SO_4) and HNO_3 remain in the gaseous rather than particulate phase without reacting. Emissions of SO_2 , on the other hand, form ambient $\text{PM}_{2.5}$ with or without NH_3 because SO_4^{2-} is particulate matter.⁹

Tract-level pollutant transport modeling methods summary

The SR structure of AP4T is based on that of AP4 (i.e., Supplementary Equation 1 through 3). AP4's Gaussian plume modeling (i.e., Supplementary Equation 4) is a direct input for some of the pollutant transport modeling in AP4T. For AP4T, we model pollutant transport in three ways:

1. **Tract-to-tract:** AP4T conducts tract-to-tract modeling (via geometric centroids) in the same manner as AP4's county-to-county modeling (via population-weighted centroids). In Supplementary Equation 1 through 4, s and r —counties in AP4¹⁰—are tracts in AP4T.
2. **Consolidated county-to-tract:** This method consolidates tract sources from the tract-to-tract transport method to the county level. Take Siskiyou County, California (shown in

⁶ SO_2 and NO_x form H_2SO_4 and HNO_3 when they react with oxygen (O_2) and water (H_2O). For example, $2\text{SO}_2 + \text{O}_2 + 2\text{H}_2\text{O} \rightarrow 2\text{H}_2\text{SO}_4$. For more information on the atmospheric behavior of the family of NO_x compounds, see [28].

⁷ $\text{H}_2\text{SO}_4 + 2\text{NH}_3 \rightarrow (\text{NH}_4)_2\text{SO}_4$.

⁸ $\text{NH}_3 + \text{HNO}_3 \rightarrow \text{NH}_4\text{NO}_3$.

⁹ As discussed by Tsimpidi et al. (2007) [27], particulate SO_4^{2-} exists in the form of ammonium bisulfate ($(\text{NH}_4)\text{HSO}_4$) or even as H_2SO_4 in extreme cases when concentrations of NH_3 are low.

¹⁰ Recall from Supplementary Equation 1 through 4 that s also represents facilities for the EGU bin of AP4. Only s as counties, however, is relevant for the comparison to the tract-to-tract transport method in AP4T.

Supplementary Fig. 20), for example. Its tract-to-tract SR matrix represents 14 sources by 72,538 receptors. We consolidate the SR matrix to represent just 72,538 marginal concentrations from Siskiyou. We use a population-weighted average across the county's tracts (i.e., the higher a tract's population, the greater its influence on the county's combined marginal concentration on each receptor tract throughout CONUS).

3. **Interpolated county-to-tract:** This method uses spatial statistics to interpolate county-to-tract (or EGU-to-tract) marginal concentrations using the county-to-county (or EGU-to-county) marginal concentrations of AP4. The procedure assumes that the tract-received marginal concentrations from any individual county (or EGU) are some linear combination of the nearby county-received marginal concentrations from that same source.

Tract-to-tract Gaussian plume calculations for AP4T are a product of preliminary work that contributed to the Rapid Estimation of Air Concentrations for Health (REACH) model [29]. The calculations are conducted similarly to county-to-county modeling in AP4; however, the Gaussian plume modeling contains a few changes that are discussed in the technical appendix. To help alleviate any resulting discrepancies, AP4T is calibrated against Gaussian plume computations in AP4 (see the “Calibration methods for AP4 & AP4T” section in this Supplementary Methods).

Only primary $\text{PM}_{2.5}$ and VOC emissions from wildland fire emission sources are modeled via the tract-to-tract transport method. Only primary $\text{PM}_{2.5}$ and VOC emissions from non-fire ground sources are modeled via the consolidated county-to-tract transport method. All other emissions are modeled via the interpolated county-to-tract transport method.

Pollutant transport modeling conceptualization

The consolidated county-to-tract transport method is derived from (and second best to) tract-to-tract transport. Our reasoning for this method for AP4T's initial buildout and application for this research is twofold: (1) to avoid further emissions distribution and (2) to keep the modeling efficient and accessible. That said, tract-to-tract and interpolated county-to-tract are AP4T's two distinct methods of pollutant transport modeling.

We refer to two main concepts to defend these distinct ways of atmospheric modeling for different emissions by bin and pollutant. This first is based on atmospheric chemistry, providing the reasoning for explicitly modeling primary $\text{PM}_{2.5}$ and VOCs via tract-to-tract (at the ground level) but not NH_3 , NO_x , and SO_2 . The second is based on atmospheric dispersion, providing the reasoning for explicitly modeling ground-level sources via tract-to-tract (for primary $\text{PM}_{2.5}$ and VOCs) but not point sources:

- **Atmospheric chemistry:** When looking at how well land-use regression modeling explains spatial variation in particulate subspecies, Robinson et al. (2019) found that primary $\text{PM}_{2.5}$ and secondary organic aerosols (from VOCs) had notably higher R^2 values than secondary inorganic species (from NH_3 , NO_x , and SO_2) [15]. In other words, variation in the more spatially heterogeneous pollution driven by emissions of primary $\text{PM}_{2.5}$ and

VOCs was better explained by variation in activity linked to the emissions. Contrarily, variation in the more spatially homogenous pollution driven by emissions of NH_3 , NO_x , and SO_2 was less well explained by land-use variable variation. This is related to the fact that inorganic subspecies of $\text{PM}_{2.5}$ form in the ambient air over time as they react (mostly in the presence of one another) and, hence, have a greater opportunity to spread and “smooth out” before settling as damaging particulates.

- **Atmospheric dispersion:** Emissions from point sources are often released through smokestacks, specifically designed to disperse pollution concentrations [30]. With the establishment of the National Ambient Air Quality Standards (NAAQS) in the 1970s, smokestacks were widely deployed at heavy-emitting facilities throughout the U.S. [31]. This was done to better enable local ground-level concentrations to achieve the standards set by the NAAQS, as smokestacks release pollution at higher elevations allowing it to traverse downwind away from the source. We again refer to pollution having a greater opportunity to spread and “smooth out” before settling in the ambient air as damaging particulates. However, it is not due to chemistry but rather particles’ physical trajectory.

These two concepts drive our choice to (1) only conduct detailed tract-to-tract modeling for primary $\text{PM}_{2.5}$ and VOC ground-level sources and (2) assume that the interpolated county-to-tract modeling (derived from AP4’s Gaussian plume-based county-to-county marginal concentrations) is sufficient for NH_3 , NO_x , and SO_2 from all bins and all pollutant species from point sources.

Spatial interpolation mathematics

Supplementary Equation 5 reissues Supplementary Equation 2 depicting the SR matrices of AP4, which model the transport (χ) of a ton of pollution from each source (s) to each receptor (r) by pollutant (p) and bin height (h). For the computation of $\chi_{s,r}$ see Supplementary Equation 4. In AP4, Supplementary Equation 5’s s represents either counties or EGUs, and its r represents counties. This makes $\text{SR}_{p,h}$ a 3,108 or 1,814 source by 3,108 receptor matrix:

Supplementary Equation 5. AP4/AP4T’s source-receptor matrices.

$$\text{SR}_{p,h} = \begin{bmatrix} \chi_{1,1} & \chi_{1,2} & \chi_{1,3} & \cdots & \chi_{1,r} \\ & \vdots & & \ddots & \vdots \\ \chi_{s,1} & \chi_{s,2} & \chi_{s,3} & \cdots & \chi_{s,r} \end{bmatrix}$$

For AP4T’s tract-to-tract pollutant transport modeling method, *both* Supplementary Equation 5’s s and r change to represent CONUS tracts, making $\text{SR}_{p,h}$ a 72,538 source by 72,538 receptor matrix. For AP4T’s (interpolated or consolidated) county-to-tract pollutant transport modeling methods, *only* Supplementary Equation 5’s r changes to represent CONUS tracts, making $\text{SR}_{p,h}$ a 3,108 or 1,814 source by 72,538 receptor matrix.

For AP4T's interpolated county-to-tract modeling, we use linear combinations of row-wise χ 's—i.e., county-received impacts from a particular source—from Supplementary Equation 5 to downscale to tract impacts. Supplementary Equation 6 shows both the general form and an example of the downscaling, where tract-received transport (τ) is the impact of a metric ton of emissions from the source represented by the first row of Supplementary Equation 5 ($s = 1$). We use the county-received impacts from the source of interest to k neighboring counties ($\chi_{1,i}, \dots, \chi_{1,k}$) to interpolate the impacts from the source to the example tract ($\tau_{1,r}$) using an inverse distance-weighted (IDW) average. The weights ($w_i, \dots, w_k$) consider each county's (χ_i 's) distance to the tract ($d[x_i, r]$), where the power parameter (p) dictates the rate of decreasing influence with distance—e.g., a greater p indicates a greater decrease in influence with distance. The weight function is from Shepard (1968) [32].

Hypothetically, let us say the example tract resides at the intersection between the three counties represented by columns one, two, and three of Supplementary Equation 5. We use $\chi_{1,1}$, $\chi_{1,2}$, and $\chi_{1,3}$, and weights w_1 , w_2 , and w_3 to interpolate $\tau_{1,r}$. The result is an average of the three surrounding counties' impacts from the source, where the closer the county is to the tract relative to the other counties, the greater its influence.

Supplementary Equation 6. AP4-to-AP4T downscaling via spatial interpolation.

$$\tau_{1,r} = \frac{\sum_{i=1}^k w_i \chi_{1,i}}{\sum_{i=1}^k w_i} = \frac{w_1 \chi_{1,1} + w_2 \chi_{1,2} + w_3 \chi_{1,3}}{w_1 + w_2 + w_3}$$

$$w_i = \frac{1}{d[x_i, r]^p}$$

We compute tract-received transport τ via Supplementary Equation 6 for every receptor tract (72,538) from every source county (3,108) and EGU (1,814) across applicable bins and pollutants. While Supplementary Equation 6's example uses three nearby county-received impacts, we could use any number of nearby neighbors to interpolate.

We propose several specifications for choosing which counties inform the tract-level downscaling via spatial interpolation shown in Supplementary Equation 6. We consider three overarching county selection methods and three specific options for each:

- **Closest counties:** Use the three, five, or ten closest counties to each tract to inform τ .
- **Counties within:** Use counties within 20, 30, or 50 miles of each tract to inform τ .¹¹
- **Adjacent counties:** Use the home county and those adjacent (one level) or additionally the next most adjacent (two levels) or additionally the next most adjacent (three levels) to inform τ .

¹¹ If no county's population-weighted centroid falls within the radius extending from the tract, we assign the impact of the closest county.

Hence, there are nine proposed specifications for county selection. We determine the distances from county population-weighted centroids to tract geometric centroids using the haversine formula (i.e., the distance between two points on the earth as a function of latitude and longitude) [33]. We also propose three power parameters: 0.5, 1, and 2. For $p = 1$, influence decreases linearly with distance. For $p = 0.5$, influence decreases less than linearly with distance. For $p = 2$, influence decreases more than linearly with distance.

Across the nine selection methods, this results in 27 possible IDW models for spatial interpolation of τ . To determine which option is best, we build out AP4T with each IDW model and evaluate the results compared to EPA Air Quality System (AQS) monitoring data [34]. We run AP4T all the way through its calibration procedure, which is detailed in an upcoming section. While all proposed IDW models perform similarly, AP4T performs better with $p = 0.5$ and using the home county plus those adjacent to it and then also those adjacent to them (i.e., two levels of adjacency) results in strong performance for both modeling both total $\text{PM}_{2.5}$ and secondary $\text{PM}_{2.5}$ and is selected as the base case procedure.¹² Supplementary Fig. 21 shows an example of AP4T's marginal concentration interpolation. Supplementary Fig. 21 shows marginal concentrations of ambient $\text{PM}_{2.5}$ in receptors from one metric ton of primary $\text{PM}_{2.5}$ emissions released from a hypothetical non-EGU point source in Siskiyou County, California (blue diamond). Supplementary Fig. 21 shows both AP4's marginal concentrations at the county level (left) as well as AP4T's marginal concentrations at the tract level (right), interpolated using the former as specified by Supplementary Equation 6.

Importantly, there are limitless specifications for AP4T's spatial interpolation. We leave further investigations and modeling development to future work, but the fact that our 27 proposed models perform similarly allows us to assume that finding the optimal IDW model is likely not all that important. Further, as discussed in the "Calibration methods for AP4 & AP4T" section in this Supplementary Methods, the model performs well within the desired standard as currently designed.

Spatial interpolation limitations

It is important to acknowledge the spatial structure of the marginal concentrations being interpolated. Supplementary Fig. 21's scale is log-transformed, meaning marginal concentrations decrease exponentially with distance away from the source. There are two key instances to discuss (both of which can be visually identified in Supplementary Fig. 21):

1. **Pulling down:** Interpolating tracts in the own county (or otherwise the county with the highest marginal concentration from the source) inherently results in a lower average marginal concentration across the tracts than for the county itself (modeled with AP4). Interpolated points between the source and the nearest known neighbors (e.g., tracts within

¹² The mean fractional errors for total $\text{PM}_{2.5}$ (modeled vs. monitored) range from 0.232 to 0.238 for the 27 models.

the county with the greatest marginal concentration) are pulled down by the influence of surrounding neighbors with lower marginal concentrations.

2. **Pulling up:** On the contrary, interpolating tracts in counties near the own county (or otherwise the county with the highest marginal concentration from the source) can result in higher average marginal concentrations across the tracts of the counties than for the counties themselves (modeled with AP4). This is due to the influence of neighbors with exponentially higher marginal concentrations.

Please see the technical appendix for an in-depth discussion (namely, how interpolation may actually help improve accuracy due to AP4's tendency to overpredict and underpredict nearest heavy emission sources).

Here, we emphasize that if point (1) above is a mischaracterization, the fact that we do not model the most immediately impactful pollutants (i.e., ground-level primary PM_{2.5} and VOCs) in this way further helps to reduce concerns. In other words, because stacks discharge pollutants high into the air and SO₂ and NO_x take some time to form sulfates and nitrates before forming PM_{2.5}, the areas nearest the source are less at risk of the heaviest concentrations of pollution, and more dilution will happen before the greatest concentrations occur (likely in multiple places). Thus, interpolation pulling estimates down will be less concerning for pollutant-bin pairs other than ground-level primary PM_{2.5} and VOCs, which we do not interpolate. Moreover, calibration efforts, discussed in the next section, help to alleviate accuracy concerns with our interpolation procedure. As further divulged therein, we achieve the desired standards [11], [12] at a performance level that exceeds AP4's (see Supplementary Table 29).

One other limitation to highlight is that counties closest to coastlines or national borders do not get interpolated with a full marginal concentration spatial profile that counties further inland do. Instead, they get more influence from their known neighboring counties in particular directions (e.g., the westernmost counties in Supplementary Fig. 21 get more influence from their eastern neighbors because there are no known data points to the West). This is a current limitation of AP4T, which future modeling development efforts should work to rectify.¹³ That said, this initial buildout for AP4T sets the foundation for the interpolation methodology of AP4T to an extent that achieves sufficient modeling performance, and we leave further development to future modeling efforts and associated research.

Calibration methods for AP4 & AP4T

AP4 and AP4T are calibrated using AQS monitoring data [34]. The process involves comparing modeled ambient PM_{2.5} concentrations to those measured at monitors and conducting several calibration steps to improve the prediction-observation fit. Here, we summarize the procedure, but please see the technical appendix for specific details.

¹³ Nearly 90% of the damages from wildland fire smoke in 2017 were associated with primary PM_{2.5} and VOC emissions (see Supplementary Table 2). Given this context, the limitation, only relevant to NH₃, NO_x, and SO₂ for the ground-level bin, has minimal impact on the conclusions of our study.

AP4's calibration involves three steps using AQS data at the county level: primary, secondary, and tertiary. The primary calibration step is an iterative process that reduces the mean fractional error (MFE) and the mean fractional bias (MFB) by adjusting calibration coefficients applied alongside the SR matrices. Supplementary Equation 7 and 8 depict these two performance metrics [11]:

Supplementary Equation 7. Mean fractional error.

$$\text{MFE} = \frac{1}{n} \sum_{i=1}^n \frac{|c_{m,i} - c_{o,i}|}{\left(\frac{c_{m,i} + c_{o,i}}{2}\right)}$$

Supplementary Equation 8. Mean fractional bias.

$$\text{MFB} = \frac{1}{n} \sum_{i=1}^n \frac{c_{m,i} - c_{o,i}}{\left(\frac{c_{m,i} + c_{o,i}}{2}\right)}$$

To further improve AP4's performance, we conduct a secondary calibration step. This process, adapted from [35], [36], [37], [38], addresses counties with the greatest discrepancies between AP4-modeled PM_{2.5} concentrations and those measured at the AQS monitors. We subsequently adjust the counties adjacent to the secondary calibration-adjusted counties as part of a tertiary calibration step. This third and final calibration step is conducted to avoid scenarios in which overpredicted (or underpredicted) counties are modeled to have notably lower (or higher) PM_{2.5} concentrations than their neighboring counties after they are adjusted during the secondary calibration step. We design this process to adjust both monitored and unmonitored counties directly adjacent to the secondary calibration-adjusted counties using data from those with AQS monitors.¹⁴

AP4T's calibration involves four steps: preliminary, primary, secondary, and tertiary. Preliminary calibration compares AP4T-specific Gaussian plume modeling (tract-to-tract and consolidated county-to-tract, see the "Tract-level pollutant transport modeling methods summary" section in this Supplementary Methods) to AP4's Gaussian plume modeling. Because AP4T is an extension of AP4 (and because AP4 performs up to desired standards) it is reasonable to use it as a check and baseline for empirical adjustment. Compared to AP4, AP4T's consolidated county-to-county transport modeling overpredicts primary PM_{2.5} and VOCs.¹⁵ We also find that this is much more so the case with own-county impacts. AP4's atmospheric dispersion modeling already

¹⁴ This process is also adapted from calibration efforts conducted in Tschofen et al. (2023) [37] and Tschofen (2023) [38].

¹⁵ AP4T's tract-level modeling is consolidated to the county level using population-weighted averages, like the consolidated county-to-tract transport method.

tends to overpredict concentrations for most pollutants, including primary PM_{2.5} and VOCs (i.e., calibration procedures bring the estimates down). Hence, we use AP4 to calibrate AP4T-specific Gaussian plume modeling (both tract-to-tract and consolidated county-to-tract) downward.

AP4T's primary, secondary, and tertiary calibration steps use AQS data at the tract level.¹⁶ AP4T upgrades the primary calibration procedure from AP4. For AP4T, the primary calibration step minimizes the MFE via optimization to determine the calibration coefficients to apply alongside the SR matrices. We employ the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm [40] using the *fmincon* MATLAB function [41]. Because we have different subspecies of PM_{2.5}, primary calibration is conducted in a stepwise fashion, beginning with VOCs, then moving to NH₃, SO₂, and NO_x (calibrated together considering interpollutant chemistry), and finalizing with primary PM_{2.5}. At each step, constraint functions are introduced to keep the MFB within desired performance levels.

For performance evaluation, we reference standards for air quality modeling from the literature [11], [12]:

- **Boylan & Russell (2006):** According to [11], the MFE being $\leq +50\%$ and the MFB being $\leq \pm 30\%$ indicates that a model has met its performance goal. Boylan and Russell (2006) also suggested that an MFE $\leq +75\%$ and an MFB $\leq \pm 60\%$ are acceptable for modeling and that minor species should have less stringent requirements. Intervention Model for Air Pollution (InMAP) [42] also considers [11].
- **Morris et al. (2005):** According to [12], the MFE being $\leq +35\%$ and the MFB being $\leq \pm 15\%$ indicates that a model achieves “excellent” performance. Morris et al. (2005) also defined the MFE being $\leq +50\%$ and the MFB being $\leq \pm 30\%$ (i.e., the primary standard from [11]) as “good” performance. The Estimating Air pollution Social Impact Using Regression (EASIUR) model [43] also considers [12].

Model performance

Supplementary Table 28 shows the performance of the models following primary calibration. Considering the guidance from Boylan & Russell (2006) [11], AP4 and AP4T perform up to standards for total PM_{2.5} and all subspecies. Considering the standards from Morris et al. (2005) [12], AP4 and AP4T achieve “excellent” performance for total PM_{2.5} and some subspecies.

Supplementary Table 29 summarizes the calibration of AP4 and AP4T. The multi-step calibration process decreases the MFE by 14%, decreases the magnitude of the MFB by 28%, and increases the correlation by 66% for AP4. AP4T's metrics improve to a great extent (MFE -18%, MFB -30%, and r +82%).

¹⁶ While the EPA does not provide census tract locations, they do provide latitude and longitude coordinates of monitoring sites. We use shapefiles provided by the U.S. Census Bureau [14] and each monitoring site's coordinates [34] to identify the census tract in which it resides using the *sf*R package [39].

Supplementary Methods 2: Concentration-response and valuation modeling

AP4T focuses on premature mortality associated with long-term exposure to PM_{2.5} [44]. These damages account for most of those from air pollution in the U.S. [45]. This also ensures we avoid cases where morbidity leads to eventual death and, consequently, the double counting of impacts [46]. Relative risk estimates of increased long-term PM_{2.5} exposure from epidemiological cohort studies (discussed below) may also incorporate some effects due to short-term exposure [45], [46].

Epidemiological literature

We use peer-reviewed dose-response (DR) functions from the epidemiological literature to associate premature mortality risk with long-term exposure to ambient PM_{2.5}. AP4T's default DR function for adult mortality is from the 2009 American Cancer Society Cancer Prevention Study II (ACS) conducted by Krewski et al. (2009) [47]. The ACS study identified the at-risk population to be anyone who is 30 or older. It reported relative risk (i.e., the chances of an event occurring in an exposed group versus the chances of it happening in a control group) of all-cause mortality associated with a 10 µg m⁻³ increase in ambient PM_{2.5} exposure.

The most recent reanalysis of the Harvard Six Cities study (H6C) found a more substantial effect of PM_{2.5} exposure and an at-risk age of 25 and older, which is also enabled in AP4T [48]. The study by Lepeule et al. (2012) also assessed relative risk of all-cause mortality associated with a 10 µg m⁻³ increase in long-term ambient PM_{2.5} exposure. Both adult DR functions are log-linear [47], [48]. Infant mortality is assessed using a distinct DR function [49]. This DR function, from Woodruff et al. (2006), is of the logistic form because the study worked with odds ratios (i.e., the odds of an event occurring in an exposed group versus the odds of it happening in a control group). This concentration-response information is summarized in Supplementary Table 20.

Other studies to consult for AP4T modeling are Di et al. (2017), the Medicare Cohort Study evaluating the effects of long-term PM_{2.5} exposure for populations 65 or older [50], and Pope et al. (2019), the National Health Interview Survey cohort study (NHIS) evaluating effects for populations 18 to 84 years old [51]. These are both large cohort studies and provide information on subpopulations and subcohorts.

Di et al. (2017) differentiated relative risk by race/ethnicity (as well as some other population attributes) and found substantially different estimates by subpopulation [50]. Supplementary Table 20 summarizes the β coefficient estimates (see Supplementary Equation 10) from the study as well as those for the ACS and H6C cohort studies [47], [48]. Subpopulations are reported as they are in Di et al. (2017), which, for race/ethnicity, aligns with the data provided by the Centers for Disease Control and Prevention (CDC) [52], [53]. Supplementary Table 20 compares each subpopulation's β coefficient to that designated as the main analysis by Di et al. (2017).¹⁷ Supplementary Table 20 shows the substantial differences in relative risk by the

¹⁷ Di et al. (2017) also reported relative risk for a low exposure analysis [50].

race/ethnicity subpopulations studied by Di et al. (2017). Di et al. (2017) also found greater relative risk for populations eligible for Medicaid, a proxy for lower-income status.

That said, Pope et al. (2019), the NHIS cohort study, reported conflicting information [51]. The study found “no consistent or coherent differences across strata for race-ethnicity, BMI, income, marital status, urban-rural designation, or survey year.” Notably, the study found greater relative risk for younger cohort members and never-smokers (which the Medicare cohort study had limited ability to assess).¹⁸

Dose-response functions

The DR functions calculate the expected change in mortality rates across populations given a change in PM_{2.5} exposure. The inputs are the β coefficient, the all-cause mortality rate of the exposed population (y_0), and the change in ambient PM_{2.5} pollution (ΔPM). The log-linear DR function for adult mortality is shown in Supplementary Equation 9:

Supplementary Equation 9. DR function: Change in mortality rate.

$$\Delta y = y_0 \left(1 - \frac{1}{\exp(\beta \times \Delta PM)} \right)$$

The β coefficient is further defined in Supplementary Equation 10. β is the natural log of the relative risk (RR) given a change in ambient PM_{2.5} pollution—a 10 $\mu\text{g m}^{-3}$ increase in PM_{2.5} for the ACS and the H6C studies [47], [48] (also in Di et al. (2017) and Pope et al. (2019) [50], [51]):

Supplementary Equation 10. DR function: Beta coefficient.

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

We then multiply the expected change in mortality rate (Δy) by the corresponding population to get the expected premature mortality associated with the change in PM_{2.5}:

Supplementary Equation 11. DR function: Change in mortality.

$$\Delta \text{Mortality} = \Delta y \times \text{Population}$$

The logistic DR function for infant mortality and its corresponding β coefficient are as follows in Supplementary Equation 12:

¹⁸ We note that the Pope et al. (2019) estimates are greater for Hispanic persons and Black persons than for white persons, just not such that there are “consistent or coherent differences.” Estimates for income of $\leq$ \$75 thousand are greater than those for income of $>$ \$75 thousand.

Supplementary Equation 12. DR function: Infant mortality.

$$\Delta y = y_0 \left(1 - \frac{1}{(1 - y_0) \times \exp(\beta \times \Delta \text{PM}) + y_0} \right)$$

$$\beta = \frac{\ln(\text{OR})}{\Delta \text{PM}}$$

The β coefficient here is calculated with the natural log of the odds ratio (OR) given a change in ambient $\text{PM}_{2.5}$ pollution—a $10 \mu\text{g m}^{-3}$ increase in $\text{PM}_{2.5}$ in the Woodruff et al. (2006) study [49].

Tract-level population data

To model $\text{PM}_{2.5}$ exposure, AP4T uses tract-level population inventories by five-year age groups from the U.S. Census Bureau’s American Community Survey characterizing 2017 [54]. Age differentiation is essential for two reasons. First, with the default DR function from Krewski et al. (2009), anyone under 30 who is not an infant is considered not to be at risk of premature mortality from long-term ambient $\text{PM}_{2.5}$ exposure [47]. Second, the effects of $\text{PM}_{2.5}$ are highest among older populations [55], [56], [57], such that senior citizens incur the majority of damages [57]. We also extract this data differentiated by race/ethnicity. We employ U.S. Census Bureau population data specific for 2017.

As reported, our U.S. Census Bureau data do not divide population by the age groups needed for AP4T.¹⁹ To differentiate age groups where necessary, we use county-level population data from the CDC (also characterizing 2017 and used for AP4) [52]. Briefly, the process involves using ratios of known county-level age groups to interpolate unknown tract-level age groups. This process is further detailed in the technical appendix.

Tract-level mortality rate data

We are unaware of any tract-level mortality data by age group. Hence, we compute county-level mortality rates (representing baseline risk) for every age group using data from the CDC characterizing 2017. The data are mortality counts by age group in every county [53], and mortality rates are calculated by dividing deaths by corresponding population counts from the CDC [52]. Where mortality data are unavailable (for privacy and confidentiality purposes or due to a lack of information), first state mortality rates and then national mortality rates are substituted in, as needed. We follow the same procedure for mortality rates differentiated by race/ethnicity. The most substantial difference between all-person mortality rates and those differentiated by

¹⁹ There are 19 age groups in AP4T: infants (i.e., less than one-year-old), 1 to 4, 5 to 9, 10 to 14, 15 to 19, 20 to 24, 25 to 29, 30 to 34, 35 to 39, 40 to 44, 45 to 49, 50 to 54, 55 to 59, 60 to 64, 65 to 69, 70 to 74, 75 to 79, 80 to 84, and 85 and older.

race/ethnicity is that there are more data gaps. We are centering in on more specific subpopulations, so privacy and confidentiality are of greater concern for data reporting.

The CDC report's race/ethnicity-specific mortality data for 2017 by subpopulations that differ than those defined by the U.S. Census Bureau (the source of our race/ethnicity-specific population data), as summarized in Supplementary Table 30. Supplementary Table 30 also attempts to best reconcile the differences, matching the data reported by the U.S. Census Bureau with their best counterparts reported by the CDC.²⁰ For most subpopulations, the best match is relatively intuitive. However, for the U.S. Census Bureau's Some Other Race Alone and Two or More Races subpopulation categories, we have no intuitive match from the CDC. The CDC mutually exclusively reports data as part of four racial groups (comprised of any ethnicity): White, Black or African American (Black), American Indian or Alaska Native (AIAN), and Asian or Pacific Islander (API). The CDC also mutually exclusively reports data as part of two ethnicity groups (comprised of any race): Hispanic or Latino and non-Hispanic or Latino. Hence, subpopulations tracked as Some Other Race Alone and Two or More Races by the U.S. Census Bureau must be within one of these subpopulations designated by the CDC in 2017.

A further difficulty comes with population data organization pertaining to Hispanic or Latino ethnicity. As suggested by Supplementary Table 30, the U.S. Census Bureau reports White populations of any ethnicity and also non-Hispanic or Latino White populations. However, White is the only racial subpopulation for which ethnicity is differentiated. For every other racial category, people of any ethnicity are included. In other words, the U.S. Census Bureau's subpopulations are not mutually exclusive. Conveniently, data provided by the CDC can be specified to align with the U.S. Census Bureau's approach to reporting ethnicity (see Supplementary Table 30

Supplementary Table 19 shows a summary of race/ethnicity-specific mortality rates (deaths per 100,000 people) by age group across the U.S. Supplementary Table 21 shows disparities in race/ethnicity-specific mortality rates when controlling for age. The data are ratios of the race/ethnicity-specific mortality rate normalized by the all-person mortality rate for each age group. Red represents greater than the age-adjusted all-person mortality rate. Blue represents less than the age-adjusted all-person mortality rate. White represents equivalent to the age-adjusted all-person mortality rate.

While we are limited to the county level for mortality rates differentiated by race/ethnicity, we use county-level mortality rates differentiated by race/ethnicity to derive more accurate mortality rates at the tract level for the total population. We do this by accounting for each county's population breakdown by tract, as shown in Supplementary Equation 13:

²⁰ The CDC reports race/ethnicity that is more aligned with the U.S. Census Bureau's approach starting for 2018 [53].

Supplementary Equation 13. Computing tract-specific mortality rates for each age group.

$$MR_{t,a} = \frac{\sum_{i=1}^g MR_{x,a,g_i} Pop_{t,a,g_i}}{\sum_{i=1}^g Pop_{t,a,g_i}}$$

In Supplementary Equation 13, the tract's mortality rate data by age group ($MR_{t,a}$) is derived using its population breakdown by race/ethnicity group (Pop_{t,a,g_i}) and its county's (x 's) race/ethnicity-specific mortality rates (MR_{x,a,g_i}). For our assessment by race/ethnicity explicitly, we are limited to county-level race/ethnicity-specific mortality rates to tracts (i.e., $MR_{r,a,g_i} = MR_{x,a,g_i}$) because there is no way to further differentiate spatially. For Some Other Race Alone and Two or More Races, however, tract-level $MR_{t,a}$ from Supplementary Equation 13 are employed. Note: MR and y_0 from Supplementary Equation 9 and Supplementary Equation 12 represent the same variable.

The greatest challenge with Supplementary Equation 13's approach is the lack of mutual exclusivity with U.S. Census Bureau data. Without addressing the lack of mutual exclusivity, we double-count non-White Hispanic or Latino persons as both Hispanic or Latino ethnicity and one of the non-White races. Therefore, we differentiate Hispanic or Latino persons away from racial groups. We do so by first determining the number of non-White Hispanic or Latino persons by tract and age group. This is straightforward, as the U.S. Census Bureau provides White population counts both including and excluding Hispanic or Latino persons (Supplementary Table 30's A and H). Then, we estimate the number of non-White Hispanic or Latino persons in each non-White racial group using the portion of the total non-White population each racial group accounts for (e.g., if the Asian population accounts for 10% of the non-White population, we assume the Asian population includes 10% of the non-White Hispanic or Latino population). The empirical exercise results in mutually exclusive and collectively exhaustive proportions of the population accounted for by each U.S. Census Bureau-defined subpopulation shown in Supplementary Table 30, where racial groups exclude Hispanic or Latino persons, accounted for as a separate group.²¹

The county-level mortality rate estimates for Black, AIAN, and API populations used for estimating all-person tract-level mortality rates via Supplementary Equation 13 are those for the non-Hispanic or Latino Black, AIAN, and API persons (i.e., the *right* columns of Supplementary Table 19 for Black, AIAN, and API). These align with the adapted, mutually exclusive populations. On the other hand, for our assessments explicitly by race/ethnicity, the county-level mortality rate estimates for Black, AIAN, and API populations are those for Black, AIAN, and API persons of any ethnicity (i.e., the *left* columns of Supplementary Table 19 for Black, AIAN, and API). These align with the U.S. Census Bureau-provided populations (see Supplementary Table 30).

²¹ We note that this process is only used for computing tract-specific mortality rates (see Supplementary Equation 13) and when conducting sensitivity analyses using differentiated relative risk for all-person calculations (see Supplementary Equation 17 and the associated discussion). The populations by race/ethnicity included in AP4T are kept as the subpopulations reported by the U.S. Census Bureau (see Supplementary Table 30).

Discussion on data differentiation by race/ethnicity

Importantly, combining more specific racial groups within broader racial groups can hide substantial differences between communities [58]. For example, Supplementary Table 19 and 21 show a substantial difference in mortality rates for AIAN persons with and without including AIAN persons with Hispanic or Latino ethnicity.²² For this work, we are limited by the required data for modeling and the data provided by the U.S. Census Bureau and CDC. We make our assumptions rigorously and with careful consideration given the constraints.

While there are positive correlations between vulnerability and race/ethnicity (see Supplementary Table 16), race/ethnicity is not the only factor linked to increased exposure to and associated effects from air pollution. Ideally, we could also differentiate population and mortality rate inventories by, for example, socioeconomic status. That said, mortality rate differentiation by other factors is challenging because, within the demographics category, the CDC only enables filtering by age, gender, and race/ethnicity [52], [53].

Value of a statistical life explained

AP4T uses the value of a statistical life (VSL) approach for mortality risk monetization [59], [60]. Critically, the VSL does not place a value on life itself but instead represents the amount a person is willing to pay (or willing to accept) to reduce (or take on additional) mortality risk. It is the marginal rate of substitution between money and mortality risk [60]. The VSL, approximately \$10 million per statistical life, is better communicated as an individual being willing to pay \$10 for a mortality risk reduction equal to one in a million (or that individual being willing to accept \$10 for a mortality risk increase of the same magnitude). The VSL can also be considered what a group of individuals is willing to pay for risk reductions that sum to a 100% chance across the group (i.e., one statistical life). The VSL is often misunderstood, leading some authors to suggest changing its name [61].

Value of a statistical life estimates

The damages of long-term PM_{2.5} exposure are estimated using expected premature deaths (the result of Supplementary Equation 11) times the VSL. The EPA's 2010 meta-analysis considered various revealed- and stated-preference studies to determine the VSL [62]. AP4T's default setting uses the EPA's recommended central VSL estimate of \$7.4 million (2006 U.S. dollars). AP4T applies the VSL uniformly across all ages and county populations, per EPA guidelines [62].

There is great uncertainty with the value of the VSL. The EPA determined the central (or mean) estimate of \$7.4 million (2006 U.S. dollars) by fitting a Weibull distribution to estimates from nearly 30 different studies [62]. The values aligning the 95% confidence interval from the distribution are \$679 thousand (low) and \$18.4 million (high) (2006 U.S. dollars).

²² Importantly, our mortality rate data are differentiated by county (or by state if county-level data are unavailable), which helps capture differences between narrower communities within broader communities if the narrower communities differ from one another spatially.

Inflation and wealth adjustments to the value of a statistical life

AP4T accounts for inflation and wealth effects, as instructed by the EPA [62]. It adjusts for inflation using July-to-July estimates from the U.S. Bureau of Labor Statistics' (BLS's) consumer price index inflation calculator [63]. The VSL is a function of income (i.e., as wealth increases, so does the VSL). Intuitively, the wealthier the population, the more people are willing to pay for risk reduction. The degree to which the VSL increases as income increases is characterized by an income elasticity. AP4T uses an income elasticity of 0.7, the EPA's central estimate consistent with the balanced approach to VSL estimation [64]. In this case, the VSL increases less than linearly with income. The following equation is used to adjust the VSL considering real income growth from the date of the VSL (i.e., 2006) [65]:

Supplementary Equation 14. VSL wealth adjustments.

$$VSL_B = VSL_A * \left(\frac{Income_B}{Income_A} \right)^{Elasticity}$$

In Supplementary Equation 14, we use the VSL from the reference year (*A*), an income ratio of the year of analysis (*B*) over the reference year, and the income elasticity to determine the VSL for the year of study. For income ratios, AP4T uses real gross domestic product (GDP) per capita data from 1998 to 2020 (2012 U.S. dollars) from Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis [66]. Supplementary Table 31 shows the VSLs for 2017 in 2020 U.S. dollars.

As shown by Supplementary Table 31, our VSL for this study is \$9.97 million 2020 U.S. dollars. The values aligning the 95% confidence interval from the distribution are \$915 thousand (low) and \$24.8 million (high) (2020 U.S. dollars).

Traditional marginal ton approach

The traditional use of APEEP computes damages *on the margin* from one additional ton of a pollutant from a specific source—i.e., marginal damages (MDs). AP4T estimates MDs by source and pollutant uniquely. This damage metric accounts for monetized impacts across all receptor locations (i.e., it is an aggregate across all downwind counties). The following algorithm computes the MDs:

1. Add 1 metric ton of emissions to the baseline for a specific source and pollutant.
2. Estimate marginal damages by subtracting baseline damages from the new damages with the marginal metric ton added.
3. Reset the model to its baseline.
4. Repeat for each source and pollutant.

Multiplying total emissions from a source of interest by its respective MDs yields total damages. See Muller et al. (2011) [67], Jaramillo & Muller (2016) [68], and Dennin & Muller (2024) [5] for examples of studies that employ this add-one-ton then reset or *marginal ton* algorithm for estimating damages with APEEP, AP2, and AP3, respectively.

Counterfactual baseline approach

AP4T can also be used to compute a counterfactual baseline without emissions from a particular source category (e.g., wildfires). AP4T models this by simply removing emissions from the source of interest in modeling the baseline (here, a counterfactual baseline). The difference between the actual and counterfactual baselines under a different national emissions profile provides the impacts. This is the approach used herein for all but computing damages by source. Moving to the tract level greatly increases the computing demands for AP4T, especially since we mostly keep impacts spatially disaggregated. We assume future users of AP4T will be most interested in disaggregated impacts as well and suggest the *counterfactual baseline approach* for increased efficiency and ease of management. Importantly, the approach foregoes special atmospheric chemistry on the margin for NH_3 and NO_x . To stay analogous with damages by source and receptor, we also forgo this chemistry when using the *marginal ton* algorithm for source damages. This does not forgo the interpollutant chemistry but rather the special treatment of additional tons of NH_3 and NO_x on the margin. Please see the technical appendix for more information.

Supplementary Methods: Other Study Components

Supplementary Methods 3: Social Vulnerability Index

Social Vulnerability Index percentile ranks

The Social Vulnerability Index (SVI) is provided by the CDC using year-specific data [69] and is based on the methodology developed by Flanagan et al. (2011) [70]. The SVI measures a community's inability to adapt to avoid suffering and loss in the event of a disaster [69], [70]. The SVIs are percentile ranks developed by comparing tracts to one another across 15 social vulnerability variables (SVVs) under four themes (or domains), as shown in Table 2 of the main document.

A percentile rank is the proportion of scores in a distribution that the score of focus is greater than or equal to [70]. The mathematical determination of census tracts' percentile ranks for the SVVs is shown by Supplementary Equation 15 [70]:

Supplementary Equation 15. Social Vulnerability Index percentile rank calculation.

$$\text{Percentile Rank} = \frac{\text{Rank} - 1}{N - 1}$$

In Supplementary Equation 15, Rank characterizes each tract's SVV compared to all other tracts. Rank increases with vulnerability from 1 to N total tracts.

For nearly all variables, the rank increases as the SVV quantitatively increases. The exception is per capita income, a vulnerability variable contributing to Theme 1's SVI (for Socioeconomic Status) [70]. Supplementary Table 38 shows an example of a percentile rank calculation across ten census tracts. The ranks are developed considering a hypothetical vulnerability variable—e.g., per capita income. Among the observations, the tract with the greatest per capita income is ranked #1 (least vulnerable), the tract with the next greatest is ranked #2 (second least vulnerable), and so on. The tract with the lowest per capita income is ranked #10 (most vulnerable). The magnitude of the differences does not factor into the equation, just the rankings compared to one another. The result is percentile ranks (from 0 to 1) for each of the 15 SVVs (again, see Table 2 of the main document).

Then, each variable contributes equal weight to (1) its theme's SVI and (2) the overall SVI. As documented by the CDC, the percentiles are summed across the variables comprising each theme, and tracts are then ordered to determine the theme-specific percentile ranks (or themed SVIs) [69]. The themes' sums are summed and then ordered to determine the overall percentile ranks (or overall SVI); this is the same as summing the percentiles across all 15 variables [69]. Therefore, the variables, rather than the themes, are given equal weight in determining the overall SVI—e.g., socioeconomic status vulnerability (four SVVs) has double the weight of minority status and language vulnerability (two SVVs). We consider percentile ranks nationally, but future work may consider using ranks within more granular boundaries (e.g., regions or states).

The CDC only reports SVI data every other year. Hence, we use the average between 2016 and 2018, where data are available for both years. For simplicity, we then keep the percentile ranks as the average between these two years.²³ Where data are available for just one of these years, we use just that year's data. This leaves just around 1% of census tracts without SVI data, but these tracts have an even smaller percentage of the U.S. population (about 0.15%).

Social Vulnerability Index deciles

For this research, we group census tracts into ten approximately equally sized groups for each SVI (themed and overall) from least to most vulnerable. Given the nature of percentile ranks (i.e., equally spaced out between 0 and 1), this is a simple grouping procedure. Tracts with an SVI of 0.1 or lower are placed in SVI decile 1, tracts with an SVI of 0.2 or lower are placed in SVI decile 2, and so on until any tract with an SVI greater than 0.9 is placed in SVI decile 10. Importantly, the tracts in theme 1's SVI decile 1 are not necessarily the same tracts in the overall SVI decile 1. On the other hand, a tract in an SVI decile remains within that SVI decile for all analyses—i.e., Fig. 3 and Fig. 4a of the main document do not redesignate the SVI groupings within each census division or state, respectively.

Geography of the Social Vulnerability Index

Supplementary Fig. 29 maps the overall SVI by census tract. Supplementary Fig. 30 maps the themed SVIs by census tract. There are a few standout geographic patterns. First, we note the standout geographic pattern for Theme 3's SVI (for Minority Status & Language), where the most vulnerable tracts tend to be along the Mexico-U.S. border and in the West. Theme 1's SVI (for Socioeconomic Status) also demonstrates spatial patterns, but they are less prominent than Theme 3's. It tends to increase (i.e., more vulnerability) in the Southeast and the West. Theme 2's SVI (for Household Composition & Disability) and Theme 4's SVI (for Housing Type & Transportation) do not demonstrate clear patterns.

Supplementary Table 13 further investigates the geographic patterns of vulnerability. Generally, the West and South census regions are more vulnerable than the Northeast and Midwest census regions, as can be observed in Supplementary Fig. 29. The West (particularly the Pacific census division) is substantially more vulnerable under Theme 3, and the Midwest is substantially less vulnerable under Theme 3. Notably, while not that apparent in Supplementary Fig. 30b, the Midwest and South are more vulnerable under Theme 2, and the Northeast and West are less vulnerable under Theme 2.

Correlations between themed Social Vulnerability Indices & variables

Supplementary Table 17 shows correlations between the different SVI themes. Notably, all assessed correlations are positive. This means that, generally, vulnerability under one theme

²³ The other procedure we could employ would be to recompute percentile ranks based on tract ranks (determined via the 2016 and 2018 averages) for 2017.

correlates relatively strongly with vulnerability under other themes. The least correlated are Theme 2's SVI (for Household Composition & Disability) and Theme 3's SVI (for Minority Status & Language).

Supplementary Table 18 shows correlations between the SVI themes and the social vulnerability variables. Of course, the social vulnerability variables within each theme are strongly correlated to their theme's SVI.²⁴ Notably we find that the percentage of people aged 65 and older is only positively correlated with Theme 2; moreover, it exhibits the strongest negative correlation of the table with Theme 3. Conversely, percentage of people who are not White is only slightly positively correlated with Theme 2's SVI, and percentage of people who speak English "less than well" is negatively correlated with Theme 2's SVI.

Social Vulnerability Index vs. age

Supplementary Table 14 shows correlations between social vulnerability and the percentage of population by age group. Focusing on the SVIs, we see that a higher percentage of younger populations correlates with greater vulnerability under nearly every theme. Contrarily, a higher percentage of older populations correlates with less vulnerability under nearly every theme. The exception is Theme 2 for the 65 and older and 85 and older populations, which is expected given that senior citizenship itself is an SVV for Theme 2. Theme 4 also correlates positively with elderly populations.

Focusing on the SVVs, we see that a higher percentage of younger populations is positively correlated with vulnerability across most variables. The exceptions are percentage of people aged 65 or older, percentage of people who are civilians with a disability, percentage of households that are mobile homes, and, to a lesser extent, percentage of people living in group quarters. On the other hand, we see that a higher percentage of older populations is negatively correlated with vulnerability across most variables. The list of exceptions is (intuitively) mostly the same as that for younger populations, although the 85 and older population tends to be more vulnerable considering percentage of households that are multi-unit structures and percentage of households with no vehicle access. Percentage of people living in group quarters is the only SVV that does not have a clear divide between the older and younger age group subpopulations, but the 85 and older population is the most vulnerable by this metric.

Social Vulnerability Index vs. race/ethnicity

Supplementary Table 16 shows correlations between the SVIs and the percentage of population by race/ethnicity, as designated by the U.S. Census Bureau [54]. Overall, a higher percentage of people of color (POC) correlates with greater vulnerability under nearly every theme. The exception is for Asian populations, which correlates negatively with the overall SVI, as well as

²⁴ The exceptions are the age variables in Theme 2 and the percentage of households that are mobile homes in Theme 4. This occurs because these variables are all negatively correlated with the other variables within their respective themes. Conversely, the variables in Theme 1 and the variables in Theme 3 are positively correlated with each other.

that for Theme 1's SVI (for Socioeconomic Status) and Theme 2's SVI (for Household Composition & Disability). On the other hand, a higher percentage of White populations correlates negatively with vulnerability overall and for every theme. The weakest negative correlation for White populations is Theme 2's SVI. This is expected given the findings of the main document, particularly Figure 6a. In summary, White populations account for more of the senior citizen population, which is an SVV for Theme 2's SVI.

It is important to discuss the very strong positive correlation between Hispanic or Latino population percentage and Theme 3's SVI (for Minority Status & Language) in Supplementary Table 16. This is likely related to the percentage of people who speak English "less than well," given the prevalence of Spanish among Hispanic or Latino populations. The heavy influence of Hispanic or Latino population percentage on Theme 3's SVI is important to acknowledge for a few reasons. First, percentage of people who speak English "less than well" SVV is particularly important when considering disaster reaction, where communication between community officials leading response efforts and at-risk populations is critical. Given that the SVI specifically characterizes a community's inability to adapt to avoid suffering and loss in the event of a disaster [69], [70], this variable's heavy influence on Theme 3 (50% of the weight) makes sense.

On the other hand, Theme 3's definition also risks discounting inequities for other POC if we do not specifically acknowledge this influence of percentage of people who speak English "less than well" on the multi-criteria informed SVI. A strong example of this risk is the chance of discounting the vulnerability of Black Americans. For a detailed assessment of the ubiquitous inequities specifically for Black people in the U.S., see Flynn et al. (2017) [71]. We emphasize that Theme 3's SVI must be considered as its holistic definition (50% weight to percentage of people who are not White and 50% weight to percentage of people who speak English "less than well") rather than a metric characterizing, for example, varying degrees of vulnerability for POC. This is a good example of the challenges associated with using multi-criteria indices when working toward environmental justice solutions.

Supplementary Methods 4: Statistical analysis

Using t-testing to identify significant differences

Supplementary Table 10 (focusing on wildfire smoke) and 11 (focusing on prescribed burn smoke) show the data comprising Fig. 2 of the main document. The differences between (1) average smoke exposures for each SVI decile and the national average and (2) damages per capita for each SVI decile and the national average are assessed using weighted t-testing. We use the *weights* R programming package [72]. We weight tract-level average smoke exposures and damages per capita by population. We employ a bootstrapping approach (random sampling with replacement) [73] with 1,000 iterations to develop 95% confidence intervals that characterize uncertainty. Notably, the two samples are different sizes (i.e., the SVI decile resamples are 10% of the size of the national resamples).

The outputs of each t-test iteration are the difference between the averages of the SVI decile's tracts and the average across all tracts (in $\mu\text{g m}^{-3}$ or \$ per person), computed considering only the bootstrapped resample, and a p-value informing us whether the differences are statistically significantly different from zero. The null hypothesis of the t-test is that the difference in group means is zero. A p-value of ≤ 0.001 , ≤ 0.01 , and ≤ 0.05 translates to the probability of the tested event occurring under the null hypothesis being less than or equal to 0.1%, 1%, and 5%, respectively. Overall, our bootstrapping approach to our t-testing results in 1,000 differences and p-values (determined with 1,000 unique resamples) for each of the SVI deciles (ten) for the overall SVI and themed SVIs (five) for exposures and damages per capita (two) from wildfires and prescribed burns (two)—200 total datasets with 1,000 testing results each.

Then, we take the average of the differences and p-values for each dataset. We also compute a 95% confidence interval for the differences, using the 2.5th and 97.5th percentiles of the 1,000 bootstrapped differences for each dataset. The final step is to normalize the differences (again, in $\mu\text{g m}^{-3}$ or \$ per person) to be percentage changes from the national averages.²⁵ The national averages are as follows: $0.708 \mu\text{g m}^{-3}$ and \$308 per person for wildfires and $0.625 \mu\text{g m}^{-3}$ and \$313 per person for prescribed burns. The percentage changes in Fig. 2 of the main document are presented as fractional changes in Supplementary Table 10 and 11.

Relative impact differences in Supplementary Table 10 and 11 are damages per capita for each SVI decile versus the national average (percent difference) minus average exposures for each SVI decile versus the national average (percent difference). Hence, relative impact differences are in units of percentage points. Red shows where damage disparities are greater than exposure disparities (percent point increase). Blue shows where damage disparities are less than exposure disparities (percent point decrease). White shows where damage disparities equal exposure disparities. Color scales are normalized for Supplementary Table 10 and 11 to distinct symmetric ranges, extending to $\pm$ the greatest absolute percentage point difference for each fire type.

²⁵ Importantly, the between- and within-state assessments in Fig. 4b of the main document, as well as Supplementary Fig. 7 and 8, differ slightly from this methodology. Instead of averaging differences and then normalizing, we average normalized differences due to the quantitative limitations of the former approach for the within-state analysis.

Regression analysis of fire smoke impacts and social vulnerability

The coefficients in Fig. 5 of the main document are determined using bivariate linear models, as shown by Supplementary Equation 16:

Supplementary Equation 16. Bivariate linear regression model.

$$\ln(y_i) = \beta_0 + \beta_1 x_i + \varepsilon_i$$

In Supplementary Equation 16, y_i are observations of the dependent variable, transformed using the natural logarithm. For our models, these are log-transformed smoke exposures (in $\mu\text{g m}^{-3}$) and damages per capita (in \$ per person) at the tract level. x_i are observations of the independent variable. These are SVV (as well as the overall SVI) percentile ranks at the tract level. Along with β_0 (the intercept), β_1 is a coefficient optimized to minimize the sum of the squared residuals—i.e., observed versus predicted impacts—and representing the associations between smoke exposures or damages per capita and the regressors. ε_i is the error term. Because there are two dependent variables and 16 independent variables (or regressors), we generate 32 unique bivariate models of the form shown in Supplementary Equation 16. We generate these models using the *lm* function included in base R programming. Like with our t-testing, we employ a bootstrapping approach (random sampling with replacement) [73] with 1,000 iterations to develop 95% confidence intervals that characterize uncertainty.

The relevant outputs of each regression are the coefficient (β_1) and a p-value informing us whether the coefficient is statistically significantly different from zero. The null hypothesis is that the coefficient is zero (i.e., there is no relationship between the dependent and independent variables). A p-value of ≤ 0.001 , ≤ 0.01 , and ≤ 0.05 translates to the probability of the tested event occurring under the null hypothesis being less than or equal to 0.1%, 1%, and 5%, respectively.

Overall, our bootstrapping approach results in 1,000 coefficients and p-values (determined with 1,000 unique resamples) for each of the SVVs and overall SVI (16) for exposures and damages per capita (two) from wildfires and prescribed burns (two)—64 total datasets with 1,000 testing results each. Then, we take the average of the coefficients and p-values for each dataset. We also compute a 95% confidence interval for the coefficients, using the 2.5th and 97.5th percentiles of the 1,000 bootstrapped coefficients for each dataset. The coefficients characterizing smoke exposures in Supplementary Equation 16 can be interpreted as the average percentage increases in smoke exposure or damages per capita per a 0.01 increase in percentile ranks, which range from 0 to 1. For example, a 0.01 increase in the overall SVI percentile rank corresponds with an average 0.53% increase in wildfire smoke exposure and an average 0.44% increase in wildfire smoke damages per capita. The difference between the coefficients (shown in Supplementary Table 12) guide the color scale in Fig. 5b of the main document. In the table, red shows where damages per capita coefficients are greater than exposure coefficients, and blue shows where damages per capita coefficients are less than exposure coefficients. White shows where damages per capita coefficients are equal to exposure coefficients. The color scale is normalized to be on a symmetric scale ranging to $\pm$ the greatest absolute value across differences.

Supplementary Methods 5: Sensitivity analysis of distributional impacts

We conduct sensitivity analyses for our distributional impact assessments in Figs. 2 and 6 of the main document using two alternative approaches: differentiated relative risk and the value of a statistical life year approach.

Differentiated relative risk

Damages are a function of exposure and susceptibility. Susceptibility modeling in AP4T is a function of two DR function inputs: relative risk and baseline risk. A higher relative risk and a higher baseline risk both translate to greater susceptibility to PM_{2.5} exposure. Our default analysis does not account for race/ethnicity-specific differences in relative risk associated with PM_{2.5} exposure, partly to manage uncertainty, as the evidence on this matter remains somewhat ambiguous. Di et al. (2017) found evidence of differences by race/ethnicity [50], while Pope et al. (2019) did not [51]. Because we treat relative risk uniformly, susceptibility disparities must be related to baseline risk (i.e., mortality rates), which we treat as variable by race/ethnicity (see Supplementary Methods 2 and Supplementary Table 19 and 21 for more information).

Notably, baseline risk varies due to two overarching factors: (1) age and (2) inequities within age groups. Supplementary Table 19 illustrates that baseline risk increases exponentially with age. Considering race/ethnicity-specific age distributions (Fig. 6a of the main document and Supplementary Fig. 11), this explains why all-age damages per capita are highest for White persons (see Fig. 6b of the main document's white diamonds and Supplementary Table 22 herein). Simply put, White persons are older on average than POC. However, this disproportionate impact does not persist within age groups, as shown by Fig. 6b of the main document's bars and Supplementary Table 22 and 23 herein.

Examining damages per capita within age groups allows us to control for the strong influence of age, focusing instead on exposure and within-age-group susceptibility disparities. This approach reveals critical insights otherwise obscured by Simpson's Paradox. Specifically, baseline risk is higher than that of the average person for Black and AIAN persons across most age groups (see Supplementary Table 19 and 21),²⁶ resulting in higher damages per capita within these groups. Notably, this trend holds for AIAN persons when excluding Hispanic or Latino AIAN persons. However, when including Hispanic or Latino AIAN persons (as in this race/ethnicity-specific analysis), older AIAN persons exhibit lower-than-average baseline risks. Importantly, our mortality rate inventories are spatially differentiated (by county where possible and otherwise by state), enabling a more precise characterization of risks for specific communities.

While age continues to influence baseline risk, our first alternative approach incorporates differentiation in relative risk based on race/ethnicity, independent of age. In our sensitivity

²⁶ The notable exceptions are for persons 85 and older. This could be related to the distribution of ages within the 85 and older age group for each race/ethnicity. If, for example, White people within the 85 and older group are older (on average) than POC within the 85 and older group (on average), it would make sense that White people in the 85 and older group have a higher average mortality rate.

analyses, we apply the race/ethnicity-specific relative risks derived from Di et al. (2017), the Medicare Cohort Study, to compute β values for the concentration-response function (see Equations 4 and 5 of the main document). Compared to the β value from the study's main analysis (which aggregates all individuals regardless of race/ethnicity), the β for White individuals is 13% lower, while those for POC are all higher: +168% for Black individuals, +56% for Hispanic or Latino individuals, +35% for Native American individuals, and +30% for Asian individuals. See Supplementary Table 20 for β values by race/ethnicity.

Two distinct methods are used to compute damages under this alternative approach, as outlined in Supplementary Equation 17. Method 1 calculates damages by race/ethnicity for each age group at the tract level ($\text{Dam}_{t,a,g}$). This method is used for the red diamonds in Fig. 7b of the main document and follows these steps:

1. **Assign β values by race/ethnicity:** Using the crosswalk from CDC-defined race/ethnicity subpopulations (employed by Di et al.) to U.S. Census Bureau-defined subpopulations (used in Fig. 7b), we assign β values by race/ethnicity group (β_g). The crosswalk is detailed in Supplementary Table 30.
2. **Use county-level mortality rates:** Mortality rates by race/ethnicity group for each age group ($\text{MR}_{x,a,g}$) are also aligned via this crosswalk.
3. **Handle other race categories:** Individuals in Some Other Race and Two or More Races categories are assigned β based on Di et al. (2017)'s main analysis, while tract-level mortality rates from Supplementary Equation 13 ($\text{MR}_{t,a}$) are used.
4. **Account for non-mutually exclusive populations:** Populations by race/ethnicity group ($\text{Pop}_{x,a,g}$) are not mutually exclusive. All racial groups except White include persons of Hispanic or Latino ethnicity. This is consistent with Fig. 6 of the main document.
5. **Apply concentration-response and valuation modeling:** ΔPM represents the fire smoke $\text{PM}_{2.5}$ exposure. Multiplying by the VSL monetizes the computed premature mortalities (see Supplementary Equation 9 through 11).

Supplementary Equation 17. Computing damages with differentiated relative risk.

$$\text{Method 1:} \quad \text{Dam}_{t,a,g} = \text{MR}_{x,a,g} \left(1 - \frac{1}{\exp(\beta_g \times \Delta\text{PM})} \right) \times \text{Pop}_{t,a,g} \times \text{VSL}$$

$$\text{Method 2:} \quad \text{Dam}_{t,a} = \sum_{i=1}^g \text{MR}_{t,a} \left(1 - \frac{1}{\exp(\beta_{g_i} \times \Delta\text{PM})} \right) \times \text{Pop}_{t,a} \times \text{Proportion}_{t,a,g_i} \times \text{VSL}$$

Method 2 computes damages without differentiating by race/ethnicity ($\text{Dam}_{t,a}$). This method applies to all other calculations for Figs. 7 and 8 in the main document (note: the red diamonds in Fig. 7b compute percentage differences from all-person damages per capita computed using Method 2). This process is slightly more complex and involves:

- **Addressing population double-counting:** The lack of mutual exclusivity in U.S. Census Bureau population data poses a challenge, as non-White Hispanic or Latino individuals are double-counted, appearing both under Hispanic or Latino ethnicity and as part of non-White racial groups.
- **Creating mutually exclusive groups:** To avoid double-counting, non-White Hispanic or Latino individuals are separated from racial groups, as outlined in Supplementary Methods 2.²⁷ This creates mutually exclusive population proportions ($\text{Proportion}_{t,a,g}$) for each U.S. Census Bureau-defined subpopulation by age group.
- **Calculating mutually exclusive populations:** Multiplying these proportions by the tract-level all-person population for each age group ($\text{Pop}_{t,a}$) yields mutually exclusive and collectively exhaustive populations by race/ethnicity for each age group.
- **Assign β values:** Like in Method 1, β values are assigned based on race/ethnicity group (β_g). Individuals in Some Other Race and Two or More Races categories are assigned β from Di et al. (2017)'s main analysis.
- **Use tract-level mortality rates:** Mortality rates for each tract ($\text{MR}_{t,a}$ from Supplementary Equation 13) are used to compute damages. Although baseline risks within tracts are not differentiated by race/ethnicity, this approach is appropriate since the results of interest pertain to all individuals within the tract. Consequently, the intermediate damages for mutually exclusive and collectively exhaustive race/ethnicity subpopulations should be interpreted not as standalone damage estimates for each race/ethnicity but as components contributing to the total population damages.
- **Aggregate to tract level:** Summing intermediate damage components across mutually exclusive race/ethnicity groups produces damages by age group at the tract level ($\text{Dam}_{t,a}$), where both baseline risk ($\text{MR}_{t,a}$ from Supplementary Equation 13) and relative risk differentiated.

Critically, we assume Di et al. (2017)'s β values, which were determined using populations 65 and older, are applicable for populations 30 and older to allow for a more consistent comparison with the base case analysis using Krewski et al. (2009) [47]. This assumption is informed by previous work [74]. Finally, for infant mortality risk, we maintain the odds ratio reported by Woodruff et al. (2006) [49] for all concentration-response modeling.

Value of a statistical life year

The VSL approach assigns an equal value to mortality risk, irrespective of remaining life expectancy, differences in risk tolerance, or disposable income—all of which are key factors influencing an individual's willingness to pay for a reduction or willingness to accept an increase in mortality risk [59], [60], [61], [75]. Our second alternative approach, the value of a statistical

²⁷ White Hispanic or Latino individuals are identified using Supplementary Table 30's A and H.

life year (VSLY) approach, adjusts mortality risk valuation by age group to address the first of these factors.

Our methodology aligns with that outlined by the Department of Health and Human Services [76]:

- We derive expected remaining life years by age group using the CDC’s life table for the total population in 2017 [77]. Expected remaining life years are calculated as survivor-weighted averages of the ages bounding each age group—for example, the expected remaining life years for the 30 to 34 age group is the survivor-weighted average of the ages for 30- and 35-year-olds. The exception is for the 85+ group, which is a survivor-weighted average of expected remaining life years for individuals aged 85, 90, 95, and 100.
- We calculate the VSLY by considering the present value of remaining life years for a 40-year-old individual (the average age reported in VSL studies), using a 3% discount rate [76]. Discounting reflects the assumption that each person’s next year (i.e., 2018) is more valuable than their year in a decade or two (i.e., 2027 or 2037).
- In 2017, a 40-year-old was expected to live an additional 40.7 years, which equates to a present value of 23.3 years. Dividing the \$9.97 million VSL by 23.3 years results in a VSLY of \$428 thousand (2020 U.S. dollars).
- We compute the value of mortality risk by age group using the group’s expected remaining life years and the VSLY, again applying a 3% discount rate.

Supplementary Equation 18 is used to compute the present value of remaining life years and the value of mortality risk:

Supplementary Equation 18. Present value of an annuity.

$$PV = A \frac{\left[1 - \frac{1}{(1+r)^n}\right]}{r}$$

In Supplementary Equation 18, A is the annuity (either 1 year or the \$428 thousand VSLY), r is the discount rate of 3%, and n is the number of expected remaining life years.

Supplementary Table 32 reports the expected remaining life years [77], the present value of expected remaining life years, the nominal value of mortality risk, and the present value of mortality risk by age group.

Supplementary Notes

Supplementary Note 1: Fire smoke damages by region, state, & county

Fire smoke damages by census division & region

Supplementary Table 4 shows damages by source and receptor, differentiated by fire type across census divisions and census regions. The census divisions and regions, as defined by the U.S. Census Bureau [78], are as follows:

- **New England (Northeast)** includes Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.
- **Middle Atlantic (Northeast)** includes New Jersey, New York, and Pennsylvania.
- **East North Central (Midwest)** includes Illinois, Indiana, Michigan, Ohio, and Wisconsin.
- **West North Central (Midwest)** includes Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota.
- **South Atlantic (South)** includes Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia.
- **East South Central (South)** includes Alabama, Kentucky, Mississippi, and Tennessee.
- **West South Central (South)** includes Arkansas, Louisiana, Oklahoma, and Texas.
- **Mountain (West)** includes Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming.
- **Pacific (West)** includes California, Oregon, and Washington.

Supplementary Table 4 also shows the percentage of damages by census division and region for each fire type, with the percentages adding up to 100% by fire type and either source or receptor. The table highlights clear regional differences in the sources and receptors of wildfire and prescribed burn smoke impacts. Over three-fourths of wildfire smoke damages came from the Pacific and Mountain census divisions (West census region). In contrast, just over 6% of prescribed burn smoke damages came from these two western divisions. Nearly two-thirds of prescribed burn smoke damages came from the South Atlantic, East South Central, and West South Central census divisions (South census region), while only 19% of wildfire smoke damages came from these three southern divisions.

Fire smoke damages by state

Supplementary Table 1 shows emissions by criteria air pollutant and fire type for the ten most wildfire and prescribed burn primary PM_{2.5}-emitting states. States are ranked by primary PM_{2.5} emissions for each type, and the percentages reported are of total wildfire and prescribed burn primary PM_{2.5} emissions across CONUS. The percentages in parentheses are the cumulative total (e.g., California and Oregon produced 41% of wildfire primary PM_{2.5} emissions). The states listed

in Supplementary Table 1 account for 89% of primary PM_{2.5} emissions from CONUS wildfires and 72% of primary PM_{2.5} emissions from CONUS prescribed burns.

Supplementary Table 5 shows the percentage of 2017 air pollution damages (or premature deaths, since the VSL is a scalar adjustment) by source (rows) and receptor (columns) for the six states causing the highest smoke damages for each fire type. The diagonal cells represent in-state impacts, while the non-diagonal cells represent exported and imported impacts. We also report totals for the states summarized in Supplementary Table 5 (identified as A) and for CONUS (identified as B).

Focusing on wildfires, we find that California was by far the greatest source of wildfire smoke damages (46% of the wildfire smoke total, or \$46 billion). We emphasize that California's contribution to damages is much more substantial than to emissions (again, 25% of primary PM_{2.5}). Most of these damages were experienced in California (40%), whereas a much smaller magnitude was exported to other states (6%). California imported 6% of total wildfire smoke damages, mostly from Oregon. Oregon was the next largest source of wildfire smoke damages but, unlike California, was a clear net exporter, producing 11% but receiving 7% of the wildfire smoke total. Most of Oregon's exports were to California and Washington. Washington is the only state evaluated in Supplementary Table 5's top panel that was a clear net importer. It produced the third most wildfire smoke damages (mostly experienced within Washington) but received the second most, a substantial amount of which came from Oregon. Oklahoma is the anomaly of the group, being far from the northwestern U.S. As such, it did not cause nor receive many damages to or from the other five states. That said, Oklahoma produced 7% of total wildfire smoke damages (\$6.5 billion), more than two-thirds of which it exported to other states. Montana and Idaho were also net exporters, likely due to their small populations (i.e., their fires cause more damage elsewhere where more people live). Overall, these six states produced 78% (\$78 billion) and received 68% (\$68 billion) of national wildfire smoke air pollution damages.

Shifting to prescribed burn smoke damages, we find that fires in the four states of Missouri, Oklahoma, Kansas, and Arkansas generated 36% of the total or \$39 billion (while only receiving 20% of the total or \$25 billion). Correspondingly, all these states were substantial exporters. However, Missouri and Arkansas imported notable prescribed burn smoke damages from their westward neighbors (Kansas and Oklahoma, respectively—a result of prevailing wind patterns), while Oklahoma and Kansas caused more of their own damages. Florida and Texas, on the other hand, were net importers, as much higher portions of their own damages stayed within state borders. Florida exchanged some damages with Georgia and Alabama, and Texas imported from Oklahoma (20% of Texas received) and Louisiana (11% of Texas received) but exported mainly to Louisiana (8.6% of Texas produced) and then Florida (3.5% of Texas produced). These six states comprised a far smaller portion of total damages from prescribed burn smoke (relative to the six wildfire smoke states), causing 51% or \$51 billion and incurring 38% or \$38 billion. The next largest sources (Georgia, Alabama, Louisiana, and South Carolina) accounted for an additional 20% and 17%, respectively.

Fire smoke damages by county

Supplementary Table 6 shows the damages and damages per capita for the counties most affected by wildfire and prescribed burn smoke in 2017. As expected, the highest county-level wildfire smoke damages occurred in California's highly populated counties. Of the 36 counties accounting for 50% of total wildfire smoke damages, 23 are in California, four in Washington, four in Oregon, two in Nevada, and one each in Arizona, Florida, and Montana. Many of these counties are home to large cities, such as Seattle, Portland, Las Vegas, Phoenix, and Miami.

For prescribed burn smoke, damages exceeded \$1 billion only in Harris County, Texas, and Cook County, Illinois, which are home to Houston and Chicago, respectively. Other counties with large damages (often higher per capita) include those in Tulsa, Oklahoma City, Dallas, Memphis, Miami, Phoenix, Kansas City, Wichita, and Fort Worth, each with damages over \$600 million. The two counties in New Orleans experienced \$730 million in prescribed burn smoke damage, while the Florida counties containing Fort Lauderdale, Cape Coral, and Tampa saw damages surpassing \$1.6 billion, in addition to Miami's nearly \$700 million. Like wildfire smoke, these counties are densely populated and near major sources of prescribed burn smoke.

Supplementary Note 2: Fire smoke damages by event

Supplementary Fig. 1 and Supplementary Table 7 present the damages from specific fires in 2017, including the following (with ignition dates provided in parentheses where available [18]):

- **Fire Event A:** Tulare County, California – Wildfires: Pier (8/29), Lion (9/25), Schaeffer (6/24), Indian (8/3), and Roadrunner (7/30)
- **Fire Event B:** Sonoma, Napa, and Solano Counties, California – Wildfires: Tubbs (10/9), Nuns (10/9), Atlas (10/9), Pocket (10/9), and Thirty Seven (10/9)
- **Fire Event C:** Ventura and Santa Barbara Counties, California – Wildfire: Thomas (12/4)
- **Fire Event D:** Collier County, Florida – Prescribed burns
- **Fire Event E:** Cameron and Vermilion Counties, Louisiana, and Jefferson and Chambers Counties, Texas – Prescribed burns

These fires were selected because they represent localized “hot spots” where high emissions from relatively small geographic areas resulted in substantial damage. Emissions data from the NEI [8] are distributed from the county level to the tract level using fire perimeters or burned area boundaries from MTBS [18] (see, for example, Supplementary Fig. 20). Damages from these emissions are then modeled using AP4T. The fires were identified by locating census tracts and counties with the highest damages by source, focusing on these “hot spots” (typically clusters of adjacent or nearby census tracts in one or more counties), and cross-referencing MTBS to match damages with specific fires.

For instance, Tulare County, California, was the largest source of wildfire smoke damages among all counties in 2017. A closer investigation revealed that these damages were primarily concentrated in two census tracts, which, according to the MTBS, were impacted by the *Pier*, *Lion*, *Schaeffer*, *Indian*, and *Roadrunner* wildfires between June and August of 2017 [18]. By isolating the damages originating from these census tracts, we can directly attribute them to these specific fires, as no other wildfires occurred in this area during the year.

Another critical resource for our analysis of the *Tubbs* wildfire in the manuscript is the California Department of Forestry and Fire Protection’s 2017 Wildfire Activity Statistics report [79]. These annual reports provide comprehensive details on each fire, including ignition and containment dates, acreage burned, structures destroyed, structures damaged, and fatalities. Supplementary Table 8 summarizes this information for the California wildfires included in Supplementary Fig. 1 and Supplementary Table 7.

It is important to note that the fires assessed herein are not all single, discrete events; several involve clusters of fire incidents. An exception to this is the *Tubbs* wildfire. As detailed in Supplementary Table 8, the *Tubbs* fire ignited on October 8, 2017, burned 37,000 acres, destroyed 5,600 structures, and resulted in 22 fatalities [79]. The *Tubbs* fire was selected for inclusion in the manuscript because it is the second most destructive wildfire in California’s history and the second deadliest of the 21st century, surpassed only by the 2018 *Camp Fire* [80], [81]. By comparing the damages from the *Tubbs* fire itself to those caused by its smoke (248 premature deaths, as derived

from Supplementary Table 7 and using a value of a statistical life at \$9.97 million), we highlight the very large impact of smoke-related damages.

The *Tubbs* fire was one of several fires in the North Bay Area that ignited in early October 2017 under severe fire weather conditions. Alongside *Tubbs*, the *Nuns*, *Atlas*, *Pocket*, and *Thirty Seven* wildfires burned a combined total of 115,000 acres, destroyed over 2,100 structures, and resulted in 9 fatalities [79]. In total, the smoke from these fires caused 549 premature deaths (797 including *Tubbs*). Physical damages from the fires amounted to more than \$6 billion [79],²⁸ while smoke damages totaled nearly \$8 billion. See Supplementary Fig. 1b for the own-state impacts of these wildfires.

The Tulare County fires present a different scenario as they did not all ignite simultaneously. However, they are considered together here because they occurred within just two census tracts, effectively making them a single source for our modeling. These wildfires were less destructive and deadly compared to those in the North Bay Area in early October 2017. Collectively, the *Pier*, *Lion*, *Schaeffer*, *Indian*, and *Roadrunner* fires burned 76 thousand acres, with the *Pier* destroying 2 structures [79]. Physical damages from these fires totaled just \$24 thousand [79].²⁹ However, these fires caused 824 premature deaths due to air pollution, surpassing the number of deaths attributed to the smoke from the *Tubbs*, *Nuns*, *Atlas*, *Pocket*, and *Thirty Seven* fires. Smoke damages from these fires amounted to more than \$8 billion. See Supplementary Fig. 1a for the own-state impacts of these wildfires.

Like the *Tubbs* wildfire, the *Thomas* wildfire is another distinct fire event. It ignited on December 4, 2017, and burned 282 thousand acres, making it the largest wildfire in California for that year [79]. The *Thomas* fire destroyed over 1 thousand structures and resulted in 2 fatalities. Notably, the *Thomas* fire continued burning into the new year, finally being contained on January 12, 2018. As a result, the total emissions from this fire event are only partially reflected in the NEI for 2017 [8]. Consequently, the 790 premature deaths attributed to its smoke reflect only 27 of its 39 days (69% of its duration). The California Department of Forestry and Fire Protection does not report physical damages for Ventura or Santa Barbara County for 2017 or 2018 [79]. See Supplementary Fig. 1c for the own-state impacts of this wildfire.

The prescribed burns in Florida, Louisiana, and Texas differ from the wildfire events discussed herein because they are not specific fires but rather encompass all prescribed burns in counties with exceptionally high smoke damages. Collier County, Florida, and Cameron County, Louisiana, are the only counties exceeding \$1 billion in smoke damages by source. The next highest is Vermilion County, Louisiana, which borders Cameron County along the Gulf Coast, with approximately \$800 million in damages. Further analysis reveals that prescribed burns in Jefferson County (\$410 million in smoke damages) and Chambers County (\$230 million in smoke damages) in Texas, adjacent to the Louisiana counties along the Gulf Coast, are also substantial. As prescribed burns, these events likely did not cause any physical damage and are therefore

²⁸ These are summed damages from Sonoma, Napa, and Solano counties and are, presumably, in 2017 U.S. dollars.

²⁹ These are reported damages from Tulare County and are, presumably, in 2017 U.S. dollars.

excluded from Supplementary Table 8. See Supplementary Fig. 1d and 1e for the own-state impacts of these prescribed burns in Florida and Texas/Louisiana, respectively.

Notably, 2017 emissions from wildfires in Siskiyou County, California (see Supplementary Fig. 20), which drove \$6.0 billion in wildfire smoke damages, were the greatest by tonnage. However, Siskiyou is located in the northern part of the state, relatively far from population centers in both California and Oregon. In contrast, emissions from fires in Tulare, Sonoma, Napa, Solano, and Ventura counties drive much higher exposures and damages per metric ton due to their proximity to major urban areas, such as San Francisco and Los Angeles. While wildfires' impacts are commonly characterized by acreage burned or structures lost, our focus on the human health effects from resulting smoke highlights how even relatively small fires, in terms of spatial extent, can lead to exorbitantly high damages if they occur upwind of densely populated areas. The fuel that fires burn and how much smoke is produced matters as well.

Census tracts in Missouri, Oklahoma, Kansas, and Arkansas that are east of Oklahoma City, south of Kansas City, and north of Little Rock drove \$28 billion in air quality damages. Additional substantial contributions to prescribed burn smoke damages include \$544 million from Berkeley County, South Carolina (north of Charleston), \$451 million from Thomas County, Georgia (north of Tallahassee), \$439 million from Russell County, Alabama (east of Montgomery), and \$429 million from Osceola County, Florida (south of Orlando).

Notably, many of the fire events identified in this Supplementary Note occurred near counties with the highest wildfire and prescribed burn smoke damages (see Supplementary Table 6). For instance, the *Pier*, *Schaeffer*, and *Lion* fires (Supplementary Fig. 1a) burned just south of Fresno, while the *Tubbs*, *Nuns*, and *Atlas* fires (Supplementary Fig. 1b) occurred west of Sacramento. The *Thomas* fire (Supplementary Fig. 1c) burned between Santa Barbara and Los Angeles. Similarly, the Collier County, Florida, burns (Supplementary Fig. 1d) occurred near Miami, Fort Lauderdale, Cape Coral, and Tampa. Houston lies to the west and New Orleans to the east of the Gulf Coast burns in Texas and Louisiana (Supplementary Fig. 1e). Additionally, other high-damage receptors are located downwind of the prescribed burn smoke-heavy areas identified in Missouri, Oklahoma, Kansas, and Arkansas, as well as other substantial tracts contributing to prescribed burn smoke damages.

Supplementary Note 3: National Emissions Inventory in 2014 & 2020 vs. 2017

For this research, we focus exclusively on 2017, though fire activity fluctuates from year to year [82], [83]. Our decision to focus on 2017 is partly to maintain simplicity and avoid introducing additional dimensions and complexity, but also because the AP4T model incorporates several 2017-specific inputs. Principal among these is the emissions inventory that AP4T and its predecessors are built upon. This initial iteration of AP4T was developed using the 2017 NEI [8]. These models assess emissions on the margin, meaning they model how emissions drive impacts on top of an existing baseline. To construct this baseline, we require national emissions data from all sources of air pollution across CONUS, which the NEI provides (Supplementary Table 3).

The NEI is released every three years, which dictates which years can be modeled using APEEP (e.g., AP3 was capable of modeling 2008, 2011, 2014, and 2017) [3], [5]. We compare emissions from the 2014 and 2020 NEIs [84], [85] with those from the 2017 NEI. For some analyses, we focus on primary $\text{PM}_{2.5}$ because it accounted for over 70% of the air pollution damages from fire emissions in 2017 (Supplementary Table 2). Our investigation must consider two key aspects: (1) emission magnitudes and (2) emission distribution. The first aspect affects total impacts, while the second influences the distribution of impacts, both of which are crucial for our study. Notably, while damages are influenced by emissions, they also depend on many other variables. Thus, we cannot assume that a 5% increase in emissions translates directly to a 5% increase in smoke damages; we would have to work through a more comprehensive analysis considering every component of the integrated assessment model to verify that fact. Nevertheless, this analysis provides insight into how sensitive our assessment may be to differing emissions occurring in different years.

Supplementary Fig. 14 shows the total emissions of NH_3 , NO_x , primary $\text{PM}_{2.5}$, SO_2 , and VOCs from all wildfires and prescribed burns in the contiguous U.S. for 2014, 2017, and 2020. Colors represent census divisions, and “color families” represent census regions. Supplementary Table 24 complements this figure by presenting emission totals for 2014 and 2020, along with percentage differences compared to 2017. We observe that wildfire emissions in 2014 were much lower than in 2017 (47% less primary $\text{PM}_{2.5}$) but higher in 2020 compared to 2017 (19% more primary $\text{PM}_{2.5}$). Prescribed burn emissions were lower in both 2014 and 2020 compared to 2017, with reductions of 11% and 19%, respectively, for primary $\text{PM}_{2.5}$. Consequently, we can infer that smoke-related damages from both wildfires and prescribed burns were lower in 2014 than in 2017. Additionally, while wildfire smoke damages were likely higher in 2020 than in 2017, prescribed burn smoke damages were likely lower in 2020.

Supplementary Table 25 complements Supplementary Fig. 14 by presenting the percentage of primary $\text{PM}_{2.5}$ from wildfires and prescribed burns across different geographic areas for each year. Both Supplementary Table 25 and Supplementary Fig. 14 indicate that the distribution of emissions remained relatively consistent, at the regional level, across the three evaluated years. Similar to 2017, most wildfire emissions originated from the West in 2014 and 2020, while most prescribed burn emissions came from the South in those same years. This consistency is particularly important for some of our paper’s main conclusions. Since between-state correlations

of vulnerability and smoke drive the national correlation, the stability of emission distribution at the regional level suggests that our conclusions would hold for other years as well.

Supplementary Fig. 15 zooms in to the state level, displaying the percentage of wildfire emissions from each state in 2014 and 2020 versus 2017. For wildfires in the West, we see a greater share of emissions came from California and lesser shares of emissions came from Montana and Idaho for both years. A smaller percentage of emissions came from Oregon and a greater percentage of emissions came from Washington in 2014, and the reverse was the case in 2020. For wildfires in the rest of the country, there was a lower percentage of emissions from Oklahoma for both years. Shares from Texas and Louisiana were higher in 2014, and shares from Colorado were higher in 2020. Overall, the biggest concern for our paper's distributional impacts assessments would be if there was a notable decrease in the percentage of emissions coming from California. As noted in the manuscript, California is a big driver of the observed trends, and we can assume this influence would increase for 2014 and 2020.

Supplementary Fig. 16 also zooms in to the state level, showing the percentage of prescribed burn emissions from each state in 2014 and 2020 compared to 2017. In the Southeast, we observe that a larger share of emissions in both years came from Florida, Georgia, and Alabama, while Oklahoma, Missouri, and Kansas contributed smaller shares. Louisiana's contribution was higher in 2014 but lower in 2020, and the reverse was the case for Texas. Arkansas maintained a relatively consistent share across the years. Interestingly, Oregon contributed a greater share of prescribed burn emissions in both 2014 and 2020 compared to 2017. Meanwhile, other western states contributed higher shares in 2014 and lower shares in 2020. Like with wildfires, nothing here suggests that we should expect vastly different outcomes to our paper's conclusions considering emissions from the other evaluated years. The emission shares increase in generally more vulnerable states (e.g., Florida, Georgia, and Alabama) and decrease in generally less vulnerable states (e.g., Kansas and Missouri), so the positive correlation between prescribed burn smoke and vulnerability could have been stronger.

Supplementary Note 4: National Emissions Inventory vs. Global Fire Emissions Database

There are large uncertainties associated with emissions estimates from fires. To better understand and quantify this uncertainty, we compare the NEI with an alternative inventory, the Global Fire Emissions Database (GFED) [86], [87]. We download the most recent, GFED5, gridded files [88]. We note that these data are part of a Beta version and that the data may change until the associated paper is published, but, for our purposes, we find that benefits of using the newest data outweigh the downside of potential changes.

We begin by comparing our primary PM_{2.5} emission totals (Supplementary Table 2 and Supplementary Table 3) to the 2017 total from the GFED. The NEI reports 1.22 million metric tons for wildfires and another 787 thousand for prescribed burns, for a total of 2.01 million metric tons of primary PM_{2.5} emissions for wildland fires overall. These totals can be verified via the Technical Support Document associated with the NEI [8]. The GFED reports 1.39 million metric tons of primary PM_{2.5} emissions across Temperate North America (TENA). TENA is effectively CONUS. Hence, the NEI reports emissions that are 45% higher than those from the GFED.

GFED provides data at a global scale in raster file format. The spatial resolution is 0.25 degrees, and the estimates are provided at daily and monthly temporal resolutions. For our purposes, the key variables of the dataset are grid area (m²) and emissions factors (g m⁻²). We compute primary PM_{2.5} emissions for all of 2017, analogous to our NEI data, by extracting monthly data to the county level and then summing across all 12 months.

Supplementary Fig. 17 shows state-level totals of primary PM_{2.5} emissions from fires as reported by the NEI (y-axis) versus the GFED (x-axis). States are colored by census division, with “color families” representing census regions. We can see that the NEI overestimates primary PM_{2.5} emissions as compared to the GFED for California (+9%), Oregon (+15%), Montana (+27%), Idaho (+132%), and Washington (+64%), the particularly wildfire smoke-damaging western states in our analysis. The NEI also overestimates emissions for Oklahoma (+403%), Kansas (+143%), Missouri (+450%), Arkansas (+112%), Texas (+43%), and Louisiana (+119%), some of the particularly prescribed burn smoke-damaging southern states in our analysis. While the NEI underestimates emissions for seven states, the two most important are Florida (-47%) and Georgia (-54%).

Supplementary Fig. 18 shows county-level differences in primary PM_{2.5} emissions from fires as reported by the NEI versus the GFED. Counties are colored red where the NEI reports higher emissions and blue where the NEI reports fewer emissions. We see substantial differences in several counties throughout the U.S. Some of the greatest differences are in:

- **Idaho County, ID:** +52.7 thousand metric tons (140% higher)
- **Siskiyou County, CA:** +48.2 thousand metric tons (81% higher)
- **Tulare County, CA:** +34.3 thousand metric tons (224% higher)
- **Curry County, OR:** -25.7 thousand metric tons (34% fewer)
- **Ventura County, CA:** -24.9 thousand metric tons (56% fewer)
- **Powell County, MT:** +24.7 thousand metric tons (121% higher)

- **Ware County, GA:** -20.4 thousand metric tons (98% fewer)
- **Kittitas County, WA:** +20.2 thousand metric tons (223% higher)
- **Yakima County, WA:** +19.2 thousand metric tons (163% higher)
- **Hood River County, OR:** +17.8 thousand metric tons (164% higher)

Supplementary Fig. 19 shows county-level fractional biases in primary PM_{2.5} emissions from fires as reported by the NEI versus GFED. The fractional bias is used to highlight relative differences between the two estimates, acknowledging that neither serves as the “absolute truth” (see Supplementary Equation 8). Counties are colored red where the NEI reports higher emissions and blue where the NEI reports fewer emissions. Large relative differences are observed across many counties in the U.S. Unlike in Supplementary Fig. 18, where large absolute differences typically occur in areas with high emissions, a county does not need to have high emissions to exhibit notable relative differences.

One of the NEI’s most greatest advantages is its focus on the U.S. and use of S/L/T data. The GFED focuses on all regions throughout the world and, like many other inventories, relies on satellite information [20]. Notably, satellites tend to better detect larger, more intense fires (like wildfires) than smaller fires (like prescribed burns) [20], suggesting that the GFED may miss some of these emissions in the Southeastern states where the NEI overestimates in comparison. More information on the GFED’s burned area, fuel consumption, and emission factors procedures can be found in Chen et al. (2023) [89], Van Wees et al. (2022) [90], and Vernooij et al. (2023) and Shahid et al. (in review) [91], [92], respectively.

While various factors may explain the discrepancies between these emissions inventories (e.g., challenges satellites face in accurately identifying prescribed burn activity), the GFED’s estimates still reinforce the validity of our findings regarding exposures and vulnerability. We emphasize that the positive relationship between smoke and the SVI is predominantly driven by regional trends (i.e., differences between regions rather than within regions). The NEI reports higher emissions than the GFED for key states within our focus regions of the West and Southeast (e.g., California and Oklahoma in the West and South). However, the GFED reports higher emissions from these regions compared to the Northeast and the Midwest. Despite the uncertainties surrounding the NEI’s estimates, our major conclusions remain robust and defensible. Still, we encourage future research to further explore the differences between these inventories and consider modeling the GFED’s data for the U.S. (for 2017 or other years).

Supplementary Note 5: Comparison to Xie et al. and Childs et al. smoke PM_{2.5} modeling

To quantify the uncertainty associated with our smoke PM_{2.5} estimates, we compare our results to those of two similar studies that evaluated fires emissions in 2017 using alternative methods. Xie et al. (2020) employed an earth systems model (ESM) [93] and the GFED [86], [87] (see Supplementary Note 4) and provided monthly smoke PM_{2.5} mixing ratios, along with surface-level temperature and pressure, over North America [83], [94]. ESMs are comparable to Chemical Transport Models (CTMs) but offer a more comprehensive assessment of environmental systems. Notably, Xie et al. found that using the GFED resulted in smoke PM_{2.5} levels much lower than those observed at monitoring stations, prompting them to increase emissions from the western U.S. and southwestern Canada by five times (the GFEDx5 experiment). Xie et al. also modeled smoke PM_{2.5} without the influence of Canadian fires, which is particularly relevant for our work, as we do not model emissions from outside of CONUS.

Because the data provided by Xie et al. are expressed as mixing ratios, we must convert them to concentrations ($\mu\text{g m}^{-3}$) for comparison with our estimates. This conversion involves multiplying the mixing ratio by the density of dry air. The density of dry air depends on pressure, temperature, and the universal gas constant, allowing us to relate the two units. Importantly, the ambient PM_{2.5} estimates by Xie et al. incorporate emissions from all sources. Hence, we use their no fires experiment to subtract non-smoke PM_{2.5} from the GFEDx5 experiment and the GFEDx5 without Canadian fire emissions experiment.

Childs et al. (2022) used a machine learning model that integrated ground, satellite, and reanalysis data to estimate smoke PM_{2.5} levels across a 10 km grid covering CONUS [82], [95]. This approach involved three main steps:

- 1. Identifying smoke days:** For each cell, “smoke days” were identified using NOAA’s HMS plume data on clear days. On cloudy days, HMS identified fire points, and the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model, coupled with aerosol optical depth (AOD) data, was used to fill gaps.
- 2. Estimating ground-level smoke PM_{2.5} at monitored sites:** On “smoke days,” ambient PM_{2.5} was compared to the median for that location and month, derived from a three-year dataset. Smoke PM_{2.5} was calculated by subtracting the median from total PM_{2.5}, with chemical composition monitors confirming smoke contributions.
- 3. Predicting PM_{2.5} at non-monitored locations:** A machine learning model was trained on monitored data and used to predict PM_{2.5} for all cells on all days.

Supplementary Table 26 shows smoke PM_{2.5} estimates from AP4T, Childs et al., and Xie et al. summarized by geographic area. Supplementary Fig. 23 maps smoke PM_{2.5} estimates at the county level. Estimates are population-weighted averages computed from the tract level. Supplementary Fig. 24 shows county-level differences in smoke PM_{2.5} between AP4T’s wildfire smoke estimates (left) or total fire smoke estimates (right) and the three comparison estimates. Supplementary Fig. 25 shows county-level relative differences (via fractional biases) of the same. The fractional bias

is used to highlight relative differences between the two estimates, acknowledging that neither serves as the “absolute truth” (see Supplementary Equation 8). For both Supplementary Fig. 24 and Supplementary Fig. 25, counties are colored red where AP4T estimates higher smoke $PM_{2.5}$ and blue where AP4T estimates lower smoke $PM_{2.5}$.

Supplementary Table 27 reports comparison statistics for AP4T, Xie et al., and Childs et al. tract-level estimates. The statistics are mean fractional error (MFE), mean fraction bias (MFB), Pearson’s correlation coefficient (r), mean absolute error (MAE), and mean error (ME). See the MFE in Supplementary Equation 7 and the MFB in Supplementary Equation 8.

AP4T underestimates concentrations in the Midwest along the Canada-U.S. border and in the Northeast compared to Xie et al. and Childs et al. Conversely, we tend to overestimate impacts in and around Oklahoma as well as in and around California. We hypothesize a few reasons for these differences. Most of these are touched on in the main document and further discussed herein:

1. **Canadian wildfires:** We hypothesize that Canadian wildfires may contribute to the discrepancies observed in the Midwest along the Canada-U.S. border and in the Northeast. Xie et al.’s experiment excluding these fires supports our hypothesis. We only model impacts from fires burning within CONUS borders (i.e., emissions tracked by the NEI). Hence, pollution coming from north of the Canada-U.S. border is excluded. Notably, British Columbia, just north of Washington, Idaho, and western Montana, had a substantial wildfire season in 2017, resulting in nearly three million acres burned [96]. Importantly, AP4T’s calibration uses ground-level data from monitors that Canadian wildfire smoke may influence. This is of increasing relevancy for AP4T, especially given the unprecedented wildfire smoke events in the northeastern and midwestern U.S. originating from Quebec and other Canadian provinces in June of 2023 [97], [98], [99].
2. **Smoke plume behavior:** Both underestimations in the Midwest along the Canada-U.S. border and in the Northeast as well as overestimations in and around California are likely related to injection heights associated with wildfire smoke. The injection height—the vertical point where smoke begins its downwind transport—is typically high for wildfires [100]. Wildfires’ intensity can result in their smoke breaking through atmospheric interfaces such that the pollution more greatly disperses. As explained by Williamson et al. (2016), there is an association between injection height and intensity because the greater intensity drives a greater rate of biomass consumption and heat release [100]. The heat drives greater buoyancy of the plume and, in turn, a greater injection height. Although not a perfect comparison, wildfires may function more like high-polluting facilities with smokestacks, such as electric generating units, which are designed to disperse pollution away from local communities [30]. This would explain how fires in the western U.S. (and Canada) could drive substantial $PM_{2.5}$ along the northern U.S. border further east in ways AP4T does not capture. It would also explain how concentrations are lower in California than we would expect if these emissions were from some other ground level source (e.g., traffic or agriculture).

3. **NEI fire emissions uncertainty:** Differences could simply be related to overestimations (and underestimations where applicable) of emissions from the NEI [8]. This is particularly relevant to our comparisons to Xie et al.'s estimates because, again, the study used the GFED emissions inventory. The NEI reports much higher emissions than GFED for key states such as California and Oklahoma (see Supplementary Fig. 17). However, Xie et al. found that using the GFED resulted in smoke $PM_{2.5}$ levels much lower than those observed at monitoring stations, prompting them to increase emissions from the western U.S. and southwestern Canada by five times [83], and the GFED has been updated since the study's publication. See Supplementary Note 4 for a full comparison of the NEI to the GFED.
4. **Temporal resolution of AP4T:** AP4T models pollutant transport considering a representation of annually averaged atmospheric conditions (see Supplementary Equation 4 and the associated description in Supplementary Methods 1). Many of the fires in California could have occurred when the specific meteorological conditions blew the smoke out of CONUS borders. Supplementary Fig. 26, showing $PM_{2.5}$ mixing ratios by month [83], provides support for this theory, especially for October and December of 2017. Like its predecessors, AP4T is an annually calibrated model. This limitation affects AP4T's performance when modeling episodic sources of air pollution as opposed to steadier ones. One of AP4T's related benefits, however, is that it enables the perspective of probabilistic expectation of $PM_{2.5}$ in receptor locations if modeled emissions are released all at once. This could be particularly useful for policymakers and planners working toward future damage mitigation efforts, providing expected effects given unknowable ignition times and corresponding weather patterns.
5. **Challenges identifying prescribed burn smoke:** For the Southeast, we can hypothesize that the cause of differences is mostly related to prescribed burn smoke. Notably, the comparison studies are not limited to wildfire smoke, but they are also heavily dependent on satellite imagery (note: the GFED relies on this information), which tends to better detect larger, more intense fires (like wildfires) than smaller fires (like prescribed burns) [20]. This provides justification for comparing both wildfire smoke and total fire smoke estimates from AP4T to the comparison studies. We can assume these studies capture some but not all prescribed burn smoke in their estimates. As such, it is not unreasonable that our wildfire smoke estimates tend to be approximately equal to or lower than the comparison estimates, while our total fire smoke estimates tend to be approximately the same or higher.

Regarding the first step in the methods from Childs et al., the success with which wildfire and prescribed burn pollution triggers “smoke days” remains unclear. While wildfire smoke events are likely to be detected, the detectability of prescribed burn smoke is less certain. Assuming a “smoke day” is triggered, Childs et al.'s methodology of examining deviations from the median $PM_{2.5}$ (the second step) helps ensure that both wildfire and prescribed burn smoke are captured. However, smoke of any kind can only be captured on days when it is detected. As such, prescribed burn smoke would not be captured if it is present but does not trigger a “smoke day.” Another important

consideration is whether frequent (and possibly unidentified) prescribed burns could notably influence a location's median $PM_{2.5}$. In such cases, the deviations identified on “smoke days” might more accurately reflect changes not from a smoke-free day but from a wildfire-smoke-free day. Ultimately, this effect would depend on the frequency of prescribed burns and the prevalence of their smoke throughout the year. These considerations point to a valuable avenue for future research aimed at further refining this type of modeling process.

This comparison provides valuable insights into the strengths and weaknesses of different modeling approaches, along with actionable recommendations for future research. Methods less reliant on satellite data, such as the NEI compared to the GFED, and source-focused modeling techniques offer substantial advantages for distinctly modeling wildfire and prescribed burn smoke. In contrast, receptor-focused modeling techniques retain the advantage of identifying where smoke ends up rather than predicting its movement. Further development of the AP4T model is crucial for accurately distinguishing pollutant transport from wildfires (and potentially prescribed burns) from other ground-level sources, leading to improved predictions of the atmospheric dispersion of fire smoke. A straightforward initial step could involve treating fire emissions similarly to smokestack emissions. However, it may also be necessary to introduce a new bin in the AP4/AP4T framework specifically for wildfires.

An important area for future research with the AP4/AP4T models is improving the calibration process, which currently relies on ground-level monitors influenced by Canadian fire smoke and other non-CONUS emission sources—neither of which are modeled or accounted for by AP4/AP4T. A potential first step to enhance the model's accuracy could involve synthesizing data from the AQS monitors used for calibration (see Supplementary Methods 1) with $PM_{2.5}$ estimates from Xie et al. This synthesis could compare estimates both with and without Canadian fire emissions. Integrating these datasets would provide a better understanding of external smoke sources and help refine AP4/AP4T calibration to improve overall performance.

Supplementary Note 6: Extended sensitivity analyses

Total smoke damages sensitivity analysis

Supplementary Table 33 shows sensitivity analysis results for wildfire smoke, prescribed burn smoke, and total wildland fire smoke damages. Supplementary Table 33 explores uncertainty with the air quality, concentration-response, and valuation modeling. Scenario 1 is the base case. The base case employs AP4T's counterfactual baseline air quality modeling approach, the ACS DR function [47], the distributional baseline risk approach (see Supplementary Equation 13), and the EPA's central VSL estimate (\$9.97 million 2020 U.S. dollars, see Supplementary Table 31) [62].

Scenarios 2-7 look at air quality modeling. Scenarios 2-4 are compared to both wildfire smoke and total smoke damages from AP4T, because we assume the comparison studies capture some but not all prescribed burn smoke in their estimates. These studies both rely on satellite imagery [82], [83], which identifies wildfire smoke more reliably than prescribed burn smoke [20]. See Supplementary Note 5 for more details:

- **Scenario 2** uses smoke $PM_{2.5}$ data from Xie et al. (2020)'s GFEDx5 experiment [83], [94].
- **Scenario 3** uses smoke $PM_{2.5}$ data from Xie et al.'s GFEDx5 without Canadian fire emissions experiment [83], [94].
- **Scenario 4** uses smoke $PM_{2.5}$ data from Childs et al. (2022) [82], [95].
- **Scenario 5** uses the marginal ton approach in AP4T; however, Scenario 5 does not employ AP4T's unique treatment of NH_3 and NO_x emissions on the margin. This enables a modeling approach nearly synonymous with the counterfactual baseline approach, with differences driven by nonlinearity in the DR function (see Supplementary Equation 9 and 12).
- **Scenario 6** uses the marginal ton approach in AP4T; Scenario 6 does employ AP4T's unique treatment of NH_3 and NO_x emissions on the margin. This results in greater marginal $PM_{2.5}$ from these emissions, based on linear models considering the interpollutant atmospheric chemistry. See Supplementary Methods 1 for more information.
- **Scenario 7** uses AP4 (and the counterfactual baseline approach) at the county level.

Scenarios 8-11 look at dose-response modeling. The odds ratio for infant mortality risk is kept constant as that reported by Woodruff et al. (2006) [49] for all concentration-response modeling. Scenarios 9 and 10 use β coefficients derived from relative risks reported by Di et al. (2017), the Medicare Cohort Study [50]. We assume these β coefficients, which were determined using populations 65 and older, are applicable for populations 30 and older to facilitate a better comparison with our base case analysis using Krewski et al. (2009), the ACS study [47]. This assumption is informed by previous work [74]:

- **Scenario 8** uses the β coefficient derived from relative risk reported by Lepeule et al. (2012), the H6C study, applicable for populations 25 and older [48]. This β coefficient can be found in Supplementary Table 20 herein.
- **Scenario 9** uses the β coefficient derived from relative risk reported by Di et al. (2017) for its main analysis [50]. This β coefficient can be found in Supplementary Table 20 herein.
- **Scenario 10** uses β coefficients derived from relative risks differentiated by race/ethnicity from Di et al. (2017) [50]. The process assigns these β coefficients, which can be found in Supplementary Table 20, to mutually exclusive and collectively exhaustive proportions of the population differentiated by race/ethnicity. See Supplementary Methods 5 for more details.
- **Scenario 11** uses the dimensional approach for baseline risk—i.e., assigning all-person county-level mortality rates from the CDC [53] to each census tract.

Scenarios 12-15 look at valuation modeling. All valuation modeling uses 2020 U.S. dollars in 2017:

- **Scenarios 12 and 13** use the 95% confidence interval of VSL values from the EPA's fitted Weibull distribution [62] (see Supplementary Table 31).
- **Scenario 14** uses an alternative estimate from Mrozek & Taylor (2002) [101] (2017 value of \$3.76 million 2020 U.S. dollars, see Supplementary Table 31).
- **Scenario 15** uses the VSLY approach, differentiating mortality risk valuation by age group. We derive the VSLY using the VSL for a 40-year-old person and a 3% discount rate [76] and then compute a present value of mortality risk for each age group. The VSLY of \$428 thousand results in a maximum value of \$12.8 million for infant mortality risk and a minimum value of \$2.11 million for individuals aged 85 and older (see Supplementary Table 32). See Supplementary Methods 5 for more details.

Supplementary Table 33 reveals that estimates are most sensitive to valuation modeling. 2017 damages could have been much lower (green) or much higher (yellow) depending on the VSL. The VSLY approach both impacts overall damages and influences the distribution of damages (see Figs. 7 and 8 of the main document and Supplementary Table 34 through 37 herein).

The next most influential is dose-response modeling. Using the H6C DR function more than doubles damages. Using the Medicare Cohort Study's main analysis DR function increases damages by 20%. As with the VSLY approach, differentiating relative risk by race/ethnicity both impacts overall damages and influences the distribution of damages (see Figs. 7 and 8 of the main document and Supplementary Table 34 through 37 herein). We see very small changes when using the dimensional approach (county-level mortality rates) versus the distributional approach (county-level mortality rates by race/ethnicity distributed to the tract level based on population breakdown by race/ethnicity) for baseline risk. This provides assurance that the distributional approach does not substantially change overall damages but instead just affects the distribution of

damages as intended. Future work should explore the differences between these two approaches at higher spatial resolutions—namely, within counties.

While less influential than the other categories, air quality modeling uncertainty is still quite substantial. When using smoke $\text{PM}_{2.5}$ estimates from Xie et al.'s GFEDx5 experiment, the estimated damages amount to \$157 billion, which is greater than our wildfire smoke damage estimate but lower than our total fire smoke damage estimate. In contrast, when using Xie et al.'s GFEDx5 estimates computed without Canadian fire emissions, damages decrease to \$96.9 billion, slightly below our wildfire smoke damage estimate and much lower than our total fire smoke damage estimate. Using smoke $\text{PM}_{2.5}$ estimates from Childs et al., the damages are estimated at \$61.6 billion, notably less than both our wildfire smoke damage and total fire smoke damage estimates. For a detailed discussion of the potential drivers behind these differences, see the comparisons of AP4T, Xie et al., and Childs et al. smoke $\text{PM}_{2.5}$ estimates in Supplementary Note 5.

Interestingly, using AP4 increases wildfire smoke damages by one-third, whereas prescribed burn smoke damages are relatively similar to those computed with AP4T. We point out that AP4 models wildland fire emissions as being released from the population-weighted centroids of the source counties. We hypothesize that the relative size of western counties (see, for example, Siskiyou County, California, in Supplementary Fig. 20), where most wildfire smoke is produced and received (see Supplementary Table 4 and 5), greatly drives this difference for wildfire smoke damages. This result emphasizes the importance of modeling wildfire emissions as released at the tract level. Otherwise, the most concentrated smoke is wrongly assumed to be released in population-dense areas far from the wildlands where the fires occur, and this greatly increases the wildfire smoke damage estimates.

Finally, we see that using the marginal ton approach rather than the counterfactual baseline approach has a relatively low influence on national damages from wildfire smoke, prescribed burn smoke, and wildland fire smoke overall. When foregoing AP4T's unique treatment of NH_3 and NO_x emissions on the margin, damages are near equivalent, with the slight decrease explained by nonlinearities in the DR function. Specifically, marginal damages decrease with increasing baseline $\text{PM}_{2.5}$ concentrations, so damage changes resulting from marginal tons (with fire smoke contributing to the baseline) are smaller than when removing all emissions from wildland fire sources (creating a counterfactual baseline with substantially less $\text{PM}_{2.5}$). The change is greater for wildfire smoke than prescribed burn smoke because wildfire smoke emissions and resulting $\text{PM}_{2.5}$ are (1) greater and (2) more spatially concentrated. When including AP4T's unique treatment of NH_3 and NO_x emissions on the margin, damages increase. This is because marginal emissions of NH_3 and NO_x are more appropriately modeled (using a system of linear regression models dependent on whether the location is ammonium- or nitrate-limited) as interacting with the existing baseline. Forgoing this modeling component is the necessary tradeoff of working with the counterfactual baseline approach, which is more convenient when working at the tract level for computational efficiency and ease of data management and storage.

Distributional impacts sensitivity analysis

Supplementary Fig. 27 replicates the overall SVI decile wildfire smoke panel (top left) from Fig. 2 in the main document and examines the effects of four sensitivity scenarios on wildfire smoke exposure and damages per capita disparities: (1) excluding tracts in California, (2) excluding tracts in Oregon and Washington, (3) excluding tracts in the Mountain census division, and (4) excluding tracts outside the Pacific and Mountain census divisions. See Supplementary Note 1 for the states included in each census division. This figure highlights California's pivotal role in the distributional impacts analysis. When California is excluded, the relative impacts on the two most vulnerable SVI deciles decrease substantially. Interestingly, focusing only on the Pacific and Mountain census divisions results in a notable decrease in relative impacts for the most vulnerable SVI decile. This can be attributed to regional patterns of social vulnerability and fire smoke. Excluding the eastern half of the U.S. removes a region that is generally less wildfire smoke-polluted and less socially vulnerable. While average exposures decline for both less vulnerable and more vulnerable groups when the eastern U.S. is included, the reduction is greater for the less vulnerable population due to the regional distribution of social vulnerability.

Supplementary Fig. 28 replicates the overall SVI decile wildfire smoke panel (top left) from Fig. 2 in the main document and includes total fire smoke disparities. It evaluates three sensitivity scenarios for smoke exposure and per capita damages disparities: (1) using smoke $PM_{2.5}$ estimates from Childs et al., (2) using smoke $PM_{2.5}$ estimates from Xie et al.'s GFEDx5 experiment, and (3) using smoke $PM_{2.5}$ estimates from Xie et al.'s GFEDx5 experiment without Canadian fire emissions [82], [83]. Both wildfire smoke and total smoke impacts are analyzed, with the assumption that these studies capture some, though not all, prescribed burn smoke. Since these studies rely on satellite imagery [82], [83], which detects wildfire smoke more reliably than prescribed burn smoke [20], their estimates may underestimate prescribed burn contributions. A comparison of smoke $PM_{2.5}$ estimates from AP4T, Xie et al., and Childs et al. is available in Supplementary Note 5.

Comparisons of these estimates (Supplementary Table 26 and 27 and Supplementary Fig. 23 through 25) suggest that AP4T overestimates smoke $PM_{2.5}$ in California. Consequently, alternative estimates lead to lower relative impacts for the most vulnerable SVI deciles. Nonetheless, all alternative estimates confirm greater exposure among more vulnerable populations (specifically SVI deciles 6 and 7) compared to less vulnerable groups (such as SVI deciles 2 and 3). The greatest uncertainty occurs at the upper end of the SVI scale, particularly for SVI deciles 9 and 10. Notably, Xie et al.'s GFEDx5 experiment without Canadian fire emissions produces results that broadly align with our findings, including the highest exposure levels for SVI decile 10, although the relationship between exposure and vulnerability appears weaker compared to our modeling.

Supplementary Tables

Supplementary Table 1. Fire smoke emissions by pollutant for the ten most emitting states.

Emission Source	Rank	State	AP4-Modeled Criteria Air Pollutants (Metric Tons)					PM _{2.5} Percentage ^A	
			NH ₃	NO _x	PM _{2.5}	SO ₂	VOC		
Wildfires	1	California	5.84E+04	4.25E+04	3.03E+05	2.49E+04	8.39E+05	25%	(25%)
	2	Oregon	3.78E+04	2.74E+04	1.96E+05	1.61E+04	5.43E+05	16%	(41%)
	3	Montana	3.56E+04	2.58E+04	1.85E+05	1.52E+04	5.12E+05	15%	(56%)
	4	Idaho	2.36E+04	1.76E+04	1.22E+05	1.02E+04	3.39E+05	10%	(66%)
	5	Washington	2.25E+04	1.45E+04	1.15E+05	9.04E+03	3.23E+05	9%	(75%)
	6	Oklahoma	1.13E+04	1.32E+04	6.21E+04	6.33E+03	1.63E+05	5%	(80%)
	7	Arizona	6.01E+03	5.53E+03	3.19E+04	2.91E+03	8.64E+04	3%	(83%)
	8	Utah	4.94E+03	3.69E+03	2.57E+04	2.14E+03	7.11E+04	2%	(85%)
	9	Texas	4.54E+03	4.02E+03	2.40E+04	2.15E+03	6.53E+04	2%	(87%)
	10	Nevada	3.24E+03	4.69E+03	1.83E+04	2.08E+03	4.65E+04	1%	(89%)
Prescribed Burns	1	Oklahoma	1.70E+04	2.12E+04	9.41E+04	9.92E+03	2.45E+05	12%	(12%)
	2	Kansas	1.48E+04	2.33E+04	8.50E+04	1.01E+04	2.12E+05	11%	(23%)
	3	Missouri	1.52E+04	1.66E+04	8.25E+04	8.15E+03	2.19E+05	10%	(33%)
	4	Florida	9.90E+03	1.01E+04	5.32E+04	5.10E+03	1.42E+05	7%	(40%)
	5	Arizona	9.39E+03	9.92E+03	5.07E+04	4.94E+03	1.35E+05	6%	(46%)
	6	Texas	9.07E+03	1.11E+04	5.00E+04	5.23E+03	1.30E+05	6%	(53%)
	7	Louisiana	9.49E+03	7.05E+03	4.93E+04	4.09E+03	1.36E+05	6%	(59%)
	8	Georgia	2.26E+03	1.08E+04	3.89E+04	2.96E+03	2.14E+04	5%	(64%)
	9	Alabama	6.08E+03	7.57E+03	3.36E+04	3.54E+03	8.74E+04	4%	(68%)
	10	Oregon	5.03E+03	3.18E+03	2.58E+04	2.00E+03	7.23E+04	3%	(72%)

Sources: Emissions data are from the EPA's NEI [8].

Notes: Data characterize 2017. States are ranked from most to least primary PM_{2.5} emissions from wildfires (top) and prescribed burns (bottom) for the ten most emitting states. A = first percentage is portion of total primary PM_{2.5} from wildfires (1.22 million metric tons) and prescribed burns (787 hundred thousand metric tons) across CONUS (see Supplementary Table 2 and 3); second percentage in parentheses is cumulative percentage.

Supplementary Table 2. Fire smoke emissions and damages by pollutant and fire type.

Pollution Variable	Emission Source	AP4T-Modeled Criteria Air Pollutant				
		NH ₃	NO _x	PM _{2.5}	SO ₂	VOCs
Emissions (Metric Tons)	Wildfires	2.33E+05	1.85E+05	1.22E+06	1.04E+05	3.35E+06
	Prescribed Burns	1.42E+05	1.61E+05	7.87E+05	7.65E+04	2.00E+06
Percent of Emissions by Fire Type	Wildfires	62%	53%	61%	58%	63%
	Prescribed Burns	38%	47%	39%	42%	37%
Damages (Billion \$)	Wildfires	1.15	2.74	70.5	6.86	17.2
	Prescribed Burns	1.91	2.27	70.7	7.51	18.3
Percent of Damages by Fire Type	Wildfires	37%	55%	50%	48%	48%
	Prescribed Burns	63%	45%	50%	52%	52%
Percent of Damages by Pollutant	Wildfires	1.2%	2.8%	72%	7.0%	17%
	Prescribed Burns	1.9%	2.3%	70%	7.5%	18%

Sources: Emissions data are from the EPA's NEI [8]. Damages are modeled with AP4T's marginal ton approach.

Notes: Data characterize 2017. Damages are in 2020 U.S. dollars. Small discrepancies in the damage totals compared to, for example, Supplementary Table 4 arise from non-linearities in the AP4T model that differ between the counterfactual baseline and marginal ton approaches. Emission totals are equivalent to Supplementary Table 3.

Supplementary Table 3. Emission totals and relative contributions by source in AP4/AP4T.

Metric	Bin	Emission Source	AP4-Modeled Criteria Air Pollutants				
			NH ₃	NO _x	PM _{2.5}	SO ₂	VOC
Emissions (Metric Tons)	Ground	Wildfires	2.33E+05	1.85E+05	1.22E+06	1.04E+05	3.35E+06
		Prescribed Burns	1.42E+05	1.61E+05	7.87E+05	7.65E+04	2.00E+06
		Non-Fire	3.42E+06	7.32E+06	2.53E+06	2.24E+05	3.02E+07
		Total	3.80E+06	7.67E+06	4.54E+06	4.05E+05	3.56E+07
	Non-EGU Point Sources		5.49E+04	1.18E+06	2.23E+05	5.64E+05	8.10E+05
	EGU Point Sources		2.28E+04	1.10E+06	1.18E+05	1.29E+06	5.41E+04
	Total		3.87E+06	9.95E+06	4.88E+06	2.26E+06	3.64E+07
Percent of Pollutant Total	Ground	Wildfires	6.0%	1.9%	25%	4.6%	9.2%
		Prescribed Burns	3.7%	1.6%	16%	3.4%	5.5%
		Non-Fire	88%	74%	52%	10%	83%
		Total	98%	78%	93%	18%	98%
	Non-EGU Point Sources		1.4%	12%	4.6%	25%	2.2%
	EGU Point Sources		0.59%	11%	2.4%	57%	0.15%
	Total		100%	100%	100%	100%	100%
Percent of Bin Total	Ground	Wildfires	4.6%	3.6%	24%	2.0%	66%
		Prescribed Burns	4.5%	5.1%	25%	2.4%	63%
		Non-Fire	7.8%	17%	5.8%	0.51%	69%
		Total	7.3%	15%	8.7%	0.78%	68%
	Non-EGU Point Sources		1.9%	42%	7.9%	20%	29%
	EGU Point Sources		0.88%	43%	4.6%	50%	2.1%
	Total		6.8%	17%	8.5%	3.9%	63%

Sources: Emissions data are from the EPA's NEI [8].

Notes: Data characterize 2017. Non-fire ground sources include nonpoint, onroad, and nonroad sources. Percent of pollutant total is relative contribution of bin to total pollutant tonnage nationally across all bins; summing by column yields 100%. Percent of bin total is relative contribution of pollutant to total bin tonnage nationally across all pollutants; summing by row yields 100%. The NEI reports emissions for 80,707 facilities: 1,814 are EGUs, and 78,893 are non-EGUs.

Supplementary Table 4. Fire damages by source and receptor for census divisions and regions.

Geography		Damages by Source				Damages by Receptor			
		Damages (Billion \$)		Percent of Damages		Damages (Billion \$)		Percent of Damages	
		WFS	PBS	WFS	PBS	WFS	PBS	WFS	PBS
Census Divisions	New England	0.07	0.10	0.1%	0.1%	0.34	0.87	0.3%	0.9%
	Middle Atlantic	0.50	1.68	0.5%	1.7%	1.44	4.60	1.4%	4.6%
	East North Central	0.61	6.28	0.6%	6.2%	3.16	12.2	3.2%	12%
	West North Central	2.95	21.4	3.0%	21%	3.00	12.9	3.0%	13%
	South Atlantic	6.43	23.0	6.5%	23%	7.70	25.9	7.7%	26%
	East South Central	2.22	13.7	2.2%	14%	2.90	14.3	2.9%	14%
	West South Central	9.95	28.5	10%	28%	7.78	22.7	7.8%	22%
	Mountain	13.2	2.38	13%	2.4%	12.0	2.86	12%	2.8%
	Pacific	63.3	3.74	64%	3.7%	61.1	4.71	61%	4.7%
Census Regions	Northeast	0.57	1.79	0.6%	1.8%	1.78	5.47	1.8%	5.4%
	Midwest	3.56	27.7	3.6%	28%	6.17	25.1	6.2%	25%
	South	18.6	65.2	19%	65%	18.4	62.9	18%	62%
	West	76.5	6.13	77%	6.1%	73.1	7.56	74%	7.5%

Sources: Census divisions and regions are defined by the U.S. Census Bureau [78]. Damages are modeled with AP4T's counterfactual baseline approach by state.

Notes: Data characterize 2017. Damages are in 2020 U.S. dollars. See Supplementary Note 1 for the states included in each census division and region. Small discrepancies in the damage totals compared to Supplementary Table 2 arise from non-linearities in the AP4T model that differ between the counterfactual baseline and marginal ton approaches. WFS is wildfire smoke. PBS is prescribed burn smoke.

Supplementary Table 5. Percentages of total smoke damages from wildfires and prescribed burns produced and received by the six most damaging states.

Emission Source	Fire Smoke Deaths/Damages (%)								
	Source	Receptor							
Wildfires (of \$99.4 billion)	State	CA	OR	WA	OK	MT	ID	Total	
	California	40.0	1.93	0.58	0.03	0.05	0.16	42.7 ^A	45.9 ^B
	Oregon	3.00	4.41	1.97	0.03	0.05	0.18	9.62	11.0
	Washington	0.54	0.55	5.04	0.01	0.06	0.21	6.42	6.96
	Oklahoma	0.12	0.01	0.01	2.02	0.00	0.00	2.16	6.58
	Montana	0.75	0.11	0.29	0.03	1.76	0.35	3.30	4.56
	Idaho	0.20	0.16	0.53	0.05	0.47	0.58	1.99	3.26
	Total	44.6 ^A	7.17	8.43	2.17	2.38	1.49	66.2	78.2
		45.7 ^B	7.26	8.53	2.54	2.43	1.57	68.0	100
Prescribed Burns (of \$101 billion)	State	MO	OK	FL	KS	AR	TX	Total	
	Missouri	3.75	0.26	0.16	0.44	0.56	0.34	5.51 ^A	10.7 ^B
	Oklahoma	0.36	3.57	0.27	0.24	1.12	1.71	7.28	10.6
	Florida	0.03	0.02	6.41	0.01	0.03	0.12	6.63	8.53
	Kansas	1.26	0.58	0.13	2.34	0.20	0.43	4.94	8.44
	Arkansas	0.55	0.33	0.15	0.11	2.08	0.49	3.70	6.64
	Texas	0.04	0.10	0.20	0.02	0.08	3.80	4.25	5.62
	Total	6.00 ^A	4.87	7.32	3.16	4.06	6.90	32.3	50.5
		6.76 ^B	5.13	9.59	3.37	4.47	8.56	37.9	100

Sources: Damages are modeled with AP4T's counterfactual baseline approach by state.

Notes: Data represent 2017. Damage totals in the emissions source column (in parentheses) are in 2020 U.S. dollars. Top panel reports percentages of wildfire smoke damages across CONUS (of \$99.4 billion total). Bottom panel reports percentages of prescribed burn smoke damages across CONUS (of \$101 billion total). States shown are those that produced the most smoke damages by fire type (e.g., California produced the most smoke damages from wildfires, and Missouri produced the most smoke damages from prescribed burns). Rows represent damages from states' fire smoke: diagonal cells (gray) are own-state impacts, and other cells (white) are exports. Columns represent fire smoke damages incurred by states' populations: diagonal cells (gray) are own-state impacts, and other cells (white) are imports. Total represents all damages caused to (right columns) and received from (bottom rows) the six states included in the table (labeled with A) and all states across CONUS (labeled with B).

Supplementary Table 6. Counties with the most smoke damages and damages per capita.

Measure	County	State	Damages (Billion \$)	Population (Thousand)	Damages Per Capita (\$ per person)
Highest Wildfire Smoke Damages	Los Angeles	CA	7.81	10,100	774
	Fresno	CA	2.92	985	2,960
	Sacramento	CA	2.42	1,530	1,580
	Santa Barbara	CA	2.31	445	5,200
	King	WA	1.96	2,210	891
	San Bernardino	CA	1.96	2,150	911
	Riverside	CA	1.85	2,410	766
	Orange	CA	1.85	3,170	582
	Sonoma	CA	1.73	502	3,450
	Kern	CA	1.53	887	1,720
Highest Wildfire Smoke Damages Per Capita	Granite	MT	0.029	3.34	8,600
	Lake	CA	0.540	64.1	8,430
	Napa	CA	0.948	140	6,780
	Josephine	OR	0.583	86.7	6,720
	Sanders	MT	0.073	11.7	6,240
	Del Norte	CA	0.169	27.4	6,180
	Ravalli	MT	0.252	42.6	5,900
	Missoula	MT	0.693	118	5,870
	Curry	OR	0.126	22.7	5,570
	Lemhi	ID	0.043	7.84	5,520
Highest Prescribed Burn Smoke Damages	Harris	TX	1.31	4,656	282
	Cook	IL	1.30	5,200	249
	Tulsa	OK	0.953	647	1,470
	Oklahoma	OK	0.804	786	1,020
	Dallas	TX	0.792	2,620	302
	Shelby	TN	0.740	936	790
	Miami-Dade	FL	0.692	2,709	255
	Jackson	MO	0.677	699	969
	Maricopa	AZ	0.630	4,329	146
	Sedgwick	KS	0.609	513	1,190
Highest Prescribed Burn Smoke Damages Per Capita	Woodson	KS	0.026	3.13	8,450
	Sharp	AR	0.071	17.1	4,140
	Latimer	OK	0.039	10.3	3,740
	Fulton	AR	0.045	12.1	3,690
	Baxter	AR	0.150	41.3	3,620
	Izard	AR	0.049	13.7	3,610
	Elk	KS	0.009	2.51	3,520
	Marion	AR	0.058	16.5	3,520
	Wright	MO	0.058	18.2	3,180
	Polk	AR	0.064	20.2	3,170

Sources: Population data for damages per capita calculations are from the U.S. Census Bureau [54]. Damages are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions).

Notes: Data represent 2017. Damages are in 2020 U.S. dollars. Table includes top ten counties for each category. Data are reported to three significant figures.

Supplementary Table 7. Fire smoke emissions and damages from specific fire events.

Fire Event	Emissions (Metric Tons)					Damages (Billion \$)	
	NH ₃	NO _x	PM _{2.5}	SO ₂	VOCs	Own-State	CONUS
A	9.58E+03	6.14E+03	4.91E+04	3.84E+03	1.38E+05	7.65	8.22
B	7.83E+03	5.03E+03	4.01E+04	3.14E+03	1.13E+05	7.40	7.95
C	4.32E+03	5.51E+03	2.40E+04	2.56E+03	6.20E+04	7.52	7.88
D	2.57E+03	1.25E+03	1.29E+04	9.10E+02	3.69E+04	1.21	1.38
E	5.10E+03	2.71E+03	2.58E+04	1.87E+03	7.33E+04	1.73	2.46
Tubbs Wildfire	3.38E+03	1.97E+03	1.72E+04	1.29E+03	4.86E+04	2.25	2.47

Sources: Fire events and associated emissions are identified using data from MTBS [18] and the EPA's NEI [8]. Damages are modeled with AP4T's counterfactual baseline approach by fire event.

Notes: Data represent 2017. Damages are in 2020 U.S. dollars. A, Emissions and damages from Tulare County, California's *Pier*, *Lion*, *Schaeffer*, *Indian*, and *Roadrunner* wildfires. B, Emissions and damages from Sonoma/Napa/Solano County, California's *Tubbs*, *Nuns*, *Atlas*, *Pocket*, and *Thirty Seven* wildfires. C, Emissions and damages from Ventura/Santa Barbara County, California's *Thomas* wildfire. D, Emissions and damages from Collier County, Florida's prescribed burns. E, Emissions and damages from Cameron/Vermilion County, Louisiana's and Jefferson/Chambers County, Texas' prescribed burns. *Tubbs* wildfire is both part of B and evaluated individually as it was the second most destructive wildfire in California's history (destroying more than 5 thousand structures and killing 22 people) [79]. The *Thomas* wildfire burned during both 2017 and 2018; however, only its 2017 emissions and damages are modeled and reported here. Own-State damages are in California for A-C and Tubbs, Florida for D, and Louisiana and Texas for E. CONUS damages are totals across the contiguous U.S. (i.e., own-state plus exports). See Supplementary Note 2 for further analysis.

Supplementary Table 8. Physical characteristics and damages from specific California wildfires.

County	Wildfire	Date Ignited	Date Contained	Acres Burnt	Structures Destroyed	Fire Fatalities	Smoke Fatalities
Tulare	Pier	8/29/17	9/24/17	36,556	2	0	824
	Lion	9/24/17	11/27/17	19,215	0	0	
	Schaeffer	6/24/17	8/5/17	16,031	0	0	
	Indian	8/3/17	8/29/17	2,295	0	0	
	Roadrunner	7/30/17	7/31/17	2,289	0	0	
Sonoma, Napa, & Solano	Tubbs	10/8/17	10/31/17	36,807	5,636	22	549
	Nuns	10/9/17	10/31/17	44,573	1,355	3	
	Atlas	10/9/17	10/28/17	51,624	783	6	
	Pocket	10/9/17	10/31/17	17,357	6	0	
	Thirty Seven	10/9/17	10/12/17	1,660	3	0	
Ventura & Santa Barbara	Thomas (2017)	12/4/17	12/31/17	281,893	1,060	2	790
	Thomas (2018)	1/1/18	1/12/18				NA

Sources: Physical characteristics and damages are from the California Department of Forestry and Fire Protection [79].

Notes: Data represent 2017. Smoke fatalities are damages from Supplementary Table 7 divided by the value of a statistical life at \$9.97 million (see Supplementary Table 31). The *Thomas* wildfire burned during both 2017 and 2018; however, only its 2017 smoke fatalities are modeled and reported here. See Supplementary Note 2 for further analysis.

Supplementary Table 9. Population count variation by county and census tract in 2017.

Geographic Boundaries	Summary Statistics					
	Mean	Standard Deviation	First Quantile	Median	Third Quantile	98th Percentile
Counties	103,868	333,057	11,150	26,047	67,929	877,105
Census Tracts	4,396	2,228	2,914	4,111	5,514	9,656

Sources: County-level population data are from the CDC [62]. Tract-level population data are from the U.S. Census Bureau [62].

Notes: Data represent 2017. Summary statistics consider counties and tracts within CONUS.

Supplementary Table 10. Wildfire smoke distributional impacts: SVI deciles vs. the national average.

WFS Impact	SVI Decile	Social Vulnerability Index									
		Overall		Theme 1		Theme 2		Theme 3		Theme 4	
Average Exposure	1	-0.395	***	-0.269	***	0.022		-0.497	***	-0.318	***
	2	-0.214	***	-0.104	**	0.030		-0.378	***	-0.243	***
	3	-0.104	**	-0.063		-0.025		-0.308	***	-0.170	***
	4	-0.110	**	-0.004		-0.031		-0.214	***	-0.088	**
	5	-0.042		0.027		0.014		-0.175	***	-0.054	
	6	0.075		0.031		0.018		-0.050		-0.036	
	7	0.078	*	0.000		0.083	*	0.058		0.054	
	8	0.112	**	0.065		0.026		0.333	***	0.167	***
	9	0.201	***	0.113	**	-0.050		0.458	***	0.268	***
	10	0.439	***	0.270	***	-0.130	**	0.580	***	0.410	***
Damages Per Capita	1	-0.406	***	-0.253	***	-0.358	***	-0.257	***	-0.332	***
	2	-0.205	***	-0.016		-0.140	**	-0.174	***	-0.251	***
	3	-0.055		0.013		-0.107	**	-0.075		-0.153	***
	4	-0.032		0.097	*	-0.041		-0.006		-0.056	
	5	0.070		0.146	**	0.070		-0.020		-0.025	
	6	0.191	***	0.116	**	0.042		0.036		-0.007	
	7	0.146	***	0.022		0.155	***	0.079		0.048	
	8	0.113	**	0.038		0.153	***	0.228	***	0.172	***
	9	0.074		-0.067	*	0.129	**	0.135	***	0.294	***
	10	0.118	**	-0.118	***	0.097	*	-0.021		0.303	***
Relative Impact Difference	1	-0.011		+0.017		-0.380		+0.239		-0.013	
	2	+0.008		+0.087		-0.170		+0.204		-0.008	
	3	+0.049		+0.076		-0.081		+0.233		+0.016	
	4	+0.078		+0.101		-0.011		+0.208		+0.032	
	5	+0.112		+0.119		+0.055		+0.156		+0.030	
	6	+0.117		+0.085		+0.024		+0.086		+0.029	
	7	+0.068		+0.023		+0.072		+0.021		-0.006	
	8	+0.000		-0.027		+0.127		-0.105		+0.004	
	9	-0.127		-0.180		+0.178		-0.324		+0.026	
	10	-0.321		-0.389		+0.227		-0.600		-0.106	

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures and damages are modeled with AP4T's counterfactual baseline approach with all wildfire emissions.

Notes: Data characterize 2017. Rows divide census tracts into deciles from least (1) to most (10) vulnerable using overall and themed SVI percentile ranks. Data represent fractional difference between SVI decile averages versus the national average for population-weighted average smoke exposure (top) and damages per capita (middle) from wildfire emissions. T-test signif. codes: *** ≤ 0.001 ; ** ≤ 0.01 ; * ≤ 0.05 . Codes indicate whether the differences are statistically significantly different from zero. Relative impact difference is damages per capita fractional difference minus average exposure fractional difference. Red represents an increase from average exposure fractional difference to damages per capita fractional difference (i.e., introducing smoke susceptibility increases impacts relative to the national average). Blue represents a decrease from average exposure fractional difference to damages per capita fractional difference (i.e., introducing smoke susceptibility decreases impacts relative to the national average). Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed SVIs. WFS is wildfire smoke.

Supplementary Table 11. Prescribed burn smoke distributional impacts: SVI deciles vs. the national average.

PBS Impact	SVI Decile	Social Vulnerability Index									
		Overall		Theme 1		Theme 2		Theme 3		Theme 4	
Average Exposure	1	-0.115	***	-0.157	***	-0.237	***	0.195	***	-0.046	**
	2	-0.119	***	-0.175	***	-0.222	***	0.097	***	0.012	
	3	-0.093	***	-0.129	***	-0.181	***	0.138	***	0.055	***
	4	-0.013		-0.075	***	-0.136	***	0.184	***	0.041	*
	5	0.018		-0.022		-0.068	***	0.174	***	0.032	
	6	0.074	***	0.087	***	-0.005		0.072	***	-0.009	
	7	0.154	***	0.167	***	0.105	***	-0.007		-0.006	
	8	0.126	***	0.220	***	0.183	***	-0.116	***	-0.009	
	9	0.077	***	0.155	***	0.294	***	-0.251	***	0.006	
	10	-0.102	***	-0.031		0.425	***	-0.395	***	-0.085	***
Damages Per Capita	1	-0.264	***	-0.243	***	-0.585	***	0.547	***	-0.199	***
	2	-0.188	***	-0.217	***	-0.424	***	0.328	***	-0.058	**
	3	-0.096	***	-0.127	***	-0.317	***	0.294	***	0.044	*
	4	0.016		-0.049	*	-0.208	***	0.304	***	0.044	*
	5	0.074	***	0.032		-0.062	**	0.219	***	0.046	*
	6	0.164	***	0.154	***	0.037		0.037		0.012	
	7	0.248	***	0.235	***	0.191	***	-0.091	***	0.044	
	8	0.180	***	0.275	***	0.339	***	-0.279	***	0.065	**
	9	0.058	*	0.120	***	0.512	***	-0.483	***	0.076	**
	10	-0.189	***	-0.156	***	0.772	***	-0.662	***	-0.090	***
Relative Impact Difference	1	-0.149		-0.086		-0.348		+0.352		-0.153	
	2	-0.070		-0.042		-0.202		+0.231		-0.070	
	3	-0.003		+0.003		-0.137		+0.156		-0.012	
	4	+0.030		+0.025		-0.072		+0.121		+0.002	
	5	+0.056		+0.055		+0.006		+0.045		+0.014	
	6	+0.090		+0.067		+0.042		-0.034		+0.021	
	7	+0.094		+0.068		+0.086		-0.085		+0.050	
	8	+0.054		+0.055		+0.156		-0.163		+0.073	
	9	-0.020		-0.036		+0.218		-0.233		+0.070	
	10	-0.087		-0.124		+0.347		-0.267		-0.004	

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures and damages are modeled with AP4T's counterfactual baseline approach with all prescribed burn emissions.

Notes: Data characterize 2017. Rows divide census tracts into deciles from least (1) to most (10) vulnerable using overall and themed SVI percentiles. Data represent fractional difference between SVI decile averages versus the national average for population-weighted average smoke exposure (top) and damages per capita (middle) from prescribed burn emissions. T-test signif. codes: *** ≤ 0.001 ; ** ≤ 0.01 ; * ≤ 0.05 . Codes indicate whether the differences are statistically significantly different from zero. Relative impact difference is damages per capita fractional difference minus average exposure fractional difference. Red represents an increase from average exposure fractional difference to damages per capita fractional difference (i.e., introducing smoke susceptibility increases impacts relative to the national average). Blue represents a decrease from average exposure fractional difference to damages per capita fractional difference (i.e., introducing smoke susceptibility decreases impacts relative to the national average). Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed SVIs. PBS is prescribed burn smoke.

Supplementary Table 12. Coefficients from regressing ln(fire smoke impacts) on SVV percentile ranks.

Emission Source	Social Vulnerability Variable	Smoke Exposure				Damages per Capita			Diff.	
		Coef.	95% CI		p-val	Coef.	95% CI			p-val
Wildfires	Overall SVI	0.53	0.50	0.56	***	0.44	0.40	0.47	***	-0.06
	Below Poverty Line	0.30	0.27	0.33	***	0.10	0.07	0.14	***	-0.17
	Unemployed	0.27	0.24	0.30	***	0.16	0.12	0.19	***	-0.08
	Per Capita Income	0.29	0.26	0.32	***	0.00	-0.04	0.04		-0.26
	No High School Diploma	0.34	0.31	0.37	***	0.23	0.19	0.26	***	-0.08
	Aged 65 Or Older	-0.31	-0.34	-0.28	***	1.30	1.26	1.33	***	+1.64
	Aged 17 Or Younger	0.37	0.33	0.40	***	-0.22	-0.26	-0.18	***	-0.56
	Civilian With a Disability	-0.07	-0.10	-0.03	**	1.01	0.98	1.05	***	+1.11
	Single-Parent Household	0.08	0.04	0.11	***	-0.29	-0.32	-0.25	***	-0.33
	Minority	0.76	0.73	0.79	***	-0.03	-0.06	0.01		-0.75
	Limited English	0.77	0.74	0.80	***	0.10	0.06	0.13	***	-0.65
	In Multi-Unit Structures	-0.02	-0.04	0.02		-0.28	-0.31	-0.25	***	-0.24
	Mobile Homes	0.49	0.47	0.52	***	0.86	0.83	0.89	***	+0.39
	Crowding	1.05	1.01	1.08	***	0.45	0.41	0.48	***	-0.57
	No Vehicle Access	-0.71	-0.74	-0.68	***	-0.69	-0.73	-0.66	***	+0.05
	Group Quarters	0.00	-0.02	0.03		0.15	0.13	0.18	***	+0.18
Prescribed Burns	Overall SVI	0.18	0.16	0.21	***	0.09	0.06	0.11	***	-0.08
	Below Poverty Line	0.46	0.44	0.48	***	0.26	0.23	0.30	***	-0.18
	Unemployed	0.03	0.00	0.05		-0.09	-0.12	-0.06	***	-0.09
	Per Capita Income	0.59	0.57	0.61	***	0.30	0.27	0.33	***	-0.27
	No High School Diploma	0.26	0.23	0.28	***	0.14	0.12	0.17	***	-0.09
	Aged 65 Or Older	0.13	0.11	0.15	***	1.74	1.71	1.76	***	+1.63
	Aged 17 Or Younger	0.27	0.25	0.29	***	-0.32	-0.35	-0.29	***	-0.57
	Civilian With a Disability	0.73	0.71	0.75	***	1.81	1.79	1.84	***	+1.11
	Single-Parent Household	0.24	0.22	0.26	***	-0.13	-0.16	-0.10	***	-0.34
	Minority	-0.27	-0.29	-0.25	***	-1.06	-1.09	-1.03	***	-0.76
	Limited English	-0.76	-0.77	-0.74	***	-1.44	-1.46	-1.41	***	-0.66
	In Multi-Unit Structures	-0.44	-0.46	-0.42	***	-0.71	-0.73	-0.68	***	-0.25
	Mobile Homes	0.70	0.69	0.72	***	1.07	1.05	1.09	***	+0.38
	Crowding	-0.34	-0.36	-0.32	***	-0.94	-0.97	-0.91	***	-0.59
	No Vehicle Access	-0.31	-0.34	-0.29	***	-0.29	-0.32	-0.26	***	+0.04
	Group Quarters	-0.17	-0.19	-0.15	***	-0.02	-0.04	0.00		+0.17

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures and damages are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions).

Notes: Data characterize 2017. Coefficients are from unique bivariate linear regressions of log-transformed smoke impacts (population-weighted average exposures and damages per capita) on SVV percentile ranks at the tract level. Coefficients are average percentage changes in impacts per 0.01 increase in percentile ranks, which range from 0 to 1 (e.g., a 0.01 increase in overall SVI percentile rank yields an average increase in smoke PM_{2.5} of 0.53%). 95% confidence intervals are derived using bootstrapping. Signif. Codes (p-val): *** ≤ 0.001; ** ≤ 0.01; * ≤ 0.05. Codes indicate whether the coefficients are statistically significantly different from zero. See Table 2 of the main document for the SVVs comprising the themed SVIs.

Supplementary Table 13. Average tract-level social vulnerability variable percentile ranks by census division.

Social Vulnerability Variable		Northeast		Midwest		South			West	
		New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
Socioeconomic Status (1)	Below Poverty Line	0.389	0.448	0.504	0.450	0.511	0.616	0.569	0.489	0.490
	Unemployed	0.459	0.502	0.507	0.336	0.520	0.553	0.467	0.465	0.555
	Income	0.354	0.436	0.526	0.483	0.505	0.628	0.581	0.514	0.462
	No High School Diploma	0.399	0.480	0.460	0.402	0.509	0.609	0.600	0.441	0.534
Household Composition & Disability (2)	Aged 65 or Older	0.553	0.527	0.515	0.536	0.527	0.534	0.424	0.455	0.437
	Aged 17 or Younger	0.388	0.433	0.507	0.546	0.455	0.512	0.612	0.548	0.506
	Civilian with a Disability	0.468	0.452	0.528	0.490	0.520	0.679	0.531	0.467	0.405
	Single-Parent Households	0.446	0.466	0.511	0.476	0.497	0.530	0.566	0.484	0.490
Minority Status & Language (3)	Minority	0.355	0.481	0.391	0.307	0.537	0.415	0.628	0.509	0.656
	Limited English	0.472	0.526	0.358	0.343	0.463	0.272	0.559	0.512	0.695
Housing Type & Transportation (4)	Multi-Unit Structures	0.525	0.525	0.455	0.478	0.465	0.358	0.447	0.446	0.543
	Mobile Homes	0.260	0.239	0.351	0.453	0.492	0.629	0.516	0.472	0.361
	Crowding	0.370	0.462	0.385	0.397	0.435	0.422	0.577	0.520	0.672
	No Vehicle	0.534	0.640	0.521	0.447	0.474	0.483	0.449	0.398	0.465
	Group Quarters	0.523	0.454	0.432	0.513	0.381	0.368	0.351	0.375	0.468

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Census divisions and regions are defined by the U.S. Census Bureau [78].

Notes: Data characterize 2017. Data show the averages of tract-level SVV percentile ranks by designated geographic area. See Supplementary Note 1 for the states included in each census division and region. Closer to 1 is more vulnerable. Closer to 0 is less vulnerable. Red indicates greater vulnerability, blue indicates less vulnerability, and white indicates median vulnerability. Color scale is normalized from 0 to 1 such that 0 is blue, 0.5 is white, and 1 is red.

Supplementary Table 14. Correlation coefficients: Age groups vs. social vulnerability metrics.

Social Vulnerability Metric		Age Group Subpopulation					
		<1	1 to 29	25 to 44	45 to 64	65+	85+
Social Vulnerability Index	Overall	0.326	0.356	0.126	-0.383	-0.199	-0.037
	Theme 1	0.286	0.408	0.082	-0.356	-0.241	-0.145
	Theme 2	0.250	0.019	-0.242	-0.069	0.152	0.130
	Theme 3	0.298	0.342	0.367	-0.345	-0.392	-0.181
	Theme 4	0.152	0.263	0.200	-0.371	-0.110	0.099
Social Vulnerability Variable	Below Poverty	0.254	0.424	0.143	-0.409	-0.226	-0.113
	Unemployed	0.158	0.242	-0.002	-0.182	-0.130	-0.093
	Income	0.310	0.482	0.037	-0.400	-0.284	-0.174
	No High School Diploma	0.274	0.248	0.107	-0.216	-0.201	-0.120
	Aged 65 or Older	-0.397	-0.699	-0.551	0.438	0.863	0.582
	Aged 17 or Younger	0.596	0.406	0.018	-0.207	-0.457	-0.332
	Civilian with a Disability	-0.078	-0.229	-0.238	0.103	0.377	0.281
	Single-Parent Households	0.451	0.406	0.174	-0.307	-0.388	-0.228
	Minority	0.310	0.395	0.355	-0.362	-0.420	-0.217
	Limited English	0.232	0.230	0.304	-0.260	-0.288	-0.111
	Multi-Unit Structures	0.089	0.173	0.346	-0.341	-0.111	0.120
	Mobile Homes	-0.038	-0.105	-0.235	0.123	0.166	-0.022
	Crowding	0.343	0.338	0.275	-0.327	-0.340	-0.209
	No Vehicle	0.158	0.211	0.232	-0.327	-0.089	0.132
	Group Quarters	-0.093	0.088	-0.019	-0.133	0.044	0.209

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54].

Notes: Data characterize 2017. Data represent Pearson's correlation coefficients (r) between tract-level SVI percentile ranks (themed and overall) and percentage of population by age group across CONUS tracts. Age group subpopulations are not mutually exclusive (85+ are included in 65+). Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs. Red shows positive correlation. Blue shows negative correlation. Color scale is normalized from -1 to 1 such that 0 is white, 1 is red, and -1 is blue.

Supplementary Table 15. Correlation coefficients: Age groups vs. race/ethnicity.

Race/Ethnicity Subpopulation	Age Group Subpopulation					
	<1	1 to 29	25 to 44	45 to 64	65+	85+
Black or African American	0.186	0.197	0.103	-0.137	-0.179	-0.105
American Indian or Alaska Native	0.048	0.058	-0.010	-0.040	-0.032	-0.038
Asian	-0.021	0.035	0.196	-0.060	-0.122	-0.033
Native Hawaiian or Other Pacific Islander	0.058	0.079	0.075	-0.080	-0.075	-0.045
Some Other Race	0.207	0.247	0.220	-0.234	-0.270	-0.150
Two or More Races	0.129	0.186	0.205	-0.175	-0.219	-0.119
Non-Hispanic or Latino White	-0.318	-0.376	-0.311	0.340	0.391	0.214
Hispanic or Latino	0.256	0.304	0.236	-0.295	-0.310	-0.169

Sources: Population data are from the U.S. Census Bureau [54].

Notes: Data characterize 2017. Data represent Pearson's correlation coefficients (r) between percentage of population by race/ethnicity and percentage of population by age group across CONUS tracts. Age group subpopulations are not mutually exclusive (85+ are included in 65+). Race/ethnicity subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). All racial groups except Non-Hispanic or Latino White include persons of Hispanic or Latino ethnicity—i.e., subgroups other than White are not mutually exclusive. Red shows positive correlation. Blue shows negative correlation. Color scale is normalized from -1 to 1 such that 0 is white, 1 is red, and -1 is blue.

Supplementary Table 16. Correlation coefficients: Overall and themed SVIs vs. race/ethnicity.

Race/Ethnicity Subpopulations	Social Vulnerability Index				
	Overall	Theme 1	Theme 2	Theme 3	Theme 4
Black or African American	0.412	0.428	0.279	0.314	0.177
American Indian or Alaska Native	0.121	0.113	0.097	0.054	0.091
Asian	-0.062	-0.148	-0.345	0.367	0.028
Native Hawaiian or Other Pacific Islander	0.063	0.043	-0.012	0.118	0.049
Some Other Race	0.398	0.352	0.035	0.57	0.249
Two or More Races	0.124	0.071	-0.012	0.255	0.095
Non-Hispanic or Latino White	-0.615	-0.548	-0.147	-0.854	-0.329
Hispanic or Latino	0.464	0.395	0.061	0.713	0.264

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54].

Notes: Data characterize 2017. Data represent Pearson's correlation coefficients (r) between tract-level SVI percentile ranks (themed and overall) and percentage of population by race/ethnicity across CONUS tracts. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs. Race/ethnicity subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). All racial groups except Non-Hispanic or Latino White include persons of Hispanic or Latino ethnicity—i.e., subgroups other than White are not mutually exclusive. Red shows positive correlation. Blue shows negative correlation. Color scale is normalized from -1 to 1 such that 0 is white, 1 is red, and -1 is blue.

Supplementary Table 17. Correlation coefficients: Overall and themed SVIs.

Social Vulnerability Index	Overall	Theme 1	Theme 2	Theme 3	Theme 4
Overall	1.00	0.912	0.639	0.562	0.759
Theme 1	0.912	1.00	0.595	0.426	0.544
Theme 2	0.639	0.595	1.00	0.012	0.293
Theme 3	0.562	0.426	0.012	1.00	0.340
Theme 4	0.759	0.544	0.293	0.340	1.00

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70].

Notes: Data characterize 2017. Data represent Pearson's correlation coefficients (r) between tract-level SVI percentile ranks (themed and overall) across CONUS tracts. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs. Red shows positive correlation. Color scale is normalized from 0 to 1 such that 0 is white and 1 is red.

Supplementary Table 18. Correlation coefficients: Overall and themed SVIs vs. SVVs.

Theme	Social Vulnerability Variable	Social Vulnerability Index				
		Overall	Theme 1	Theme 2	Theme 3	Theme 4
1	Below Poverty	0.839	0.896	0.523	0.356	0.589
	Unemployed	0.649	0.767	0.411	0.321	0.322
	Income	0.826	0.921	0.604	0.325	0.473
	No High School Diploma	0.842	0.877	0.523	0.492	0.494
2	Aged 65 or Older	-0.208	-0.261	0.216	-0.472	-0.110
	Aged 17 or Younger	0.286	0.254	0.394	0.267	-0.013
	Civilian with a Disability	0.481	0.499	0.736	-0.178	0.285
	Single-Parent Households	0.685	0.642	0.643	0.413	0.332
3	Minority	0.596	0.508	0.104	0.897	0.331
	Limited English	0.423	0.270	-0.080	0.906	0.284
4	Multi-Unit Structures	0.266	0.076	-0.118	0.333	0.527
	Mobile Homes	0.205	0.212	0.333	-0.272	0.232
	Crowding	0.631	0.518	0.175	0.601	0.557
	No Vehicle	0.649	0.562	0.308	0.333	0.659
	Group Quarters	0.272	0.116	0.068	-0.003	0.583

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54].

Notes: Data characterize 2017. Data represent Pearson's correlation coefficients (r) between tract-level SVI percentile ranks (themed and overall) and tract-level SVV percentile ranks across CONUS tracts. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. Red shows positive correlation. Blue shows negative correlation. Color scale is normalized from -1 to 1 such that 0 is white, 1 is red, and -1 is blue.

Supplementary Table 19. Crude mortality rates (per 100,000) by race/ethnicity and age group.

Age Group	Total	Black or African American		American Indian or Alaska Native		Asian or Pacific Islander		White	Hispanic or Latino
		Any Ethnicity	Not Hispanic or Latino	Any Ethnicity	Not Hispanic or Latino	Any Ethnicity	Not Hispanic or Latino	Not Hispanic or Latino	Any Race
Total	864	742	788	435	703	349	360	1083	335
<1	567	1050	1111	440	724	421	431	459	466
1 to 4	24	38	40	26	45	15	16	22	19
5 to 9	12	17	19	11	19	8	8	11	10
10 to 14	16	22	23	18	31	9	9	15	13
15 to 19	52	75	80	63	100	26	27	48	44
20 to 24	96	134	141	101	163	44	44	95	76
25 to 29	121	163	171	152	246	39	39	128	87
30 to 34	145	192	204	198	343	48	47	159	96
35 to 39	174	242	258	223	394	58	58	188	114
40 to 44	218	313	332	267	466	82	83	234	141
45 to 49	313	440	461	361	584	136	138	327	209
50 to 54	488	676	704	528	784	210	211	500	333
55 to 59	737	1,060	1,090	691	970	312	313	742	493
60 to 64	1,050	1,540	1,580	942	1,250	474	475	1,040	755
65 to 69	1,470	2,110	2,170	1,290	1,650	737	737	1,460	1,090
70 to 74	2,210	2,830	2,900	1,860	2,360	1,120	1,120	2,240	1,630
75 to 79	3,520	4,160	4,260	2,900	3,600	1,960	1,960	3,600	2,650
80 to 84	5,870	6,210	6,360	4,640	5,810	3,520	3,530	6,080	4,460
85+	13,600	12,000	12,100	7,470	9,160	8,590	8,570	14,300	9,910

Sources: CDC's WONDER database [53].

Notes: Data characterize 2017. Data are reported to three significant figures. Crude mortality rates are number of all-cause mortality cases per 100,000 across the U.S. (CONUS plus Alaska and Hawaii) by race/ethnicity and age group. Color system considers all race/ethnicity-age combinations: green represents lower crude rates and red represents higher crude rates (middle of scale, yellow, is set as the all-person crude rate of 864 per 100,000). Race/ethnicity subpopulations are defined by the CDC (see Supplementary Table 30). Black or African American, American Indian or Alaska Native, and Asian or Pacific Islander all provide data including Hispanic or Latino persons (Any Ethnicity) and excluding Hispanic or Latino persons (Not Hispanic or Latino). The former align with the county-level mortality rates informing the assessments focused on race/ethnicity herein. The latter align with the county-level mortality rates informing Supplementary Equation 13, the determination of tract-level mortality rates accounting for tract-level population by race/ethnicity.

Supplementary Table 20. Dose-response information from the epidemiological literature.

Epidemiological Study	Dose-Response Information			
	At-Risk Group		Beta Coefficient	Functional Form
	Age	Race/Ethnicity		
ACS: Krewski et al. (2009)	30 & Older	All	0.00583	Log-Linear
H6C: Lepeule et al. (2012)	25 & Older	All	0.01310	Log-Linear
Woodruff et al. (2006)	Infants	All	0.00677 ^A	Logistic
Medicare Cohort Study: Di et al. (2017)	65 & Older	All (Main Analysis)	0.00705	Log-Linear
		White	0.00611 (-13.2%) ^B	Log-Linear
		Black	0.01890 (+168%)	Log-Linear
		Native American	0.00953 (+35.3%)	Log-Linear
		Asian	0.00917 (+30.1%)	Log-Linear
		Hispanic	0.01098 (+55.8%)	Log-Linear

Source: Dose-response data are from Krewski et al. (2009) [47], Lepeule et al. (2012) [48], Woodruff et al. (2006) [49], and Di et al. (2017) [50].
Notes: ACS is the default for AP4T. Race/ethnicity subpopulations are defined by Di et al. (2017) [50] and align with the CDC [52], [53] (see Supplementary Table 30). A = beta coefficient is derived via an odds ratio (see Supplementary Equation 12); all other beta coefficients are derived via relative risk (see Supplementary Equation 10). B = percentage differences are from the all-person main analysis from Di et al. (2017) [50].

Supplementary Table 21. Disparities in mortality rates by race/ethnicity within age groups.

Age Group	Total	Black or African American		American Indian or Alaska Native		Asian or Pacific Islander		White	Hispanic or Latino
		Any Ethnicity	Not Hispanic or Latino	Any Ethnicity	Not Hispanic or Latino	Any Ethnicity	Not Hispanic or Latino	Not Hispanic or Latino	Any Race
Total	1.00	0.86	0.91	0.50	0.81	0.40	0.42	1.25	0.39
<1	1.00	1.85	1.96	0.78	1.28	0.74	0.76	0.81	0.82
1 to 4	1.00	1.55	1.65	1.06	1.85	0.63	0.66	0.92	0.80
5 to 9	1.00	1.50	1.64	0.98	1.64	0.72	0.69	0.91	0.85
10 to 14	1.00	1.41	1.48	1.15	2.00	0.57	0.58	0.97	0.81
15 to 19	1.00	1.46	1.55	1.22	1.94	0.51	0.52	0.94	0.86
20 to 24	1.00	1.40	1.47	1.05	1.71	0.46	0.46	0.99	0.80
25 to 29	1.00	1.35	1.41	1.25	2.03	0.32	0.32	1.06	0.72
30 to 34	1.00	1.32	1.40	1.36	2.36	0.33	0.32	1.10	0.66
35 to 39	1.00	1.39	1.48	1.28	2.27	0.33	0.33	1.08	0.65
40 to 44	1.00	1.43	1.52	1.22	2.13	0.38	0.38	1.07	0.65
45 to 49	1.00	1.40	1.47	1.15	1.86	0.43	0.44	1.04	0.67
50 to 54	1.00	1.38	1.44	1.08	1.61	0.43	0.43	1.02	0.68
55 to 59	1.00	1.43	1.48	0.94	1.32	0.42	0.42	1.01	0.67
60 to 64	1.00	1.47	1.51	0.90	1.19	0.45	0.45	0.99	0.72
65 to 69	1.00	1.43	1.47	0.87	1.12	0.50	0.50	0.99	0.74
70 to 74	1.00	1.28	1.31	0.84	1.07	0.51	0.51	1.02	0.74
75 to 79	1.00	1.18	1.21	0.82	1.02	0.56	0.56	1.02	0.75
80 to 84	1.00	1.06	1.08	0.79	0.99	0.60	0.60	1.04	0.76
85+	1.00	0.88	0.89	0.55	0.67	0.63	0.63	1.05	0.73

Sources: CDC's WONDER database [53].

Notes: Data characterize 2017. Data are ratios of crude mortality rates (number of all-cause mortality cases per 100,000 across the CONUS plus Alaska and Hawaii from Supplementary Table 19) for race/ethnicity subpopulations versus the all-person average within age groups. Color system considers all race/ethnicity-age combinations: blue represents a lower race/ethnicity-specific mortality rate compared to the all-person mortality rate and red represents a higher race/ethnicity-specific mortality rate compared to the all-person mortality rate (middle of scale, white, is set as 1.0 or no difference between race/ethnicity-specific and all-person mortality rate). Race/ethnicity subpopulations are defined by the CDC (see Supplementary Table 30). Black or African American, American Indian or Alaska Native, and Asian or Pacific Islander all provide data including Hispanic or Latino persons (Any Ethnicity) and excluding Hispanic or Latino persons (Not Hispanic or Latino). The former align with the county-level mortality rates informing the assessments focused on race/ethnicity herein. The latter align with the county-level mortality rates informing Supplementary Equation 13, the determination of tract-level mortality rates accounting for tract-level population by race/ethnicity.

Supplementary Table 22. Fire smoke damages per capita by race/ethnicity and age group.

Emission Source	Age Group	Race/Ethnicity Subpopulation								
		Total	Black or African American	American Indian or Alaska Native	Asian	Native Hawaiian or Other Pacific Islander	Some Other Race	Two or More Races	Non-Hispanic or Latino White	Hispanic or Latino
Wildfires	Total	308	147	368	241	226	202	165	369	179
	<1	220	229	449	228	371	344	262	156	326
	30 to 34	48.2	38.8	165	28.2	44.9	66.8	64.0	46.3	56.4
	35 to 39	59.9	51.2	202	37.4	69.9	85.0	81.0	57.0	67.5
	40 to 44	76.6	63.5	231	48.4	90.7	110	105	73.4	86.6
	45 to 49	112	94.4	307	90	153	173	164	108	127
	50 to 54	173	140	435	134	221	274	254	166	207
	55 to 59	266	219	571	218	343	423	410	264	313
	60 to 64	384	319	779	319	519	617	592	379	462
	65 to 69	547	446	1,110	524	808	875	849	534	654
	70 to 74	807	570	1,490	782	1,280	1,280	1,250	807	916
	75 to 79	1,290	843	2,380	1,400	2,020	2,040	1,910	1,280	1,550
	80 to 84	2,140	1,260	3,570	2,660	3,600	3,350	3,140	2,120	2,500
	85+	5,000	2,360	6,060	7,130	8,140	8,140	8,180	5,080	5,930
Prescribed Burns	Total	313	319	261	61.8	48.0	66.0	114	393	72.7
	<1	254	571	355	122	158	155	233	220	161
	30 to 34	54.7	91.9	110	10.1	12.2	29.8	47.4	61.3	25.4
	35 to 39	68.0	121	122	12.8	16.1	36.5	60.3	74.7	29.7
	40 to 44	85.7	152	152	18.0	21.9	45.9	78.0	94.4	36.7
	45 to 49	122	200	201	28.5	31.0	62.6	113	132	52.9
	50 to 54	190	306	312	41.9	46.1	100	178	200	81.0
	55 to 59	294	486	413	65.8	74.7	142	293	303	120
	60 to 64	415	710	563	97.9	113	209	416	419	182
	65 to 69	576	962	735	154	170	277	600	587	264
	70 to 74	864	1,270	1,160	241	254	414	899	898	394
	75 to 79	1,360	1,860	1,660	383	421	606	1,390	1,420	635
	80 to 84	2,200	2,690	2,710	658	736	997	2,230	2,330	1,070
	85+	4,530	4,650	4,290	1,300	1,540	2,050	4,590	4,780	2,250

Sources: Population data are from the U.S. Census Bureau [54]. Damages are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions).

Notes: Data characterize 2017. Damages are in 2020 U.S. dollars. Data are reported to three significant figures. Data represent damages per capita from wildfire emissions (top) and prescribed burns (bottom). Color system considers all race/ethnicity-age combinations across both fire types: white represents lower damages per capita, and red represents higher damages per capita. Race/ethnicity subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). Subpopulations other than Non-Hispanic or Latino White are not mutually exclusive. All racial groups except Non-Hispanic or Latino White include persons of Hispanic or Latino ethnicity. Hispanic or Latino ethnicity includes persons of all racial groups.

Supplementary Table 23. Fire smoke damages per capita disparities by race/ethnicity within age groups.

Emission Source	Age Group	Race/Ethnicity Subpopulation							
		Black or African American	American Indian or Alaska Native	Asian	Native Hawaiian or Other Pacific Islander	Some Other Race	Two or More Races	Non-Hispanic or Latino White	Hispanic or Latino
Wildfires	Total	0.48	1.19	0.78	0.73	0.66	0.54	1.20	0.58
	<1	1.04	2.04	1.04	1.69	1.56	1.19	0.71	1.48
	30 to 34	0.80	3.43	0.58	0.93	1.38	1.33	0.96	1.17
	35 to 39	0.86	3.37	0.62	1.17	1.42	1.35	0.95	1.13
	40 to 44	0.83	3.02	0.63	1.18	1.43	1.38	0.96	1.13
	45 to 49	0.85	2.76	0.81	1.37	1.55	1.47	0.97	1.14
	50 to 54	0.81	2.52	0.78	1.28	1.59	1.47	0.96	1.20
	55 to 59	0.82	2.14	0.82	1.29	1.59	1.54	0.99	1.17
	60 to 64	0.83	2.03	0.83	1.35	1.61	1.54	0.99	1.20
	65 to 69	0.82	2.04	0.96	1.48	1.60	1.55	0.98	1.20
	70 to 74	0.71	1.85	0.97	1.58	1.59	1.54	1.00	1.13
	75 to 79	0.65	1.84	1.08	1.57	1.58	1.48	0.99	1.20
	80 to 84	0.59	1.67	1.24	1.69	1.57	1.47	0.99	1.17
	85+	0.47	1.21	1.42	1.63	1.63	1.63	1.01	1.19
Prescribed Burns	Total	1.02	0.83	0.20	0.15	0.21	0.36	1.25	0.23
	<1	2.25	1.40	0.48	0.62	0.61	0.92	0.87	0.63
	30 to 34	1.68	2.02	0.18	0.22	0.55	0.87	1.12	0.46
	35 to 39	1.78	1.80	0.19	0.24	0.54	0.89	1.10	0.44
	40 to 44	1.78	1.77	0.21	0.26	0.54	0.91	1.10	0.43
	45 to 49	1.64	1.64	0.23	0.25	0.51	0.93	1.08	0.43
	50 to 54	1.61	1.64	0.22	0.24	0.52	0.93	1.05	0.43
	55 to 59	1.66	1.41	0.22	0.25	0.48	1.00	1.03	0.41
	60 to 64	1.71	1.36	0.24	0.27	0.50	1.00	1.01	0.44
	65 to 69	1.67	1.28	0.27	0.29	0.48	1.04	1.02	0.46
	70 to 74	1.47	1.34	0.28	0.29	0.48	1.04	1.04	0.46
	75 to 79	1.36	1.21	0.28	0.31	0.44	1.02	1.04	0.47
	80 to 84	1.22	1.23	0.30	0.33	0.45	1.01	1.06	0.48
	85+	1.03	0.95	0.29	0.34	0.45	1.02	1.06	0.50

Sources: Population data are from the U.S. Census Bureau [54]. Damages are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions).

Notes: Data characterize 2017. Data represent ratios of subpopulation-specific damages per capita against all-person damages per capita within age groups. Color system considers all race/ethnicity-age combinations across both fire types: blue represents a lower race/ethnicity-specific damages per capita compared to the all-person damages per capita, and red represents a higher race/ethnicity-specific damages per capita compared to the all-person damages per capita (middle of scale, white, is set as 1.0 or no difference between race/ethnicity-specific and all-person damages per capita). Race/ethnicity subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). Subpopulations other than Non-Hispanic or Latino White are not mutually exclusive. All racial groups except Non-Hispanic or Latino White include persons of Hispanic or Latino ethnicity. Hispanic or Latino ethnicity includes persons of all racial groups.

Supplementary Table 24. Emissions from wildfires and prescribed burns in 2014 and 2020 compared to 2017.

Fire Type	Pollutant	2014		2020	
		Metric Tons	vs. 2017	Metric Tons	vs. 2017
Wildfire Emissions	NH ₃	1.25E+05	-47%	2.79E+05	+20%
	NO _x	9.18E+04	-50%	2.19E+05	+19%
	Primary PM _{2.5}	6.48E+05	-47%	1.46E+06	+19%
	SO ₂	5.35E+04	-49%	1.24E+05	+19%
	VOCs	1.79E+06	-47%	4.02E+06	+20%
Prescribed Burn Emissions	NH ₃	1.24E+05	-13%	1.11E+05	-21%
	NO _x	1.32E+05	-18%	1.29E+05	-20%
	Primary PM _{2.5}	6.97E+05	-11%	6.36E+05	-19%
	SO ₂	6.45E+04	-16%	6.21E+04	-19%
	VOCs	1.77E+06	-12%	1.64E+06	-18%

Sources: Emissions data are from the EPA's NEI [8], [84], [85].

Notes: Emissions are from all wildfires and prescribed burns across the contiguous U.S. See Supplementary Table 2 and 3 for 2017 emissions.

Supplementary Table 25. Percentage of wildfire and prescribed burn primary PM_{2.5} emissions by geographic area in 2014, 2017, and 2020.

Geography		Wildfire Emissions			Prescribed Burn Emissions		
		2014	2017	2020	2014	2017	2020
Census Divisions	New England	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%
	Middle Atlantic	0.8%	0.1%	0.1%	0.8%	0.6%	1.0%
	East North Central	0.3%	0.2%	0.0%	3.0%	3.7%	1.6%
	West North Central	2.7%	4.2%	0.4%	18%	26%	18%
	South Atlantic	3.7%	2.5%	0.6%	25%	17%	28%
	East South Central	5.7%	0.9%	0.1%	13%	10%	12%
	West South Central	10%	7.8%	0.9%	21%	31%	29%
	Mountain	11%	34%	24%	8.6%	6.7%	1.9%
	Pacific	66%	50%	74%	10%	5.3%	8.5%
Census Regions	Northeast	0.9%	0.2%	0.1%	0.9%	0.7%	1.1%
	Midwest	3.0%	4.5%	0.5%	21%	30%	20%
	South	19%	11%	1.6%	60%	58%	69%
	West	77%	84%	98%	19%	12%	10%

Sources: Emissions data are from the EPA's NEI [8], [84], [85].

Notes: Emissions are from all wildfires and prescribed burns across the contiguous U.S. Emission shares are computed considering primary PM_{2.5}, which accounted for more than 70% of the air pollution damages from fire smoke in 2017 (see Supplementary Table 2). Color scales show lowest (blue) to highest (red) share and are unique for each fire type and geographic breakdown (i.e., there are four unique color scales).

Supplementary Table 26. Average smoke PM_{2.5} by geographic area estimated by AP4T, Childs et al., and Xie et al.

Geography		AP4T			Comparison		
		Wildfires	Prescribed Burns	Wildland Fires	Childs et al.	Xie et al. GFEDx5	Xie et al. No Canada
Census Divisions	New England	0.05	0.12	0.17	0.19	0.57	0.23
	Middle Atlantic	0.07	0.22	0.29	0.18	0.67	0.27
	East North Central	0.13	0.51	0.64	0.33	0.84	0.29
	West North Central	0.28	1.17	1.45	0.55	0.90	0.41
	South Atlantic	0.24	0.80	1.04	0.17	0.64	0.38
	East South Central	0.26	1.31	1.56	0.19	0.82	0.41
	West South Central	0.41	1.19	1.60	0.36	0.69	0.42
	Mountain	1.10	0.28	1.39	0.66	1.19	1.05
	Pacific	2.94	0.23	3.17	1.02	2.66	2.10
Census Regions	Northeast	0.06	0.19	0.25	0.18	0.65	0.26
	Midwest	0.18	0.71	0.89	0.40	0.86	0.33
	South	0.30	1.00	1.30	0.23	0.69	0.40
	West	2.35	0.24	2.59	0.90	2.19	1.76
Contiguous U.S.		0.71	0.63	1.33	0.42	1.07	0.67

Sources: Smoke PM_{2.5} estimates for comparison are from Xie et al. (2020) [83] and Childs et al. (2022) [82]. Base case smoke PM_{2.5} are modeled with AP4T's counterfactual baseline approach by fire type.

Notes: Data represent 2017. Smoke PM_{2.5} estimates are in $\mu\text{g m}^{-3}$. Smoke PM_{2.5} estimates are computed using population-weighted averages across tract-level observations within each census division and region. See Supplementary Note 1 for the states included in each census division and region. See Supplementary Note 5 for further analysis.

Supplementary Table 27. Comparison statistics for smoke PM_{2.5} estimates from AP4T, Childs et al., and Xie et al.

Comparison Specification	Census Region	AP4T: Wildfire Smoke PM _{2.5}					AP4T: Total Fire Smoke PM _{2.5}				
		MFE	MFB	r	MAE	ME	MFE	MFB	r	MAE	ME
Childs et al. (2022)	Northeast	0.964	-0.961	-0.019	0.124	-0.123	0.410	0.241	0.016	0.104	0.070
	Midwest	0.843	-0.825	0.507	0.238	-0.225	0.609	0.565	0.229	0.490	0.465
	South	0.450	0.132	0.376	0.142	0.068	1.332	1.328	0.377	1.100	1.098
	West	0.961	0.905	0.536	1.525	1.433	1.046	1.024	0.547	1.731	1.678
	CONUS	0.748	-0.132	0.658	0.459	0.257	0.928	0.880	0.589	0.906	0.882
Xie et al. (2020) GFEDx5	Northeast	1.648	-1.648	0.483	0.583	-0.583	0.913	-0.912	0.528	0.390	-0.390
	Midwest	1.362	-1.359	0.387	0.688	-0.683	0.425	-0.186	0.333	0.414	0.008
	South	0.940	-0.884	0.073	0.444	-0.391	0.587	0.487	0.364	0.697	0.639
	West	0.485	0.074	0.484	1.185	0.167	0.491	0.223	0.484	1.225	0.412
	CONUS	1.074	-0.933	0.674	0.687	-0.376	0.589	0.011	0.577	0.686	0.249
Xie et al. (2020) GFEDx5 No Canada	Northeast	1.226	-1.225	0.558	0.194	-0.194	0.337	-0.091	0.619	0.088	-0.001
	Midwest	0.699	-0.678	0.647	0.168	-0.153	0.742	0.737	0.507	0.541	0.537
	South	0.606	-0.456	0.355	0.203	-0.093	0.951	0.950	0.587	0.937	0.936
	West	0.482	0.259	0.504	1.073	0.585	0.537	0.407	0.505	1.191	0.830
	CONUS	0.717	-0.498	0.712	0.380	0.020	0.698	0.589	0.613	0.740	0.645

Sources: Smoke PM_{2.5} estimates for comparison are from Xie et al. (2020) [83] and Childs et al. (2022) [82]. Base case smoke PM_{2.5} are modeled with AP4T's counterfactual baseline approach by fire type.

Notes: Data represent 2017. Statistics are computed from tract-level smoke PM_{2.5} estimates. Statistics are mean fractional error (MFE, see Supplementary Equation 7), mean fraction bias (MFB, see Supplementary Equation 8), Pearson's correlation coefficient (r), mean absolute error (MAE), and mean error (ME). MFB, MFE, and r are unitless. MAE and ME are in $\mu\text{g m}^{-3}$. For MFE, red indicates greater relative difference and white indicates lower relative difference. Color scale is normalized from 0 to 2 such that 0 is white and 2 is red. For MFB, red indicates greater overestimation by AP4T, blue indicates greater underestimation by AP4T, and white indicates agreement. See Supplementary Note 1 for the states included in each census region. See Supplementary Note 5 for further analysis.

Supplementary Table 28. AP4 and AP4T performance statistics following primary calibration.

Year	Ambient Pollutant	Calibration Metrics			
		MFE	MFB	r	n
AP4	Total PM_{2.5}	0.278	-0.042	0.395	749
	Ammonium Nitrate	0.431	+0.001	0.617	136
	Ammonium Sulfate	0.305	+0.005	0.750	136
	Organic Carbon (VOCs)	0.356	-0.001	0.440	248
	Non-Primary PM _{2.5}	0.291	-0.040	0.530	136
AP4T	Total PM_{2.5}	0.282	-0.044	0.373	1,232
	Ammonium Nitrate	0.444	+0.083	0.573	144
	Ammonium Sulfate	0.300	-0.090	0.749	144
	Organic Carbon (VOCs)	0.304	-0.004	0.603	274
	Non-Primary PM _{2.5}	0.248	-0.064	0.660	144

Sources: Monitored data are from EPA's AQS [34].

Notes: MFE is mean fractional error (see Supplementary Equation 7). MFB is mean fraction bias (see Supplementary Equation 8). r is Pearson's correlation coefficient. n is the number of AQS-monitored counties for AP4 and census tracts for AP4T for each pollutant. Ammonium nitrate, ammonium sulfate, organic carbon, and non-primary PM_{2.5} are AQS parameter codes 88344, 88339, 88320, and 88344 + 88339 + 88320, respectively [34].

Supplementary Table 29. AP4 and AP4T performance statistics at each stage of the calibration process.

Model	Calibration Step	Calibration Metrics		
		MFE	MFB	r
AP4	Primary	0.278	-0.042	0.395
	Secondary	0.242	-0.038	0.644
	Tertiary	0.238	-0.030	0.656
	Primary-to-Secondary	-13%	-8.6%	+63%
	Secondary-to-Tertiary	-1.7%	-21%	+1.9%
	Primary-to-Tertiary	-14%	-28%	+66%
AP4T	Primary	0.282	-0.044	0.373
	Secondary	0.251	-0.052	0.638
	Tertiary	0.233	-0.031	0.679
	Primary-to-Secondary	-11%	+19%	+71%
	Secondary-to-Tertiary	-7.4%	-41%	+6.5%
	Primary-to-Tertiary	-18%	-30%	+82%

Sources: Monitored data are from EPA's AQS [34].

Notes: MFE is mean fractional error (see Supplementary Equation 7). MFB is mean fraction bias (see Supplementary Equation 8). r is Pearson's correlation coefficient. All statistics consider 749 AQS-monitored counties for AP4 and 1,232 AQS-monitored tracts for AP4T.

Supplementary Table 30. Crosswalk for race/ethnicity subpopulations reported by U.S. Census Bureau and CDC.

Race/Ethnicity Subpopulations		
U.S. Census Bureau American Community Survey		Centers for Disease Control and Prevention WONDER
A	White Alone, Any Ethnicity	White, Any Ethnicity
B	Black or African American Alone	Black or African American, Any Ethnicity
C	American Indian and Alaska Native Alone	American Indian or Alaska Native, Any Ethnicity
D	Asian Alone	Asian or Pacific Islander, Any Ethnicity
E	Native Hawaiian and Other Pacific Islander Alone	
F	Some Other Race Alone	NA
G	Two or More Races	
H	White Alone, Not Hispanic or Latino	White, Not Hispanic or Latino
I	Hispanic or Latino	Hispanic or Latino, Any Race

Sources: Subpopulations are defined by the U.S. Census Bureau's American Community Survey [54] and the CDC's WONDER [52], [53].

Notes: Lettering system is from the U.S. Census Bureau's American Community Survey [54]. Race/ethnicity subpopulations are matched to best reconcile differences between data sources. Hispanic or Latino is classified as ethnicity by both data sources, while every other subpopulation is classified as race. For U.S. Census Bureau's American Community Survey, race is mutually exclusive, but race/ethnicity is not mutually exclusive. All racial groups except White Alone, Not Hispanic or Latino include persons of Hispanic or Latino ethnicity. Hispanic or Latino ethnicity includes persons of all racial groups. For assessments involving mutually exclusive and collectively exhaustive subpopulations by race/ethnicity, non-White Hispanic or Latino individuals are categorized separately from their non-White racial groups (see Supplementary Methods 2).

Supplementary Table 31. Value of a statical life for mortality risk monetization in AP4T for 2017.

Mortality Risk Valuation Study	Reference Year	VSL Estimate	Reference Year VSL (Million \$)	2017 VSL (Million 2020 U.S. dollars)
EPA Meta-Analysis (2014)	2006	Low	0.679	0.915
		Base Case	7.40	9.97
		High	18.4	24.8
Mrozek & Taylor (2002)	1998	Alternate	2.00	3.76

Sources: Original VSL data are from the EPA [62] and Mrozek & Taylor [101].

Notes: Final VSL values for each year are for 2017 in 2020 U.S. dollars. AP4T's base case is the EPA's central estimate. Low is 2.5th percentile from the EPA's Weibull distribution. High is 97.5th percentile from the EPA's Weibull distribution.

Supplementary Table 32. Value of mortality risk by age group using the value of a statistical life year approach.

Age Group	Expected Remaining Years	PV of Expected Remaining Years	Nominal Mortality Risk Valuation	PV of Mortality Risk Valuation
<1	78.4	30.0	\$33.5	\$12.8
1 to 4	76.1	29.8	\$32.5	\$12.7
5 to 9	71.7	29.3	\$30.6	\$12.5
10 to 14	66.7	28.7	\$28.5	\$12.3
15 to 19	61.8	28.0	\$26.4	\$12.0
20 to 24	57.1	27.2	\$24.4	\$11.6
25 to 29	52.4	26.2	\$22.4	\$11.2
30 to 34	47.7	25.2	\$20.4	\$10.8
35 to 39	43.0	24.0	\$18.4	\$10.3
40 to 44	38.4	22.6	\$16.4	\$9.67
45 to 49	33.9	21.1	\$14.5	\$9.02
50 to 54	29.5	19.4	\$12.6	\$8.30
55 to 59	25.4	17.6	\$10.9	\$7.52
60 to 64	21.4	15.6	\$9.15	\$6.68
65 to 69	17.6	13.5	\$7.53	\$5.79
70 to 74	14.1	11.4	\$6.03	\$4.86
75 to 79	10.9	9.17	\$4.66	\$3.92
80 to 84	8.10	7.10	\$3.46	\$3.03
85+	5.41	4.93	\$2.32	\$2.11

Sources: Expected remaining years are from CDC life tables [77]. Methodology is from the Department of Health and Human Services [76].

Notes: Data characterize 2017. Values are in 2020 U.S. dollars. Expected remaining life years are calculated as survivor-weighted averages of the ages bounding each age group—for example, the expected remaining life years for the 30 to 34 age group is the survivor-weighted average of the ages for 30- and 35-year-olds. The exception is for the 85+ group, which is a survivor-weighted average of expected remaining life years for individuals aged 85, 90, 95, and 100. Value of a statistical life year is \$428 thousand and is derived from a VSL of \$9.97 million, considering a 40-year-old's present value (PV) of remaining life years. Discount rate is 3%.

Supplementary Table 33. Sensitivity analysis of U.S. fire smoke damage estimates in 2017.

Topic	Scenario	Smoke Damages					
		Wildfires		Prescribed Burns		Wildland Fires	
		Estimate	Change	Estimate	Change	Estimate	Change
	1: Base Case	9.94E+10	<i>NA</i>	1.01E+11	<i>NA</i>	2.01E+11	<i>NA</i>
Air Quality Modeling	2: Xie et al. GFEDx5	1.57E+11	+58%	<i>NA</i>	<i>NA</i>	1.57E+11	-22%
	3: Xie et al. No Canada	9.69E+10	-2%	<i>NA</i>	<i>NA</i>	9.69E+10	-52%
	4: Childs et al. (2022)	6.16E+10	-38%	<i>NA</i>	<i>NA</i>	6.16E+10	-69%
	5: Marginal Ton Approach ^A	9.85E+10	-1%	1.01E+11	-0.3%	1.99E+11	-1%
	6: Marginal Ton Approach ^B	1.07E+11	+8%	1.09E+11	+8%	2.17E+11	+8%
	7: AP4	1.31E+11	+32%	1.04E+11	+3%	2.35E+11	+17%
	8: Lepeule et al. (2012)	2.10E+11	+112%	2.14E+11	+111%	4.25E+11	+112%
Dose-Response	9: Di et al. (2017)	1.19E+11	+20%	1.21E+11	+20%	2.40E+11	+20%
	10: Diff. Relative Risk	1.25E+11	+26%	1.33E+11	+31%	2.58E+11	+29%
	11: Dimensional Approach	9.92E+10	-0.2%	1.01E+11	-0.1%	2.00E+11	-0.1%
Valuation	12: Lower Bound VSL	9.12E+09	-91%	9.27E+09	-91%	1.84E+10	-91%
	13: Upper Bound VSL	2.47E+11	+149%	2.51E+11	+149%	4.99E+11	+149%
	14: Mrozek & Taylor (2002)	3.75E+10	-62%	3.81E+10	-62%	7.57E+10	-62%
	15: Value of Stat. Life Year	4.49E+10	-55%	4.73E+10	-53%	9.23E+10	-54%

Sources: Air quality modeling [82], [83], [94], [95]; dose-response [47], [48], [50], [52], [53]; valuation [62], [75], [76], [101].

Notes: Data characterize 2017. Values are in 2020 U.S. dollars. Change variables are percentage changes compared to the base case estimates. Yellow indicates more damages, and green indicates fewer damages. Scenarios: #1, AP4T via counterfactual baseline approach, ACS for relative risk [47], distributional approach for baseline risk, and EPA's central estimate VSL [62]; #2, smoke PM_{2.5} estimates from Xie et al.'s GFEDx5 experiment [83], [94]; #3, smoke PM_{2.5} estimates from Xie et al.'s GFEDx5 without Canadian fire emissions experiment [83], [94]; #4, smoke PM_{2.5} estimates from Childs et al. [82], [95]; #5, AP4T via marginal ton approach (A = forego interpollutant chemistry on the margin for NH₃ and NO_x); #6, AP4T via marginal ton approach (B = employ interpollutant chemistry on the margin for NH₃ and NO_x); #7, county-level AP4 via counterfactual baseline approach; #8, H6C for relative risk [48]; #9, Medicare Cohort Study's all-person main analysis relative risk [50]; #10, Medicare Cohort Study's relative risk differentiated by race/ethnicity [50]; #11, dimensional approach for baseline risk (county-level mortality rates); #12, 2.5th percentile VSL estimate from EPA's fitted Weibull distribution [62]; #13, 97.5th percentile VSL estimate from EPA's fitted Weibull distribution [62]; #14, VSL estimate from Mrozek & Taylor [101]; #15, VSLY approach [76]. See Supplementary Note 6 for further detail and analysis.

Supplementary Table 34. Sensitivity analysis of wildfire smoke damages per capita (\$ per person) by SVI decile using differentiated relative risk and the value of a statistical life year.

SVI Decile	Social Vulnerability Index Theme														
	Overall			Socioeconomic Status			Household Composition & Disability			Minority Status & Language			Housing Type & Transportation		
	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY
Total	308^A	388	139	308	388	139	308	388	139	308	388	139	308	388	139
1	183 ^B	207	84	230	264	100	198	252	94	229	244	103	206	245	95
2	244	282	110	303	351	130	265	329	122	255	277	114	230	278	108
3	291	340	129	312	369	136	275	340	124	284	315	125	261	318	121
4	298	352	132	338	401	148	295	366	131	306	348	133	291	356	134
5	330	391	145	353	422	155	329	408	145	302	361	134	301	374	138
6	367	445	162	343	419	156	321	403	145	319	390	142	306	383	138
7	352	439	159	315	396	144	355	444	161	333	416	148	323	410	146
8	342	446	155	319	418	148	355	447	160	378	491	171	360	461	160
9	330	465	153	287	411	138	347	442	157	349	492	163	398	513	174
10	344	523	165	271	441	138	338	455	152	301	490	146	401	533	176
1	-41% ^C	-47%	-40%	-25%	-32%	-28%	-36%	-35%	-33%	-26%	-37%	-26%	-33%	-37%	-32%
2	-21%	-27%	-21%	-2%	-9%	-7%	-14%	-15%	-12%	-17%	-29%	-18%	-25%	-28%	-23%
3	-5%	-12%	-8%	1%	-5%	-3%	-11%	-12%	-11%	-8%	-19%	-10%	-15%	-18%	-13%
4	-3%	-9%	-5%	10%	4%	6%	-4%	-6%	-6%	-1%	-10%	-4%	-6%	-8%	-4%
5	7%	1%	4%	15%	9%	12%	7%	5%	4%	-2%	-7%	-4%	-2%	-4%	-1%
6	19%	15%	16%	11%	8%	12%	4%	4%	4%	4%	1%	2%	-1%	-1%	-1%
7	14%	13%	14%	2%	2%	3%	15%	15%	15%	8%	7%	6%	5%	6%	5%
8	11%	15%	12%	4%	8%	7%	15%	15%	15%	23%	27%	23%	17%	19%	15%
9	7%	20%	10%	-7%	6%	-1%	13%	14%	13%	13%	27%	17%	29%	32%	25%
10	12%	35%	18%	-12%	14%	-1%	10%	17%	9%	-2%	26%	5%	30%	37%	26%

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Damages are modeled with AP4T's counterfactual baseline approach with all wildfire emissions.

Notes: Data characterize 2017. Damages are in 2020 U.S. dollars. Damages are from all wildfire emissions. A = all-person damages per capita. B = Social Vulnerability Index (SVI) decile damages per capita. C = percentage difference of SVI decile damages per capita from all-person damages per capita. Color scales are symmetrical and unique to each SVI theme: white shows no difference, red shows greater damages per capita for the SVI decile than for the total population, and blue shows fewer damages per capita for the SVI decile than for the total population. Base case estimates differentiate baseline risk (mortality rates) by race/ethnicity but not relative risk. Base case estimates use a uniform VSL approach (\$9.97 million). Alternative approaches differentiate relative risk by race/ethnicity according to Di et al. (2017) [50] and use a VSLY approach (\$428 thousand per year) [75], [76]. See Supplementary Methods 5 for more details.

Supplementary Table 35. Sensitivity analysis of prescribed burn smoke damages per capita (\$ per person) by SVI decile using differentiated relative risk and the value of a statistical life year.

SVI Decile	Social Vulnerability Index Theme														
	Overall			Socioeconomic Status			Household Composition & Disability			Minority Status & Language			Housing Type & Transportation		
	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY	Base	Diff. RR	VSLY
Total	313^A	411	147	313	411	147	313	411	147	313	411	147	313	411	147
1	230 ^B	261	110	237	269	107	130	169	64	484	519	224	251	304	121
2	254	294	118	245	285	111	180	223	87	415	459	188	295	359	142
3	282	331	129	273	321	123	214	265	101	405	470	185	327	409	157
4	318	378	146	297	355	135	248	306	115	408	504	188	326	417	156
5	336	403	155	323	390	148	293	365	134	381	527	179	327	429	155
6	364	451	169	361	446	168	324	409	150	324	470	154	317	420	148
7	391	508	182	386	498	182	372	477	174	284	424	135	327	434	150
8	369	519	174	399	545	191	419	550	196	226	343	109	333	448	152
9	331	529	159	350	540	172	473	648	222	161	260	80	337	468	154
10	254	456	124	264	517	136	554	849	259	106	187	53	285	418	129
1	-26% ^C	-36%	-25%	-24%	-35%	-27%	-59%	-59%	-56%	55%	26%	52%	-20%	-26%	-17%
2	-19%	-29%	-20%	-22%	-31%	-24%	-42%	-46%	-41%	33%	12%	29%	-6%	-13%	-3%
3	-10%	-19%	-12%	-13%	-22%	-16%	-32%	-36%	-31%	29%	14%	26%	4%	-1%	7%
4	2%	-8%	0%	-5%	-14%	-8%	-21%	-26%	-22%	30%	22%	28%	4%	1%	6%
5	7%	-2%	6%	3%	-5%	1%	-6%	-11%	-8%	22%	28%	22%	5%	4%	6%
6	16%	10%	15%	15%	8%	15%	4%	-1%	2%	4%	14%	5%	1%	2%	1%
7	25%	24%	24%	23%	21%	24%	19%	16%	19%	-9%	3%	-8%	4%	5%	3%
8	18%	26%	19%	27%	32%	30%	34%	34%	34%	-28%	-16%	-26%	6%	9%	4%
9	6%	29%	9%	12%	31%	17%	51%	57%	51%	-48%	-37%	-45%	8%	14%	5%
10	-19%	11%	-16%	-16%	26%	-8%	77%	106%	77%	-66%	-55%	-64%	-9%	2%	-12%

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Damages are modeled with AP4T's counterfactual baseline approach with all prescribed burn emissions. *Notes:* Data characterize 2017. Damages are in 2020 U.S. dollars. Damages are from all prescribed burn emissions. A = all-person damages per capita. B = Social Vulnerability Index (SVI) decile damages per capita. C = percentage difference of SVI decile damages per capita from all-person damages per capita. Color scales are symmetrical and unique to each SVI theme: white shows no difference, red shows greater damages per capita for the SVI decile than for the total population, and blue shows fewer damages per capita for the SVI decile than for the total population. Base case estimates differentiate baseline risk (mortality rates) by race/ethnicity but not relative risk. Base case estimates use a uniform VSL approach (\$9.97 million). Alternative approaches differentiate relative risk by race/ethnicity according to Di et al. (2017) [50] and use a VSLY approach (\$428 thousand per year) [75], [76]. See Supplementary Methods 5 for more details.

Supplementary Table 36. Sensitivity analysis of fire smoke damages per capita (\$ per person) by race/ethnicity using differentiated relative risk and the value of a statistical life year.

Race/Ethnicity Subpopulation	Wildfires			Prescribed Burns		
	Base Case	Diff. RR	VSLY	Base Case	Diff. RR	VSLY
Total	308^A	388	139	313	411	147
Black or African American	147 ^B	423	82	319	918	182
American Indian or Alaska Native	368	582	221	261	411	155
Asian	241	367	108	62	94	31
Native Hawaiian or Other Pacific Islander	226	344	123	48	72	28
Some Other Race	202	241	118	66	79	42
Two or More Races	165	197	92	114	135	67
Non-Hispanic or Latino White	369	386	159	393	411	176
Hispanic or Latino	179	318	98	73	130	41
Black or African American	-52% ^C	9%	-41%	2%	123%	24%
American Indian or Alaska Native	19%	50%	59%	-17%	0%	6%
Asian	-22%	-5%	-23%	-80%	-77%	-79%
Native Hawaiian or Other Pacific Islander	-27%	-11%	-12%	-85%	-82%	-81%
Some Other Race	-34%	-38%	-15%	-79%	-81%	-72%
Two or More Races	-46%	-49%	-34%	-64%	-67%	-55%
Non-Hispanic or Latino White	20%	0%	14%	25%	0%	20%
Hispanic or Latino	-42%	-18%	-30%	-77%	-69%	-72%

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Damages are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions).

Notes: Data characterize 2017. Damages are in 2020 U.S. dollars. Damages are from all wildfire and prescribed burn emissions. A = all-person damages per capita. B = race/ethnicity damages per capita. C = percentage difference of race/ethnicity damages per capita from all-person damages per capita. Color scales are symmetrical and unique to each fire type: white shows no difference, red shows greater damages per capita for the race/ethnicity subpopulation than for the total population, and blue shows fewer damages per capita for the race/ethnicity subpopulation than for the total population. Base case estimates differentiate baseline risk (mortality rates) by race/ethnicity but not relative risk. Base case estimates use a uniform VSL approach (\$9.97 million). Alternative approaches differentiate relative risk by race/ethnicity according to Di et al. (2017) [50] and use a VSLY approach (\$428 thousand per year) [75], [76]. See Supplementary Methods 5 for more details. Race/ethnicity subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). Subpopulations other than Non-Hispanic or Latino White are not mutually exclusive. All racial groups except Non-Hispanic or Latino White include persons of Hispanic or Latino ethnicity. Hispanic or Latino ethnicity includes persons of all racial groups.

Supplementary Table 37. Sensitivity analysis of total fire smoke damages by age group using differentiated relative risk and the value of a statistical life year.

Age Group	Totals				Percentages of Total			
	Population (Millions)	Smoke Damages (Billion \$)			Population	Smoke Damages		
		Base Case	Diff. RR	VSLY		Base Case	Diff RR.	VSYL
<1	3.87	1.84	1.84	2.36	1.2%	0.9%	0.7%	2.6%
30 to 34	21.8	2.24	3.29	2.42	6.7%	1.1%	1.3%	2.6%
35 to 39	21.0	2.69	3.95	2.77	6.5%	1.3%	1.5%	3.0%
40 to 44	19.4	3.16	4.60	3.07	6.0%	1.6%	1.8%	3.3%
45 to 49	20.8	4.86	6.93	4.39	6.4%	2.4%	2.7%	4.8%
50 to 54	21.2	7.70	10.8	6.41	6.6%	3.8%	4.2%	6.9%
55 to 59	21.8	12.2	16.8	9.22	6.8%	6.1%	6.5%	10%
60 to 64	19.8	15.8	21.4	10.6	6.1%	7.9%	8.3%	11%
65 to 69	16.7	18.8	24.8	10.9	5.2%	9.3%	9.6%	12%
70 to 74	12.7	21.3	27.2	10.4	3.9%	11%	11%	11%
75 to 79	8.67	23.0	29.3	9.06	2.7%	11%	11%	9.8%
80 to 84	5.92	25.7	32.4	7.84	1.8%	13%	13%	8.5%
85+	6.42	61.2	75.0	12.9	2.0%	31%	29%	14%
Total	200	201	258	92.3	62.0%	100%	100%	100%

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Damages are modeled with AP4T's counterfactual baseline approach.

Notes: Data characterize 2017. Damages are in 2020 U.S. dollars. Smoke damages consider both wildfire and prescribed burn emissions. Population percentages consider totals across the contiguous U.S. [54]. Ages 1 to 29 experience no damage [47], [49]. Base case estimates differentiate baseline risk (mortality rates) by race/ethnicity but not relative risk. Base case estimates use a uniform VSL approach (\$9.97 million). Alternative approaches differentiate relative risk by race/ethnicity according to Di et al. (2017) [50] and use a VSLY approach (\$428 thousand per year) [75], [76]. See Supplementary Methods 5 for more details.

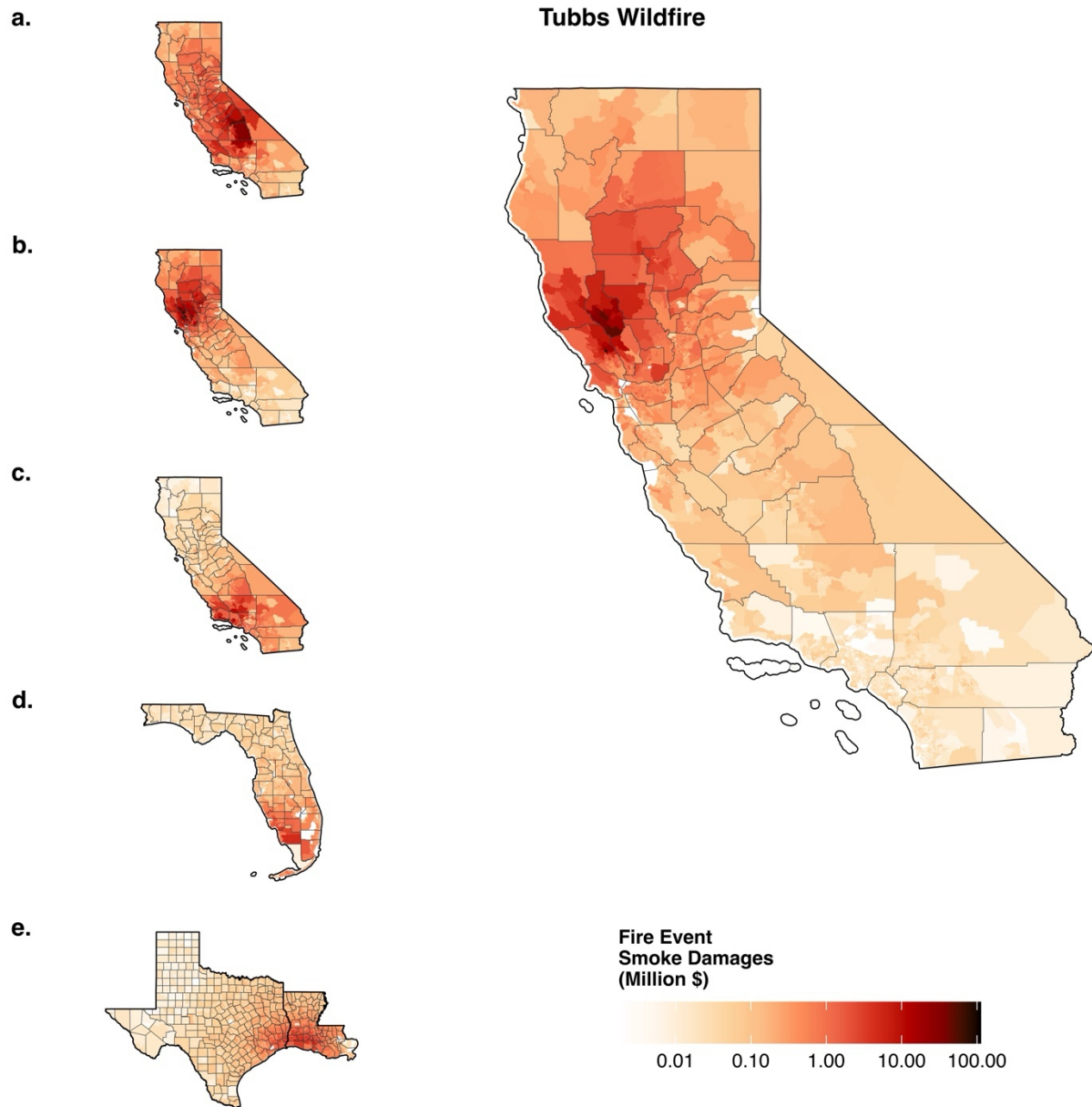
Supplementary Table 38. SVI percentile rank calculation example.

Ranks	1	2	3	4	5	6	7	8	9	10
Percentile Ranks	0.000	0.111	0.222	0.333	0.444	0.556	0.667	0.778	0.889	1.00
Vulnerability	Least				Median					Most

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70].

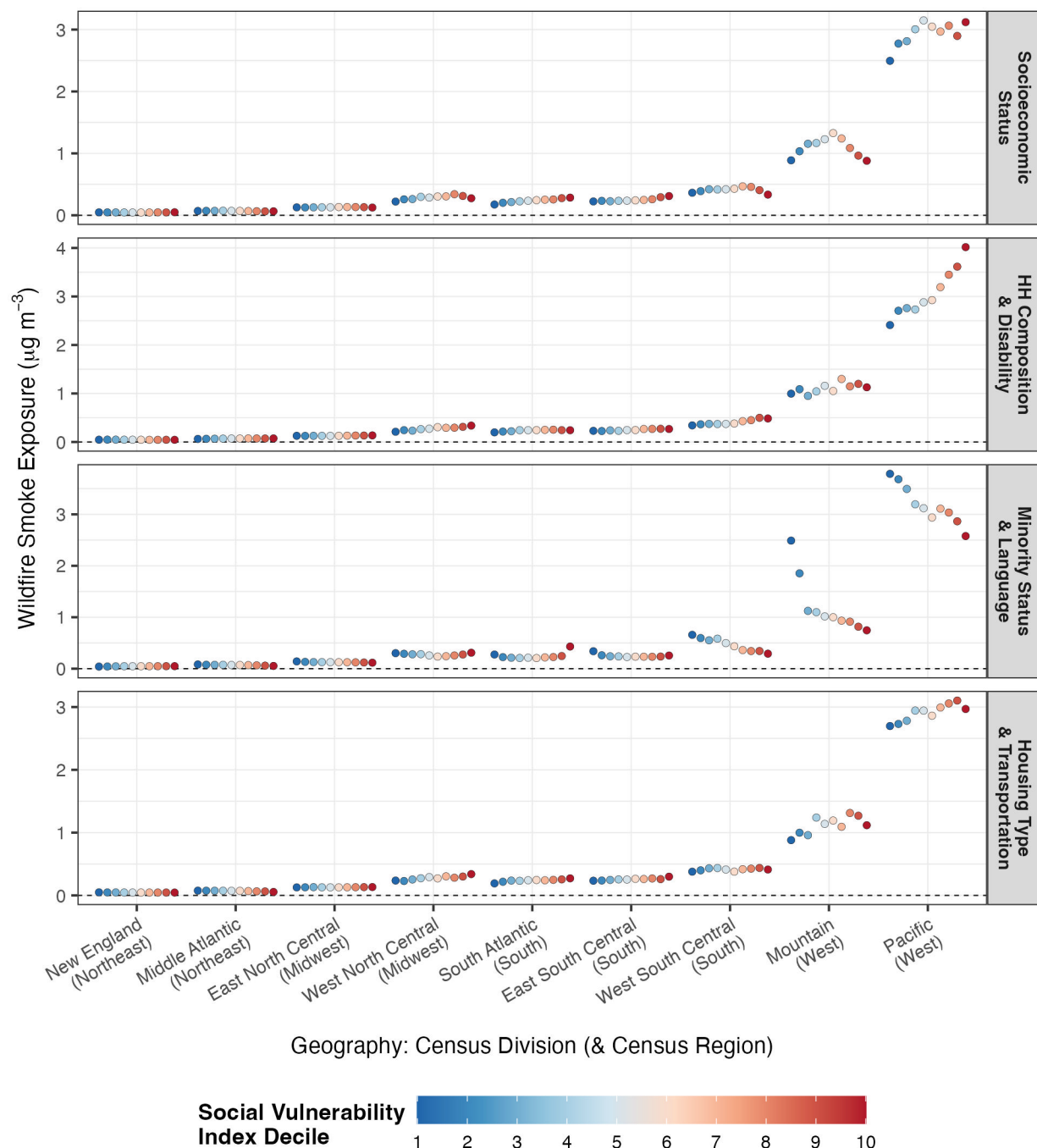
Notes: For this example, $N = 10$, and the 10 observations are ranked from least (1) to most (10) vulnerable. SVI percentile ranks are computed using Supplementary Equation 15.

Supplementary Figures



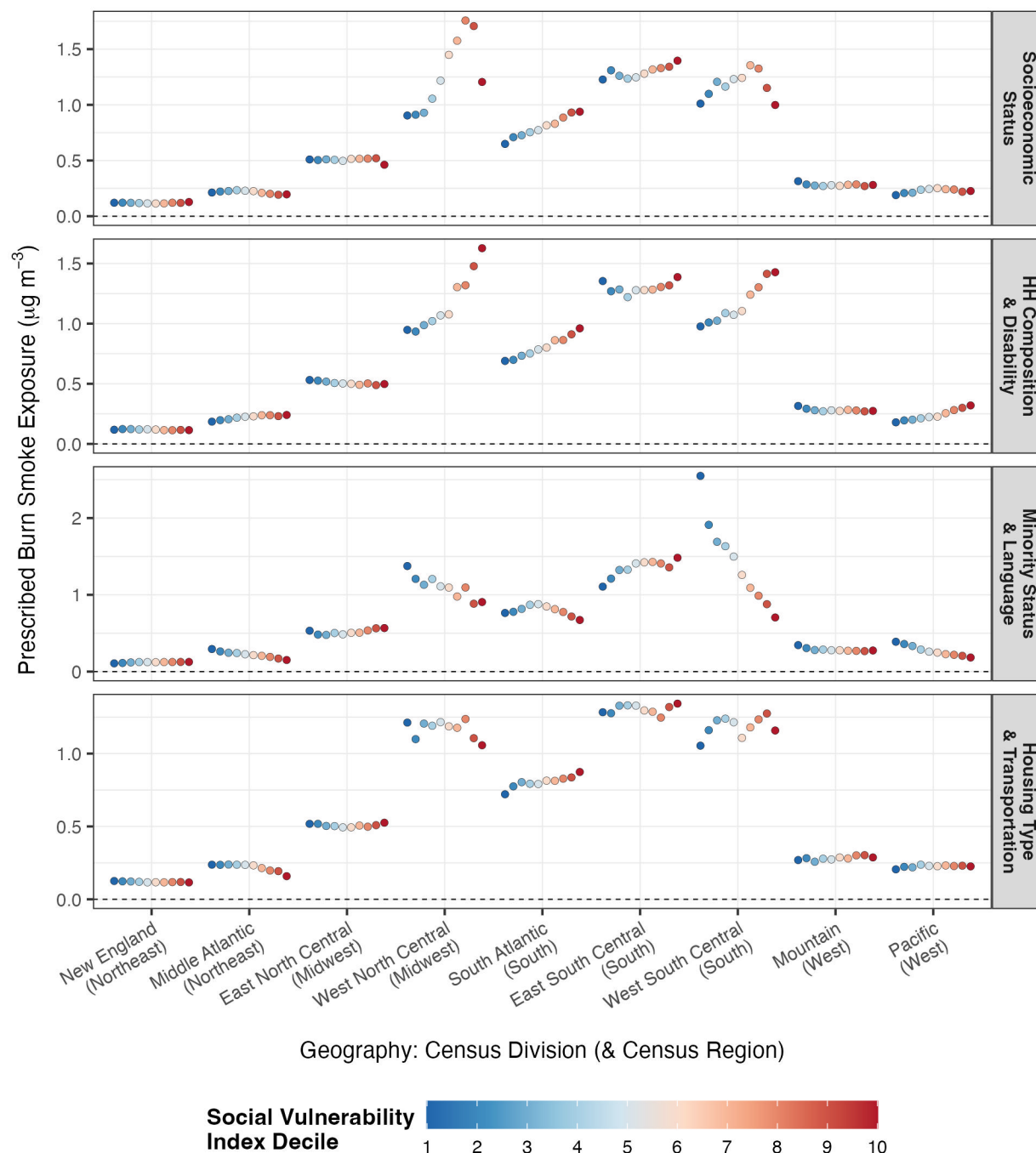
Supplementary Fig. 1 | Own-state tract-level smoke damages from specific fire events in 2017. Data represent 2017. Damages are in 2020 U.S. dollars. Color scale is log-transformed. a, Damages from Tulare County, California's *Pier*, *Lion*, *Schaeffer*, *Indian*, and *Roadrunner* wildfires. b, Damages from Sonoma/Napa/Solano County, California's *Tubbs*, *Nuns*, *Atlas*, *Pocket*, and *Thirty Seven* wildfires. c, Damages from Ventura/Santa Barbara County, California's *Thomas* wildfire. d, Damages from Collier County, Florida's prescribed burns. e, Damages from Cameron/Vermilion County, Louisiana's and Jefferson/Chambers County, Texas' prescribed burns. *Tubbs* wildfire is both part of b and evaluated individually as it was the second most destructive wildfire in California's history [79]. The *Thomas* wildfire burned during both 2017 and 2018; however, only its 2017 emissions and damages are modeled and mapped here.

Sources: Fire events and associated emissions are identified using data from MTBS [18] and the EPA's NEI [8]. Mapping uses the *rgdal* R package [102]. Plotting uses the *ggplot2* R package [103].



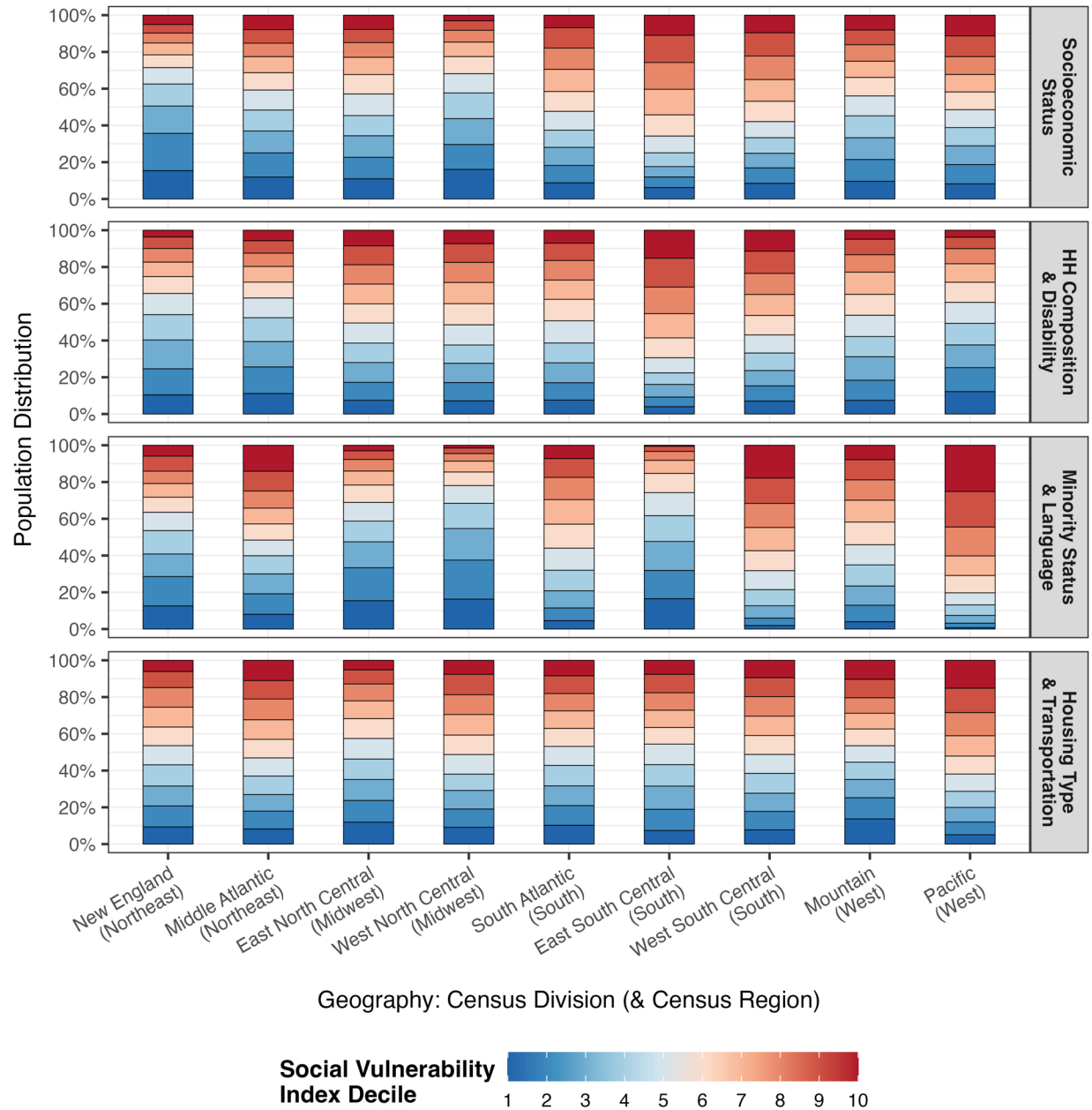
Supplementary Fig. 2 | Population-weighted average wildfire smoke exposure vs. themed SVI decile by census division. Data characterize 2017. Red represents more vulnerable (from 10 down), and blue represents less vulnerable (from 1 up). See Supplementary Note 1 for the states included in each census division and region. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures are modeled with AP4T's counterfactual baseline approach with all wildfire emissions. Plotting uses the *ggplot2* R package [103].



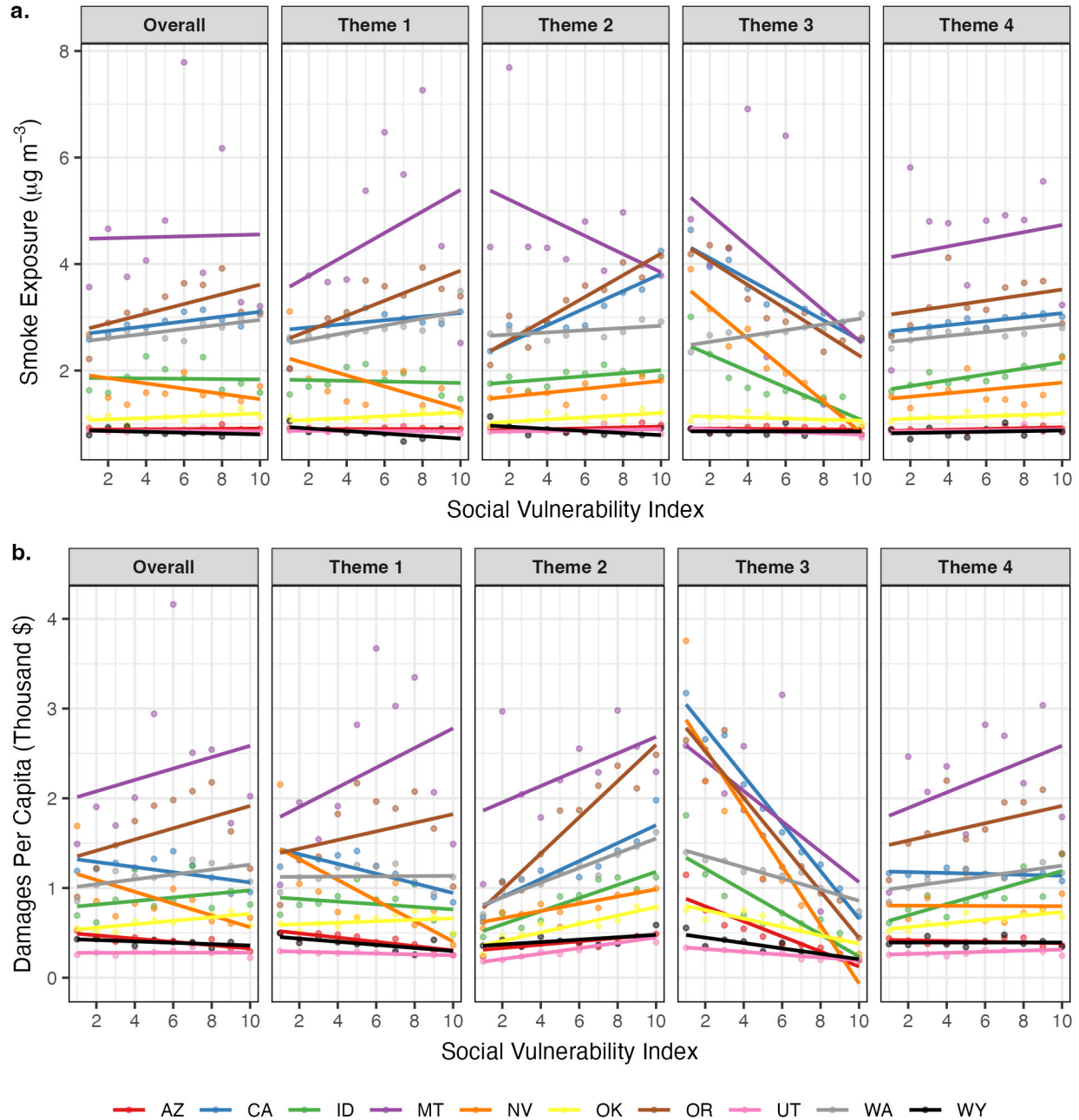
Supplementary Fig. 3 | Population-weighted average prescribed burn smoke exposure vs. themed SVI by census division. Data characterize 2017. Red represents more vulnerable (from 10 down), and blue represents less vulnerable (from 1 up). See Supplementary Note 1 for the states included in each census division and region. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures are modeled with AP4T's counterfactual baseline approach with all prescribed burn emissions. Plotting uses the *ggplot2* R package [103].



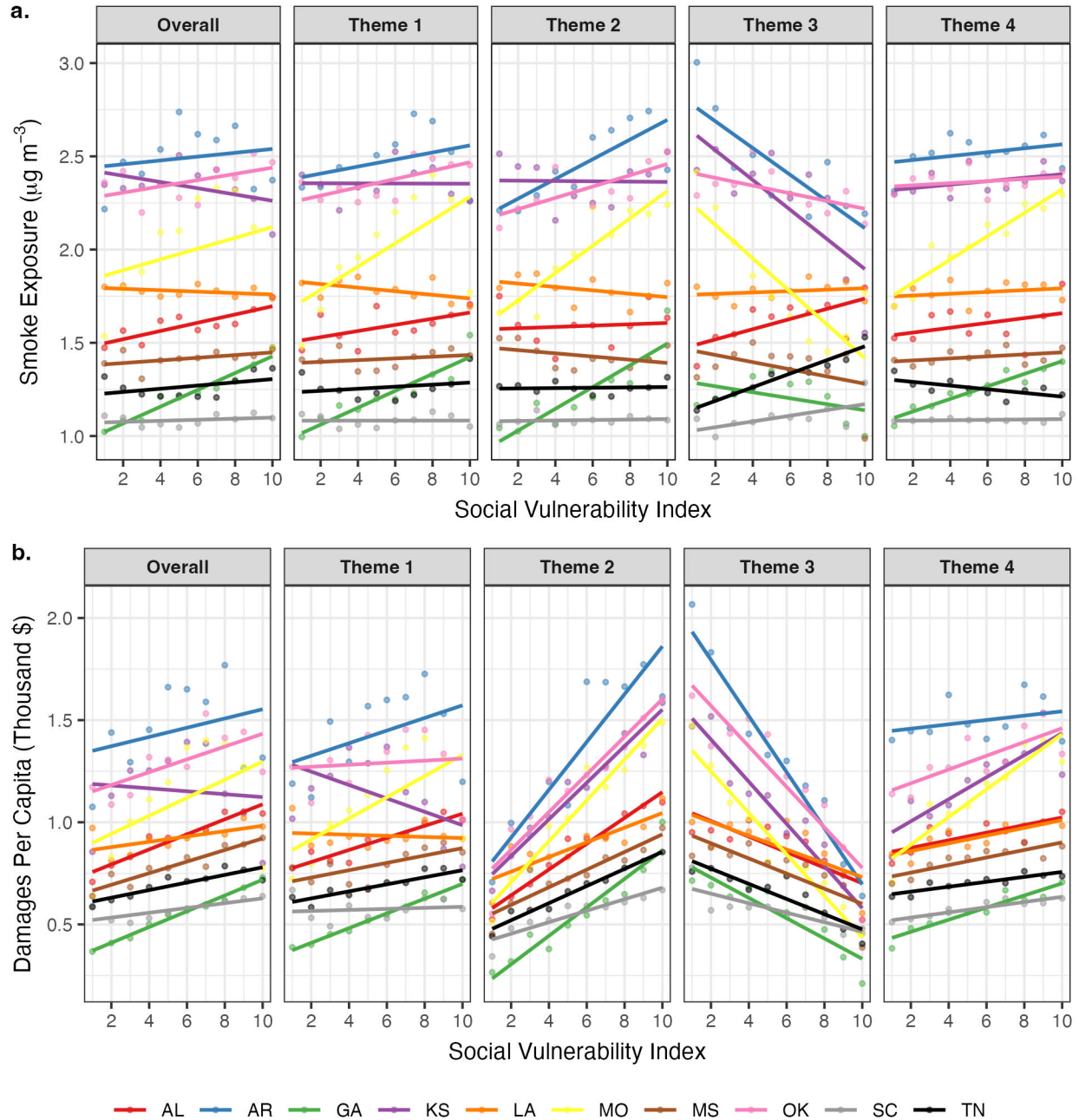
Supplementary Fig. 4 | Percentage of census divisions' populations by themed SVI decile. Data characterize 2017. Each panel breaks down census divisions' populations by themed SVI decile. Red represents more vulnerable (from 10 down), and blue represents less vulnerable (from 1 up). An equal distribution of vulnerability across the contiguous U.S. would result in each SVI decile accounting for 10% of every census division's population. See Supplementary Note 1 for the states included in each census division and region. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs.

Sources: SVI data are from the CDC [69] based on methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Plotting uses the *ggplot2* R package [103].



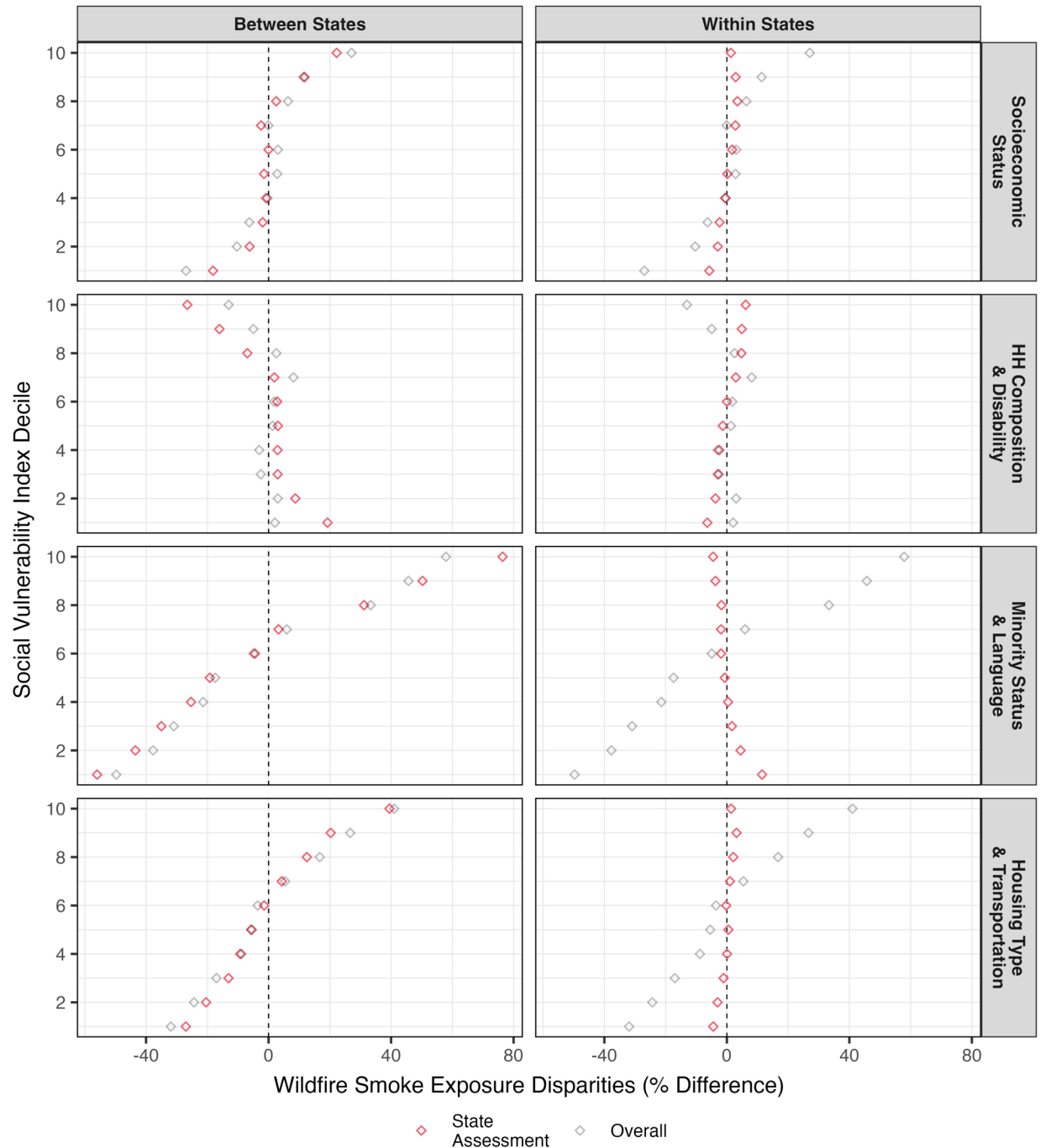
Supplementary Fig. 5 | Wildfire smoke impacts by SVI decile within states. Data characterize 2017. (a) population-weighted exposures and (b) damages per capita by overall and themed SVI deciles with fitted linear models within the ten most wildfire smoke-polluted states (considering population-weighted exposures). SVI deciles are not redesignated within states (e.g., a tract in SVI decile 10 nationally remains in 10). AZ is Arizona, CA is California, ID is Idaho, MT is Montana, NV is Nevada, OK is Oklahoma, OR is Oregon, UT is Utah, WA is Washington, and WY is Wyoming. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed SVIs.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures and damages are modeled with AP4T's counterfactual baseline approach with all wildfire emissions. Plotting uses the *ggplot2* R package [103].



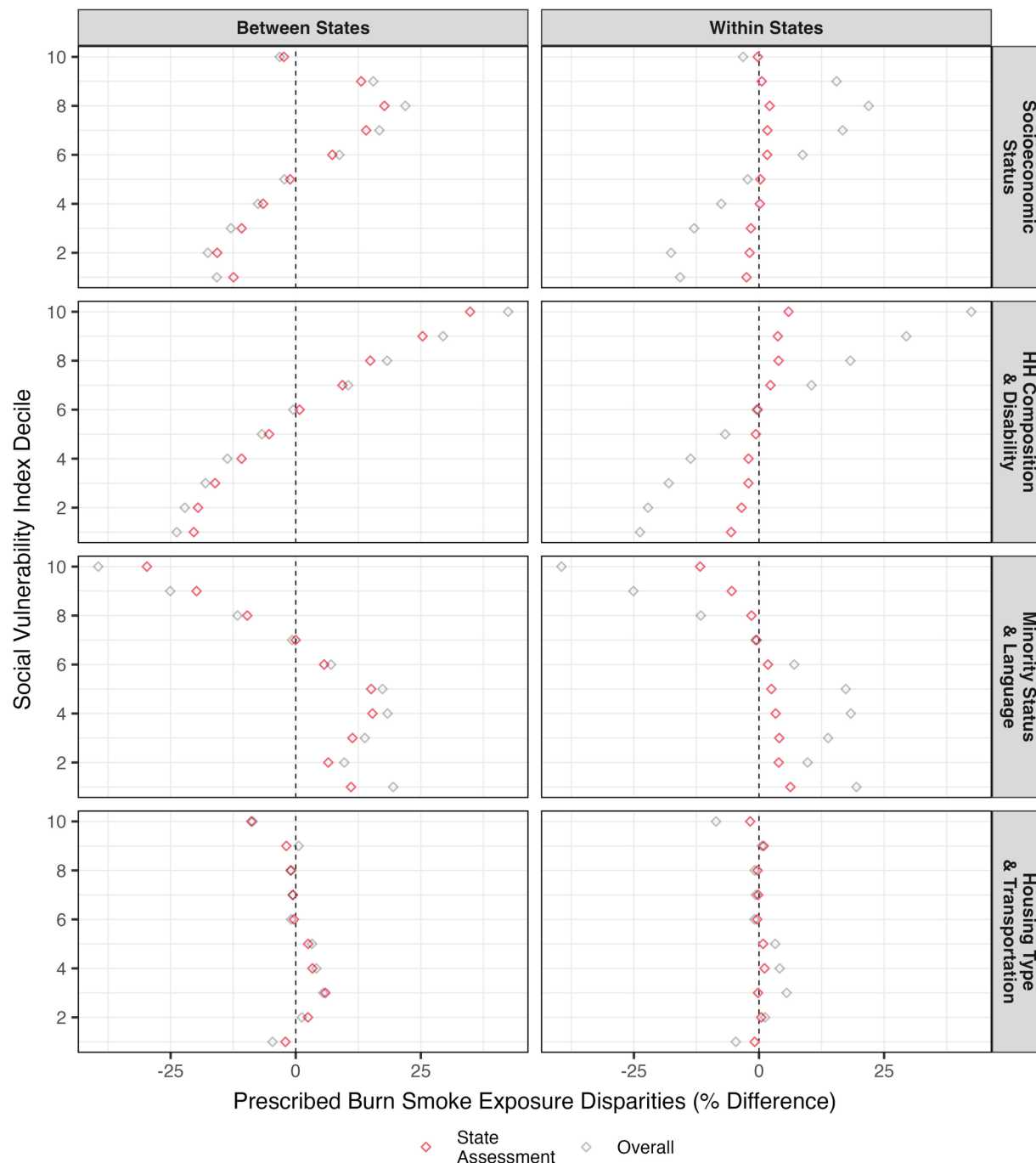
Supplementary Fig. 6 | Prescribed burn smoke impacts by SVI decile within states. Data characterize 2017. (a) population-weighted exposures and (b) damages per capita by overall and themed SVI deciles with fitted linear models within the ten most prescribed burn smoke-polluted states (considering population-weighted exposures). SVI deciles are not redesignated within states (e.g., a tract in SVI decile 10 nationally remains in 10). AL is Alabama, AR is Arkansas, GA is Georgia, KS is Kansas, LA is Louisiana, MO is Missouri, MS is Mississippi, OK is Oklahoma, SC is South Carolina, and TN is Tennessee. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed SVIs.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures and damages are modeled with AP4T's counterfactual baseline approach with all prescribed burn emissions. Plotting uses the *ggplot2* R package [103].



Supplementary Fig. 7 | Wildfire smoke exposure vs. themed SVI decile within and between states. Data characterize 2017. Between-state analysis assigns each person their state’s population-weighted average smoke exposure. Within-state analysis compares each person’s tract-level smoke exposure to their state’s population-weighted average smoke exposure. Theme 1’s SVI is for Socioeconomic Status. Theme 2’s SVI is for Household Composition & Disability. Theme 3’s SVI is for Minority Status & Language. Theme 4’s SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs.

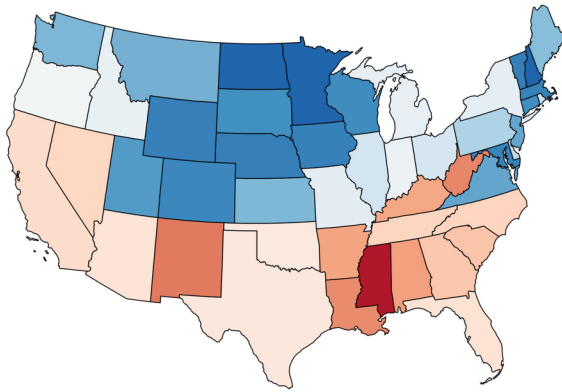
Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures are modeled with AP4T’s counterfactual baseline approach with all wildfire emissions. Plotting uses the *ggplot2* R package [103].



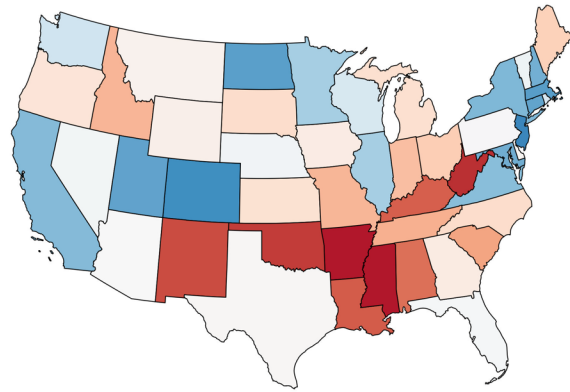
Supplementary Fig. 8 | Prescribed burn smoke exposure vs. themed SVI decile within and between states. Data characterize 2017. Between-state analysis assigns each person their state’s population-weighted average smoke exposure. Within-state analysis compares each person’s tract-level smoke exposure to their state’s population-weighted average smoke exposure. Theme 1’s SVI is for Socioeconomic Status. Theme 2’s SVI is for Household Composition & Disability. Theme 3’s SVI is for Minority Status & Language. Theme 4’s SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures are modeled with AP4T’s counterfactual baseline approach with all prescribed burn emissions. Plotting uses the *ggplot2* R package [103].

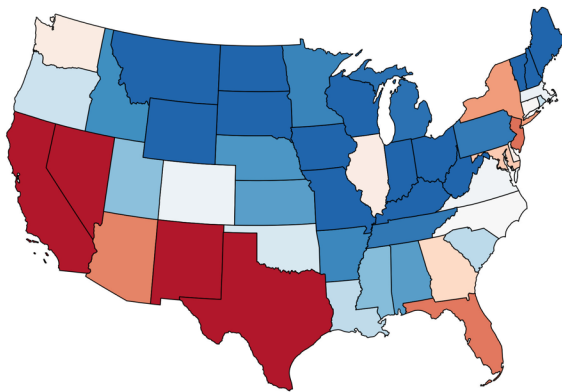
a. Socioeconomic Status



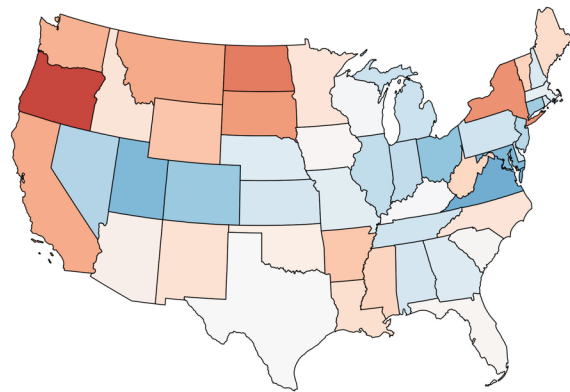
b. Household Composition & Disability



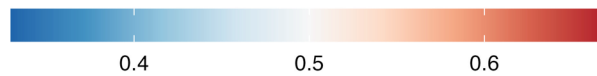
c. Minority Status & Language



d. Housing Type & Transportation

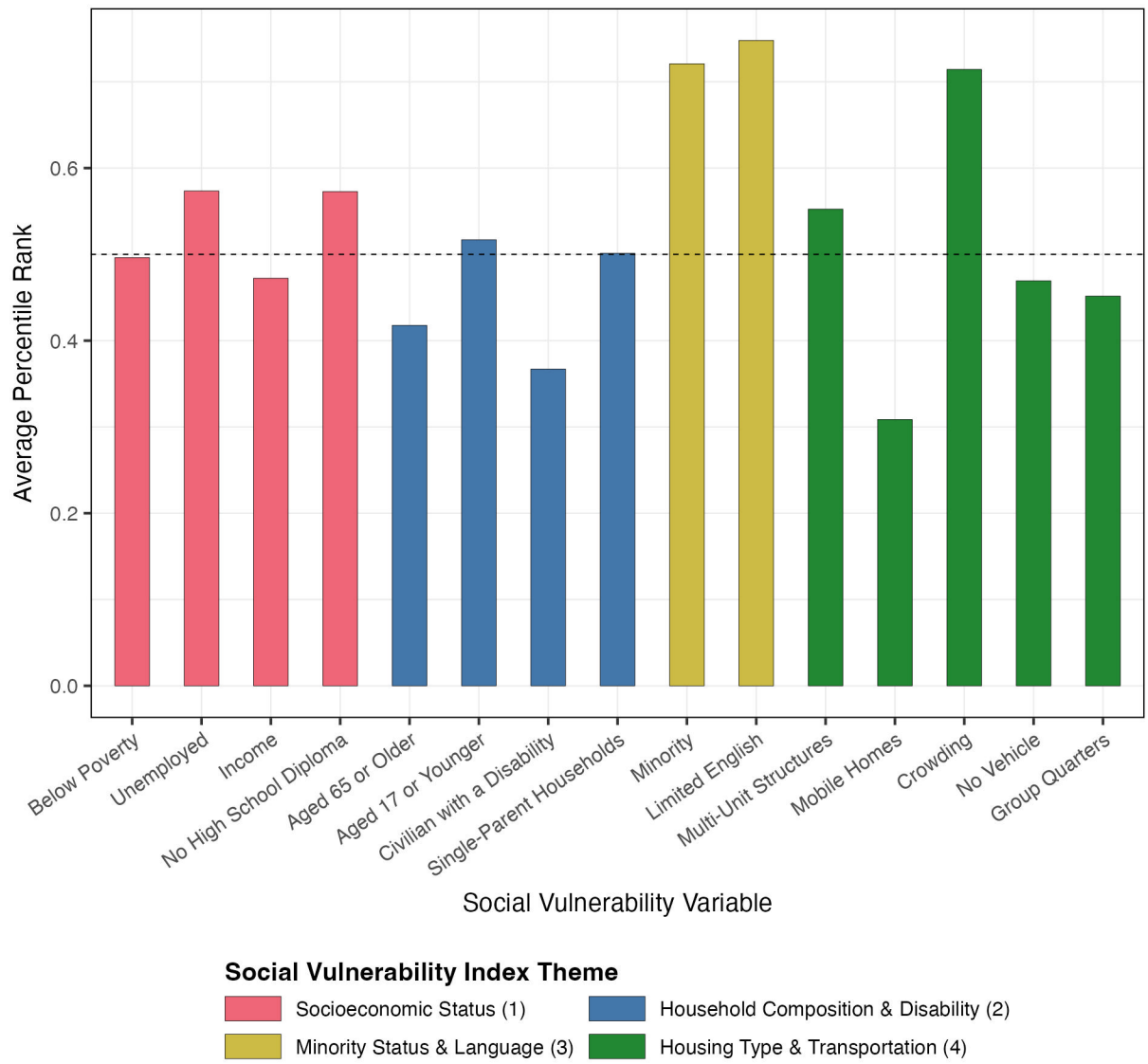


Average Social Vulnerability Index Percentile Rank



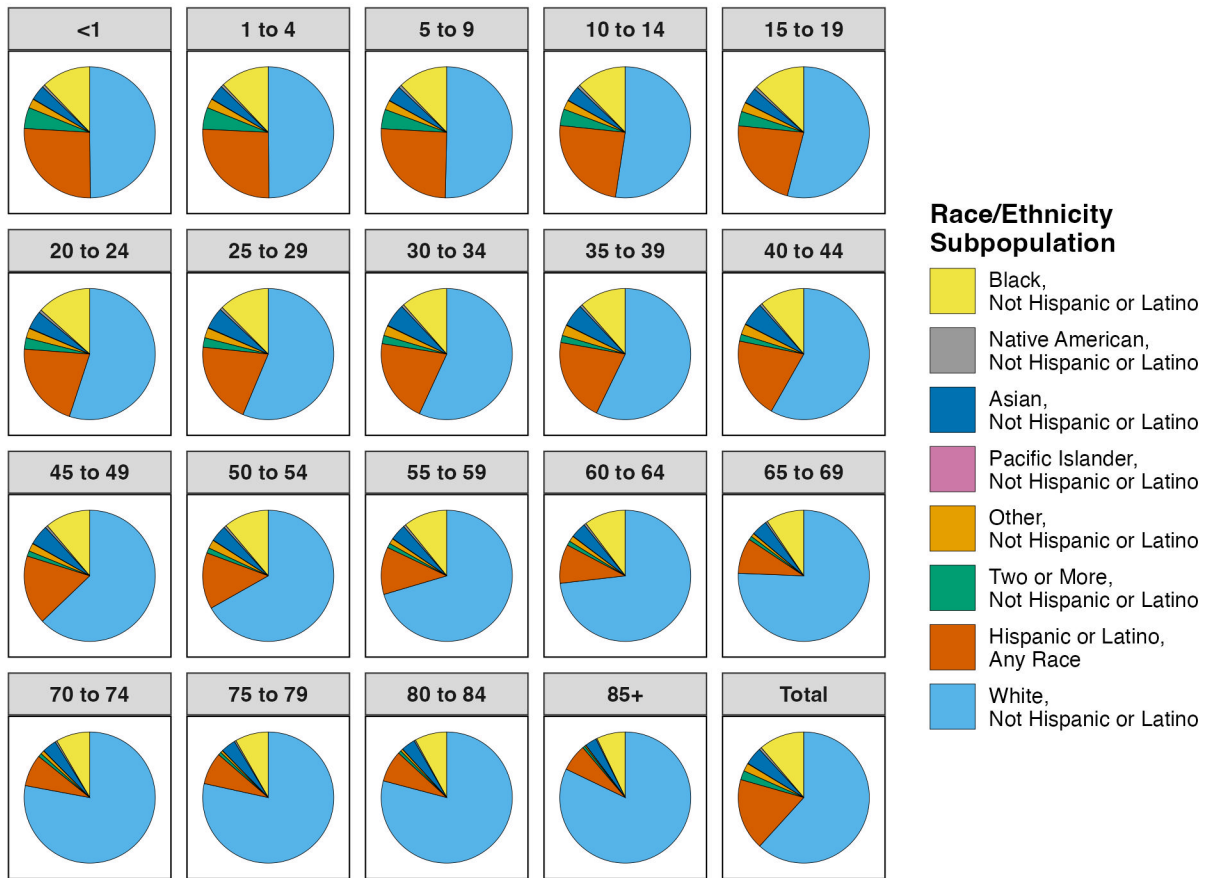
Supplementary Fig. 9 | Population-weighted average themed SVI percentile rank by state. Data characterize 2017. White represents 0.5, median vulnerability. Red represents > 0.5 , more vulnerable on average. Blue represents < 0.5 , less vulnerable on average. Theme 1's SVI is for Socioeconomic Status. Theme 2's SVI is for Household Composition & Disability. Theme 3's SVI is for Minority Status & Language. Theme 4's SVI is for Housing Type & Transportation. See Table 2 of the main document for the SVVs comprising the themed and overall SVIs.

Sources: SVI data are from the CDC [69] based on methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].



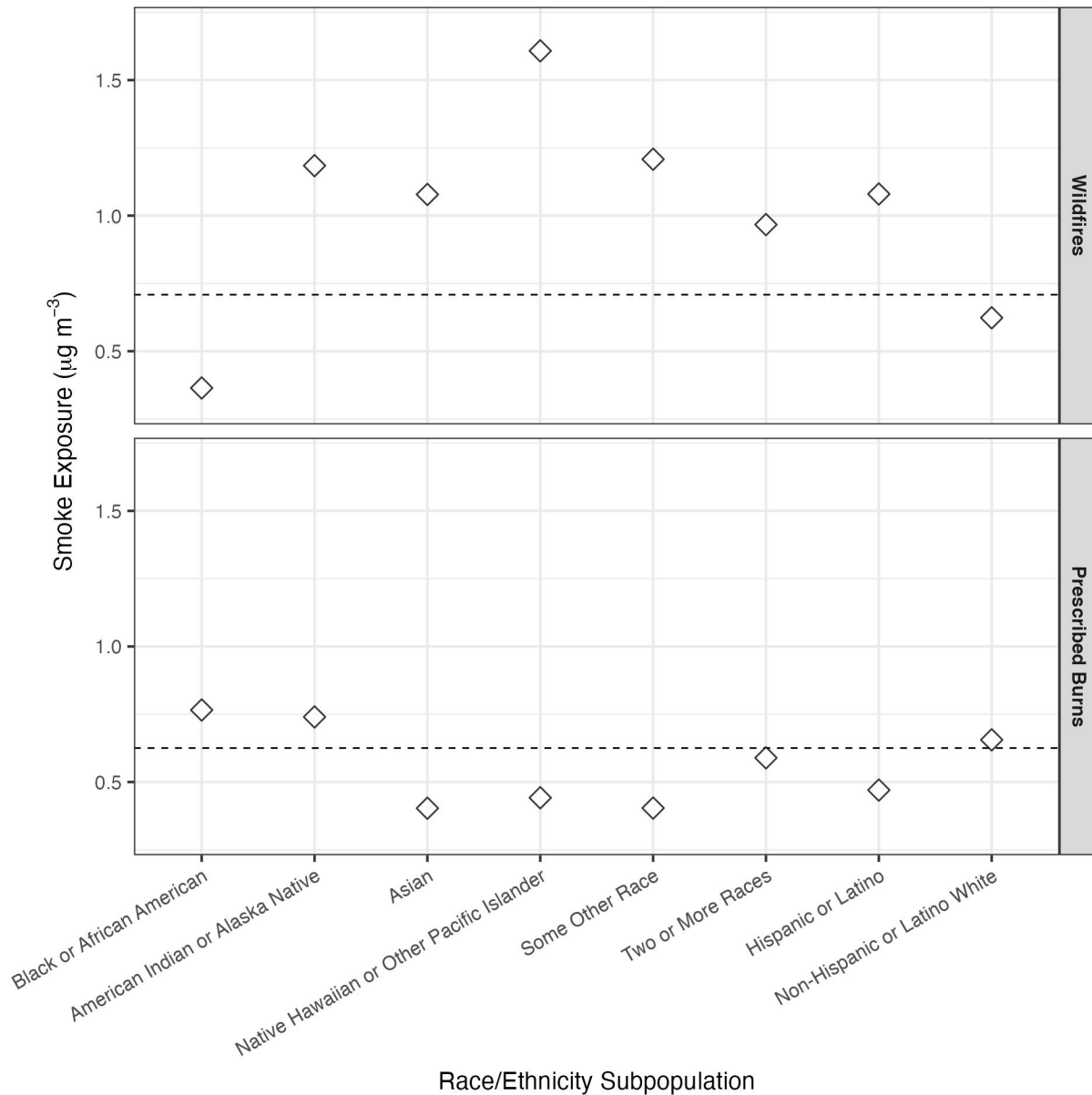
Supplementary Fig. 10 | Population-weighted average SVV percentile ranks in California. Data characterize 2017. SVV bars are colored based on their corresponding SVI theme, as detailed in Table 2 of the main document. The dashed line at 0.5 indicates the median vulnerability.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Plotting uses the *ggplot2* R package [103].



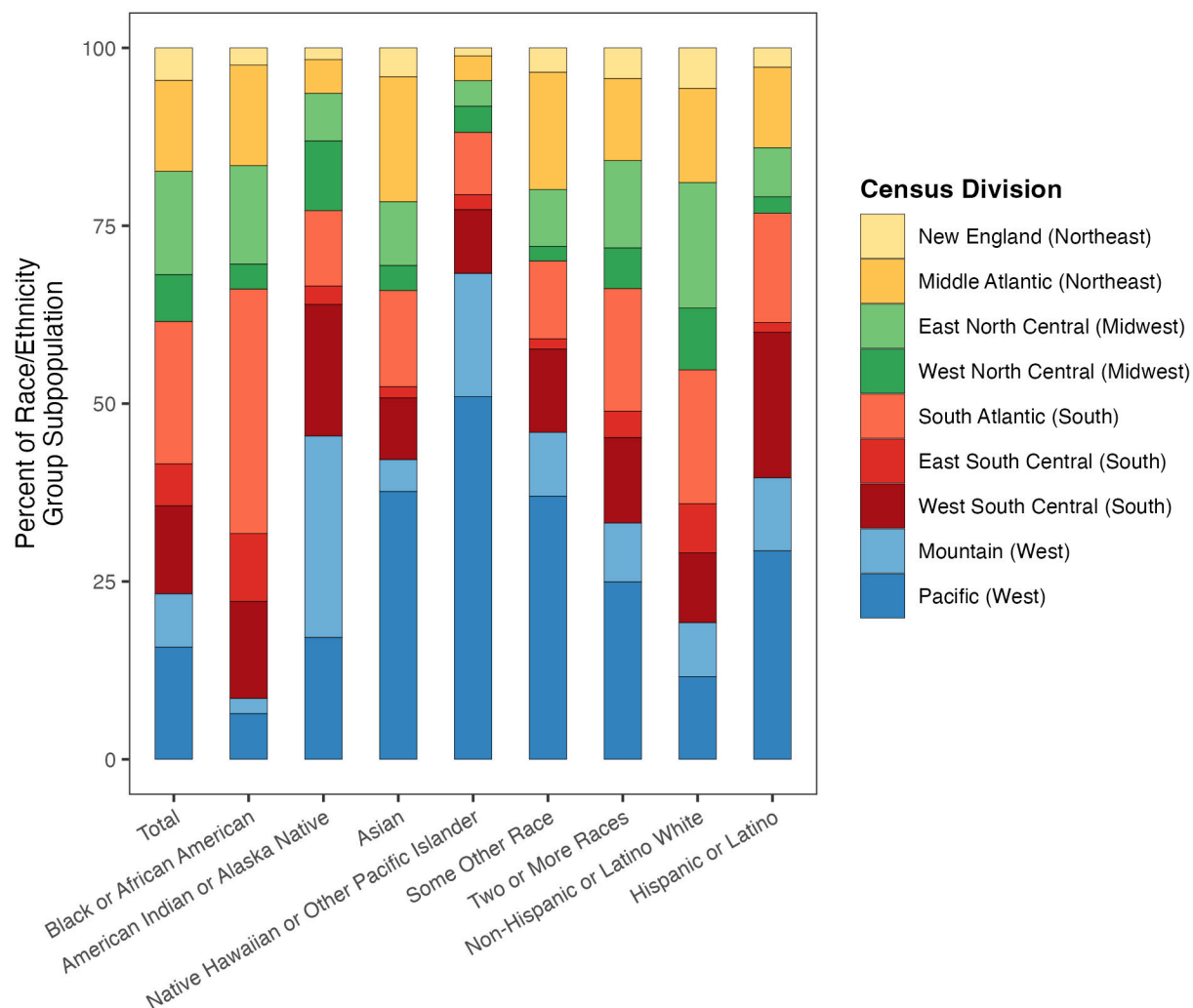
Supplementary Fig. 11 | Age group breakdown by race/ethnicity. Data characterize 2017. Age subgroup population breakdown by race/ethnicity considering totals across CONUS. Race/ethnicity subpopulations are adapted from those defined by the U.S. Census Bureau (see Supplementary Table 30) to be mutually exclusive and collectively exhaustive (see Supplementary Methods 2).

Sources: Population data are from the U.S. Census Bureau [54]. Plotting uses the *ggplot2* R package [103].

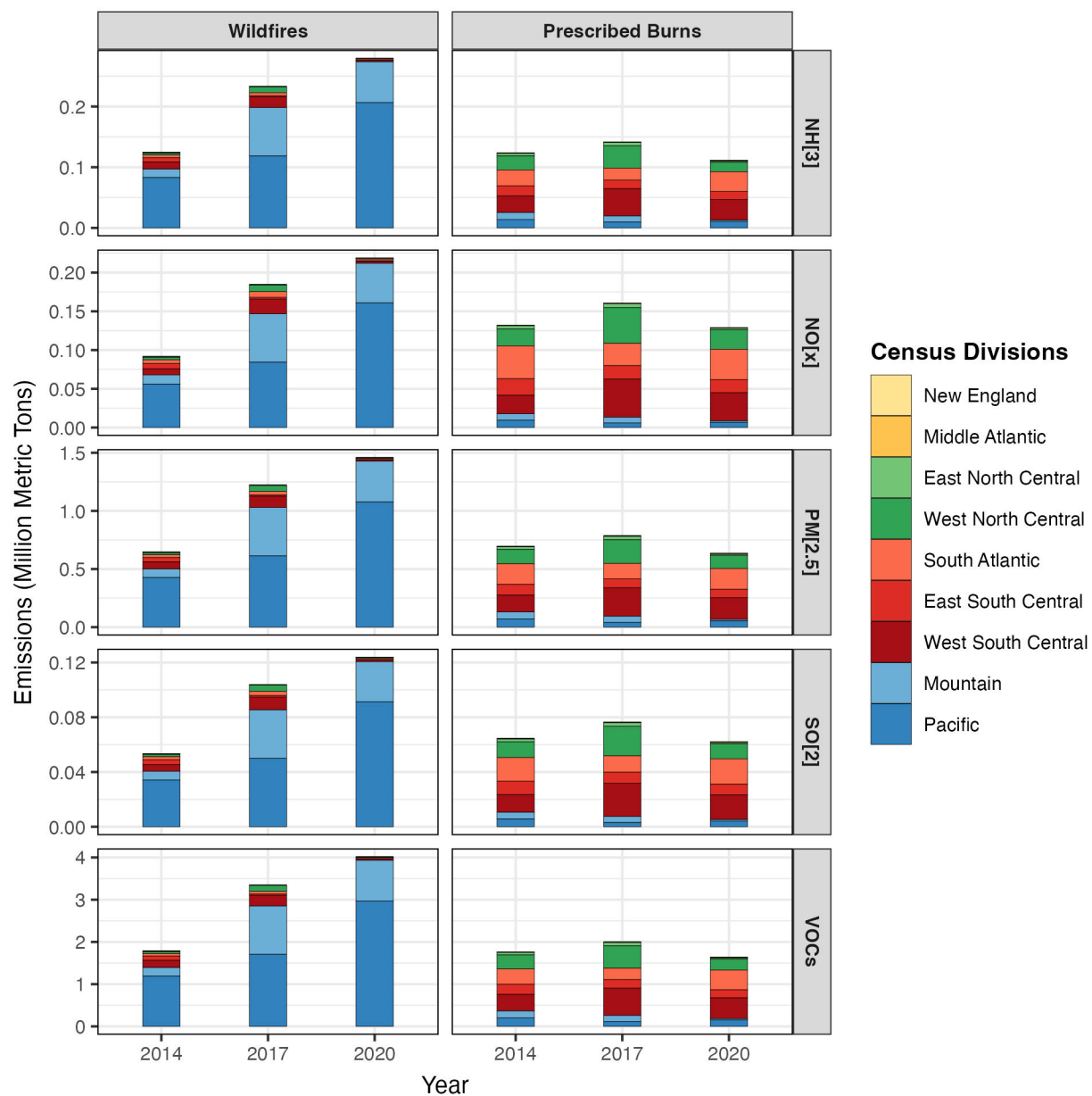


Supplementary Fig. 12 | Fire smoke PM_{2.5} exposures by race/ethnicity. Data characterize 2017. Data are population-weighted average PM_{2.5} exposures from wildfire smoke (top) and prescribed burn smoke (bottom) by race/ethnicity across CONUS. Subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). Subpopulations other than Non-Hispanic White are not mutually exclusive. All racial groups except Non-Hispanic White include persons of Hispanic or Latino ethnicity. Hispanic or Latino ethnicity includes persons of all racial groups. Dashed lines show all-person population-weighted smoke PM_{2.5} exposures for each fire type: 0.708 µg m⁻³ wildfires and 0.625 µg m⁻³ for prescribed burns.

Sources: Population data are from the U.S. Census Bureau [54]. Exposures are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions). Plotting uses the *ggplot2* R package [103].

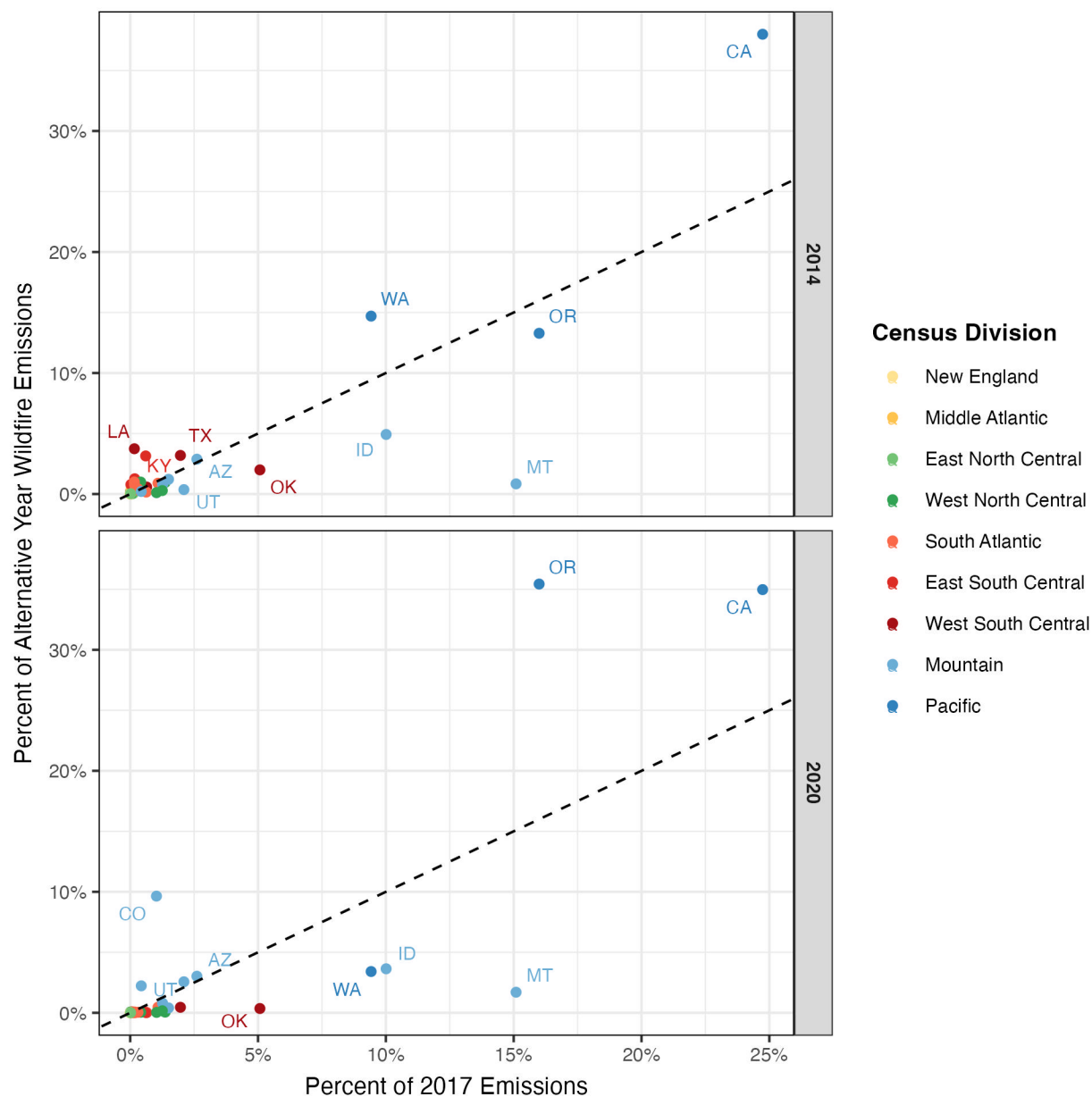


Supplementary Fig. 13 | Race/ethnicity breakdown by census division. Data characterize 2017. Race/ethnicity subpopulations by census division consider totals across CONUS. “Color families” show census regions: yellow is Northeast, green is Midwest, red is South, and blue is West. See Supplementary Note 1 for the states included in each census division and region. Race/ethnicity subpopulations are defined by the U.S. Census Bureau (see Supplementary Table 30). Hispanic or Latino is Hispanic or Latino ethnicity, comprised of any racial group. All racial groups except White include persons of Hispanic or Latino ethnicity—i.e., subgroups other than White are not mutually exclusive. *Sources:* Population data are from the U.S. Census Bureau [54]. Census divisions and regions are defined by the U.S. Census Bureau [78]. Plotting uses the *ggplot2* R package [103].



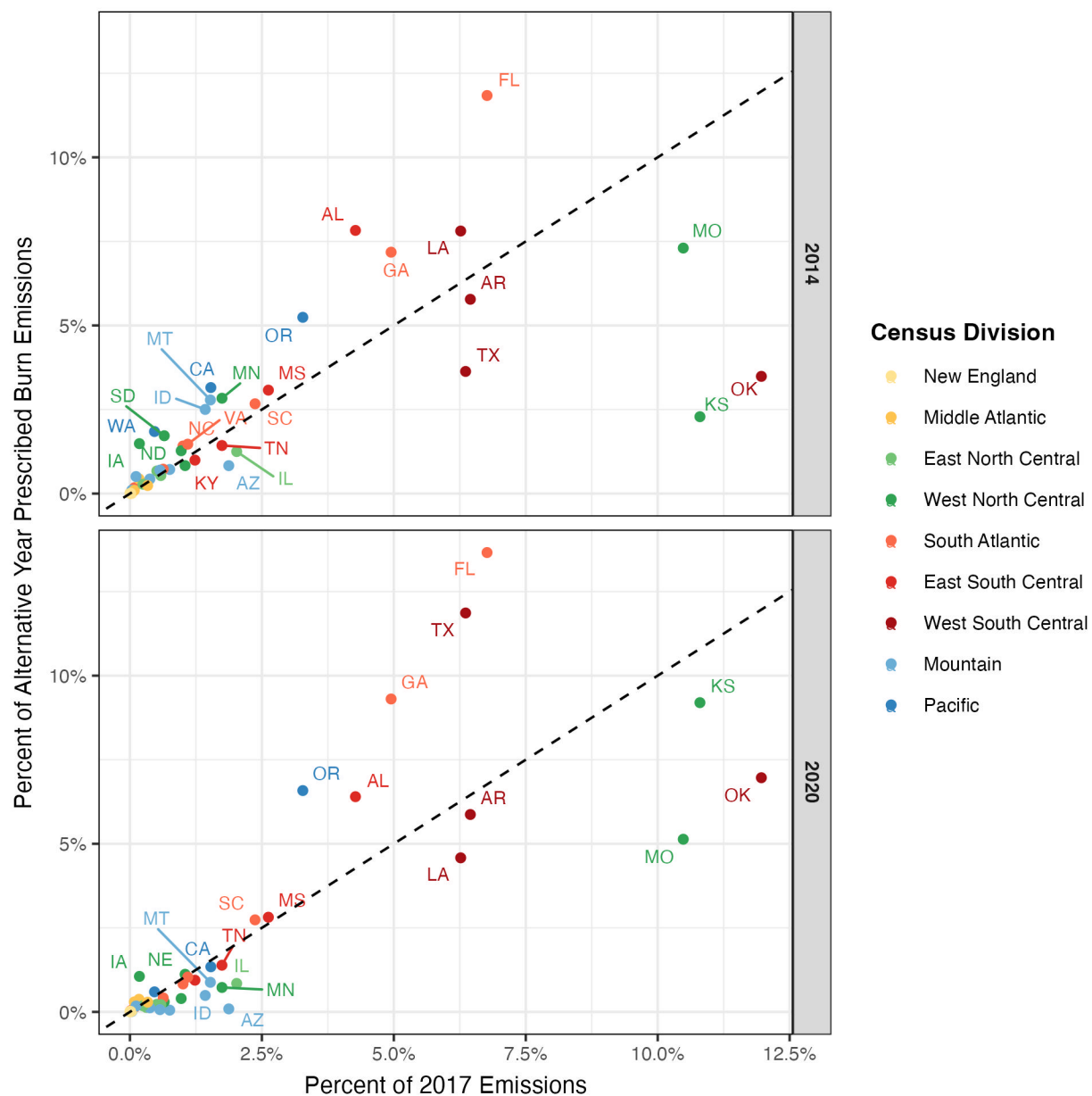
Supplementary Fig. 14 | Emissions from wildfires and prescribed burns in 2014, 2017, and 2020. Emissions are from all wildfires and prescribed burns across the contiguous U.S. “Color families” show census regions: yellow is Northeast, green is Midwest, red is South, and blue is West. See Supplementary Note 1 for the states included in each census division and region.

Sources: Emissions data are from the EPA’s NEI [8], [84], [85]. Plotting uses the *ggplot2* R package [103].



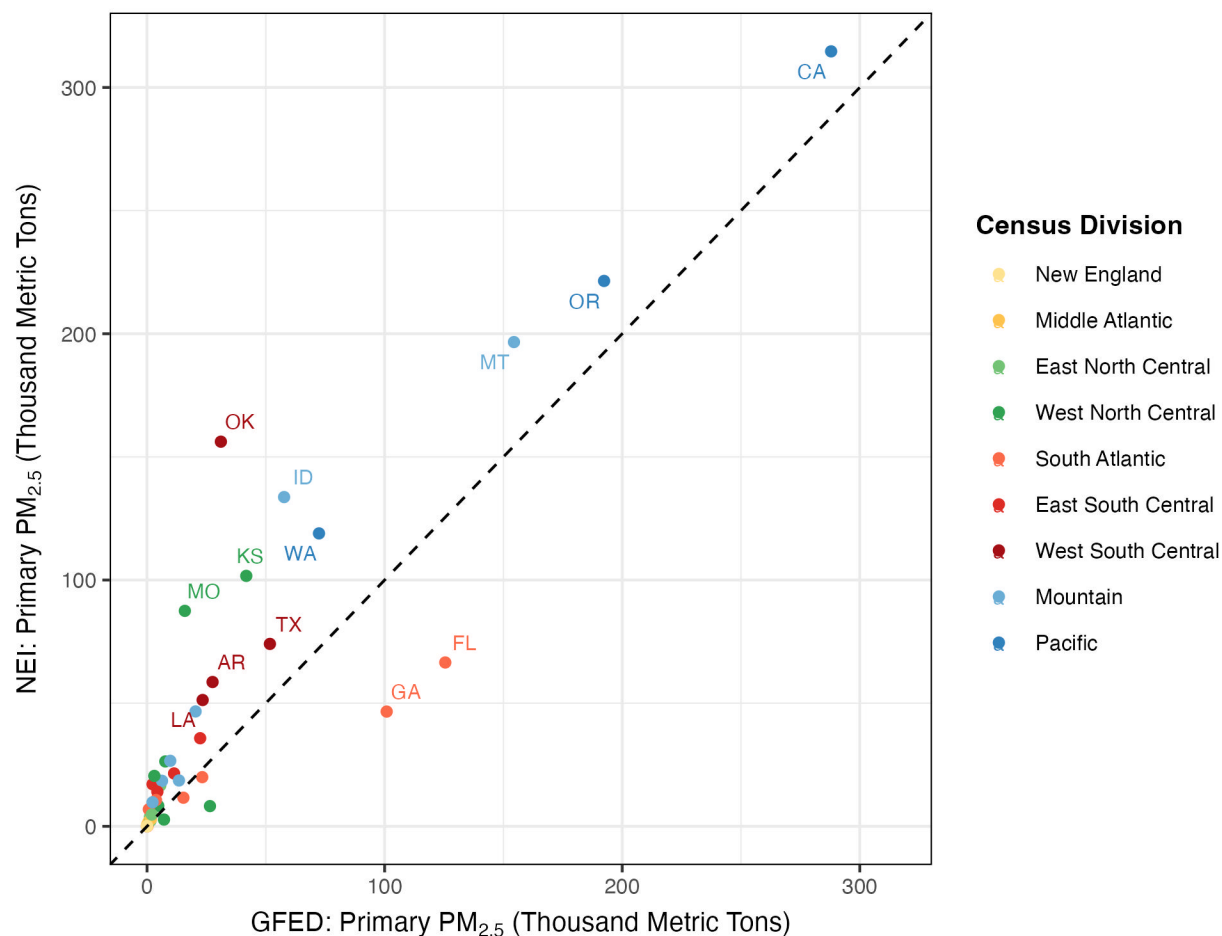
Supplementary Fig. 15 | Wildfire emission percentages by state in 2014 and 2020 compared to 2017. Emissions are from all wildfires across the contiguous U.S. “Color families” show census regions: yellow is Northeast, green is Midwest, red is South, and blue is West. See Supplementary Note 1 for the states included in each census division and region. Points being above the dashed line represents greater shares in the alternative years. Points being below the dashed line represents greater shares in 2017.

Sources: Emissions data are from the EPA’s NEI [8], [84], [85]. Plotting uses the *ggplot2* R package [103].



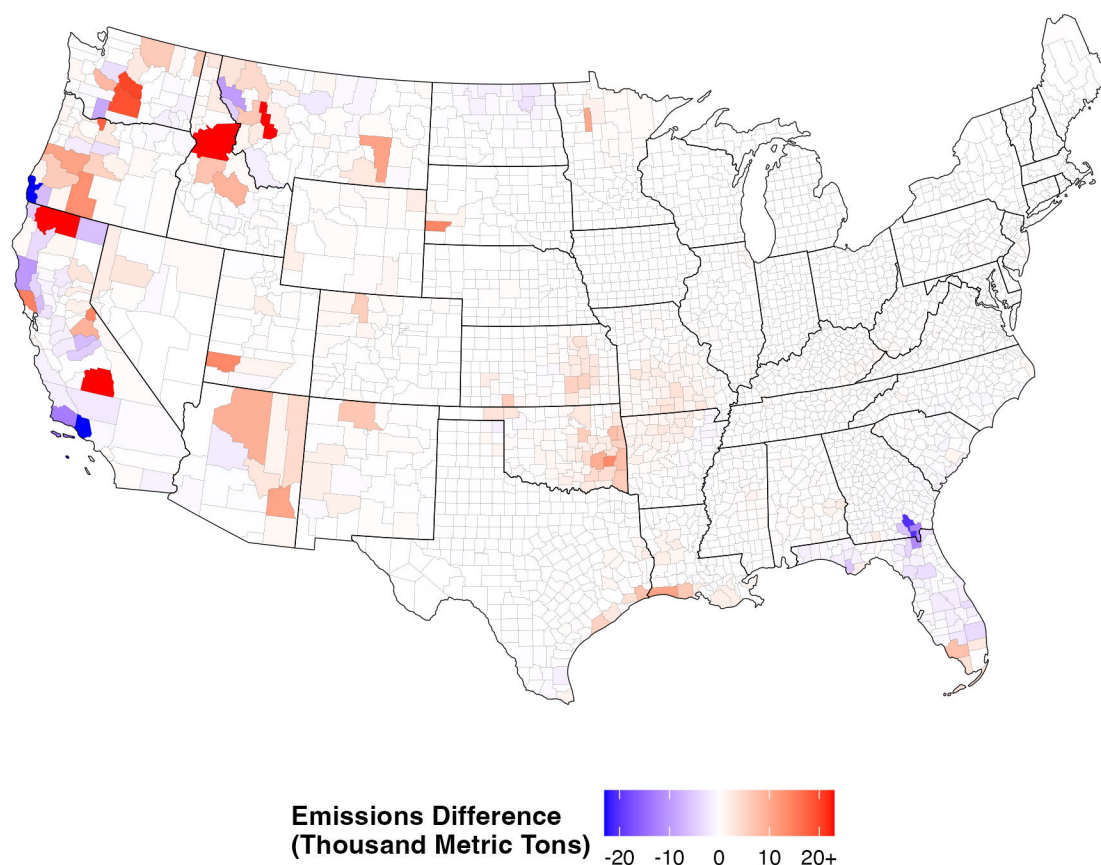
Supplementary Fig. 16 | Prescribed burn emission percentages by state in 2014 and 2020 compared to 2017. Emissions are from all prescribed burns across the contiguous U.S. “Color families” show census regions: yellow is Northeast, green is Midwest, red is South, and blue is West. See Supplementary Note 1 for the states included in each census division and region. Points being above the dashed line represents greater shares in the alternative years. Points being below the dashed line represents greater shares in 2017.

Sources: Emissions data are from the EPA’s NEI [8], [84], [85]. Plotting uses the *ggplot2* R package [103].



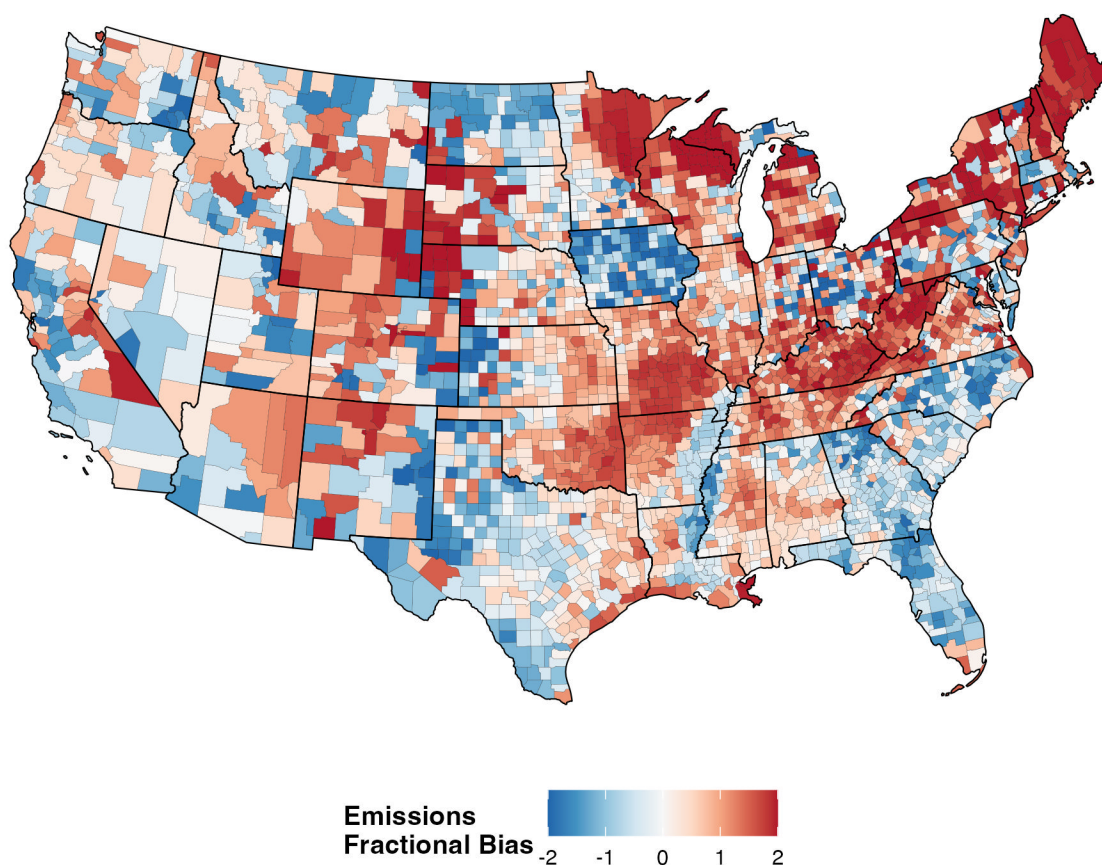
Supplementary Fig. 17 | Fire primary $PM_{2.5}$ emissions by state: National Emission Inventory vs. Global Fire Emissions Database. Data characterize 2017. NEI primary $PM_{2.5}$ emissions are from all wildfires and prescribed burns across the contiguous U.S. “Color families” show census regions: yellow is Northeast, green is Midwest, red is South, and blue is West. See Supplementary Note 1 for the states included in each census division and region. States with primary $PM_{2.5}$ emissions greater than 50 thousand metric tons in either dataset are labeled. States above the line are overestimated by the NEI as compared to the GFED. States below the line are underestimated by the NEI as compared to the GFED.

Sources: Emissions data are from the EPA’s NEI [8] and the GFED [86], [87], [88]. Plotting uses the *ggplot2* R package [103].



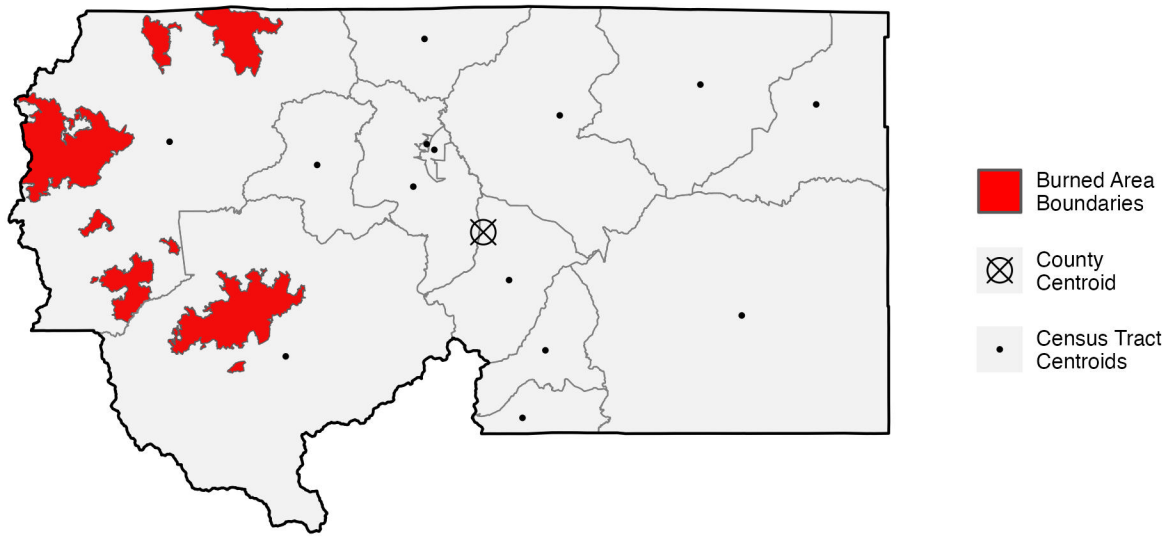
Supplementary Fig. 18 | Fire primary PM_{2.5} emissions differences by county: National Emission Inventory vs. Global Fire Emissions Database. Data characterize 2017. NEI primary PM_{2.5} emissions are from all wildfires and prescribed burns across the contiguous U.S. Red counties are overestimated by the NEI as compared to the GFED. Blue counties are underestimated by the NEI as compared to the GFED. Counties with a primary PM_{2.5} emission difference of more than 20 thousand metric tons ($n = 8$) are assigned the darkest colors.

Sources: Emissions data are from the EPA's NEI [8] and the GFED [86], [87], [88]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].



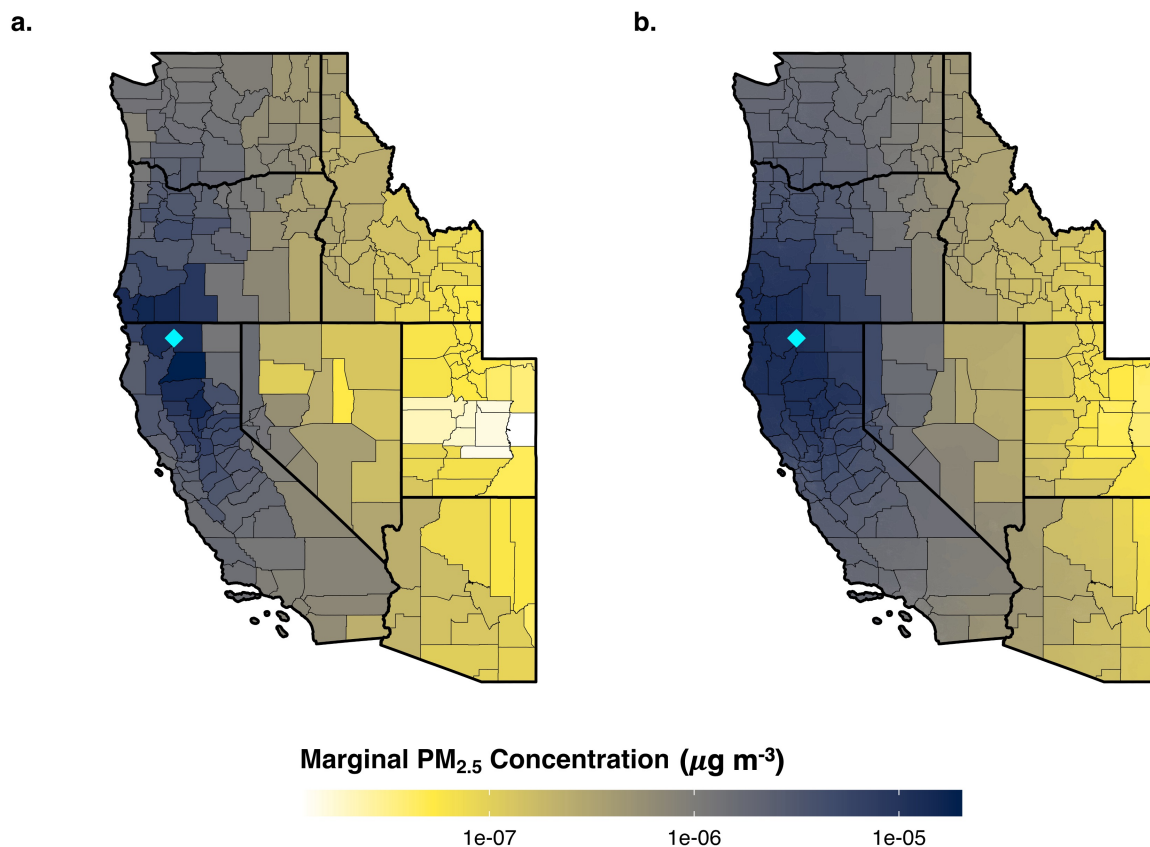
Supplementary Fig. 19 | Fire primary PM_{2.5} emissions relative differences by county: National Emission Inventory vs. Global Fire Emissions Database. Data characterize 2017. Relative differences employ fractional biases. NEI primary PM_{2.5} emissions are from all wildfires and prescribed burns across the contiguous U.S. Red counties are overestimated by the NEI as compared to the GFED. Blue counties are underestimated by the NEI as compared to the GFED.

Sources: Emissions data are from the EPA's NEI [8] and the GFED [86], [87], [88]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].



Supplementary Fig. 20 | Burned area boundaries for county-to-tract fire emissions attribution in Siskiyou County, California. Data characterize 2017. Map shows burned area boundaries in Siskiyou County, California [18]. County-level primary $PM_{2.5}$ and VOC emissions from fires, provided by the NEI [8], are distributed to the tract level by percentage of the county's aggregate burned area in each tract. Fire primary $PM_{2.5}$ and VOC emissions are then modeled from the census tracts' geometric centroids (points). All fire primary $PM_{2.5}$ and VOC emissions for Siskiyou County, California, are attributed to and modeled from its two westernmost tracts. The circled cross is the county's population-weighted centroid.

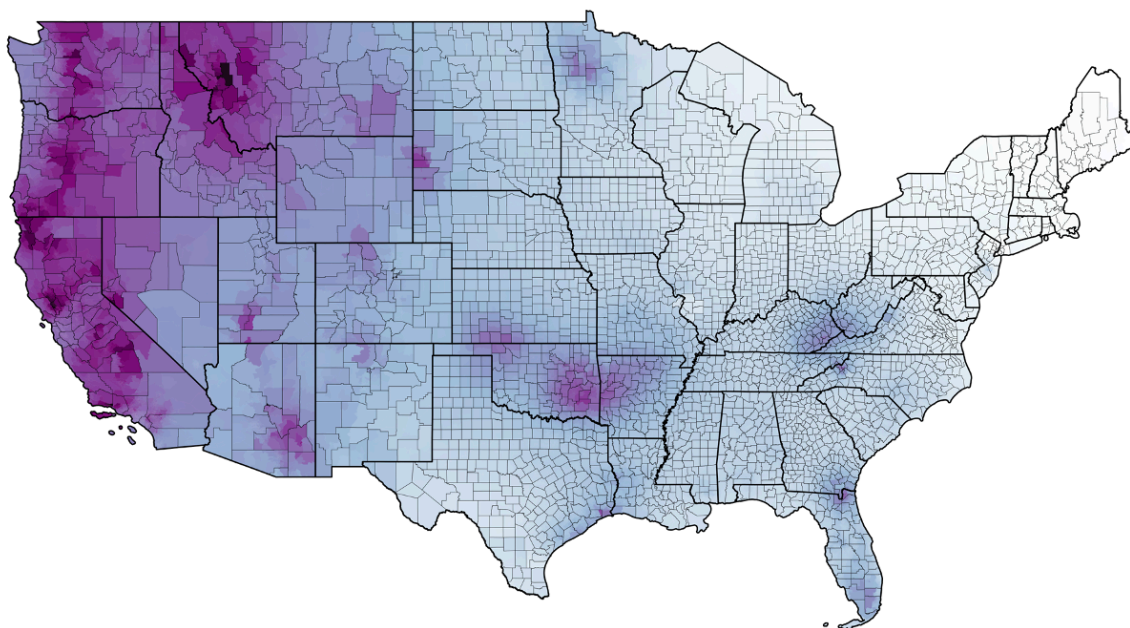
Sources: MTBS [18] and U.S. Census Bureau [14]. Mapping uses the *rgdal* R package [102]. Plotting uses the *ggplot2* R package [103].



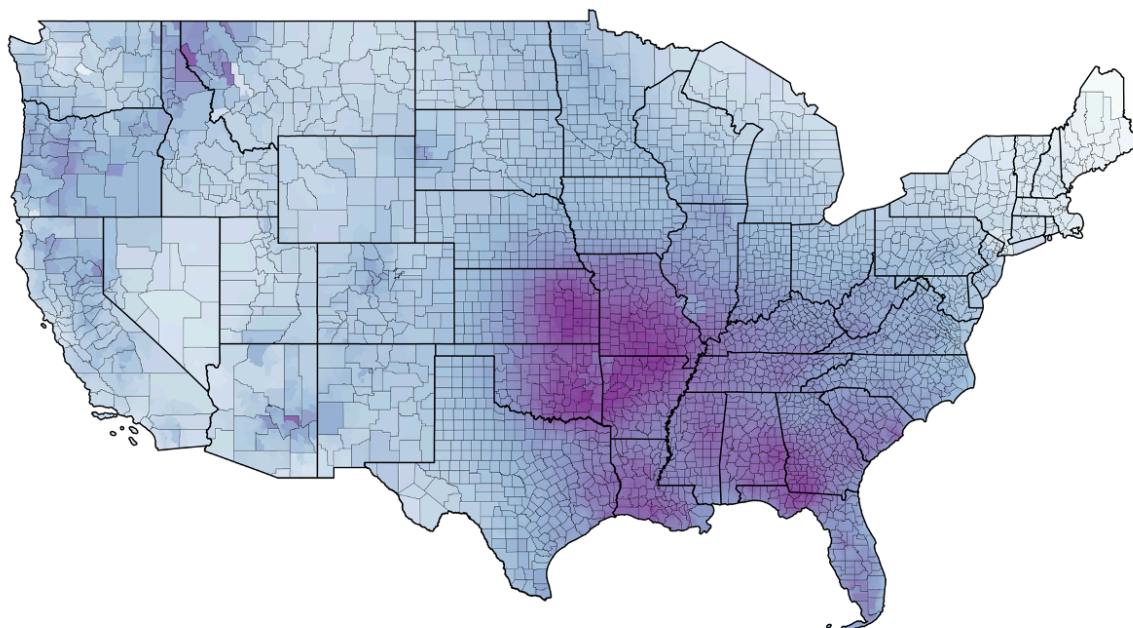
Supplementary Fig. 21 | Marginal concentrations of ambient PM_{2.5} from primary PM_{2.5} emissions released from non-EGU facilities in Siskiyou County, California, in downwind receptor counties and tracts in select western states. Data characterize 2017. Maps show marginal concentrations of ambient PM_{2.5} in receptor counties (a) and census tracts (b) from one metric ton of primary PM_{2.5} emissions released from a hypothetical non-EGU facility in Siskiyou County, California. Receptor counties (a) and census tracts (b) are those throughout California, Oregon, Nevada, Washington, Arizona, Idaho, and Utah. Marginal concentrations are in $\mu\text{g m}^{-3}$ and shown via a log-transformed color scale. (a) is modeled in AP4. (b) is interpolated using information from AP4 and according to Supplementary Equation 6. The blue diamond is the source location, the population-weighted county centroid.

Sources: Mapping uses the *rgdal* R package [102]. Plotting uses the *ggplot2* R package [103].

a.



b.

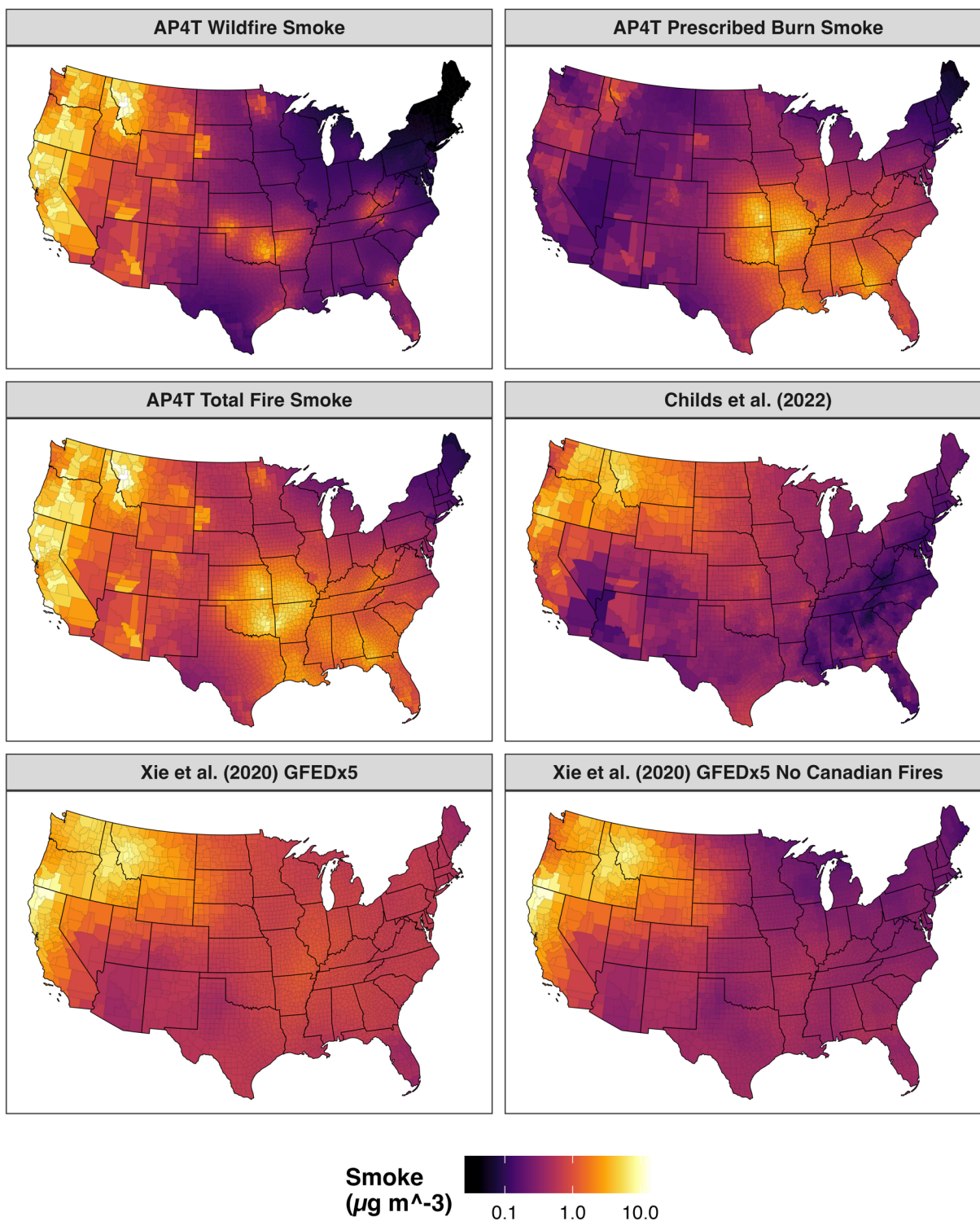


Smoke PM_{2.5} (µg m⁻³)

0.1 1.0 10.0

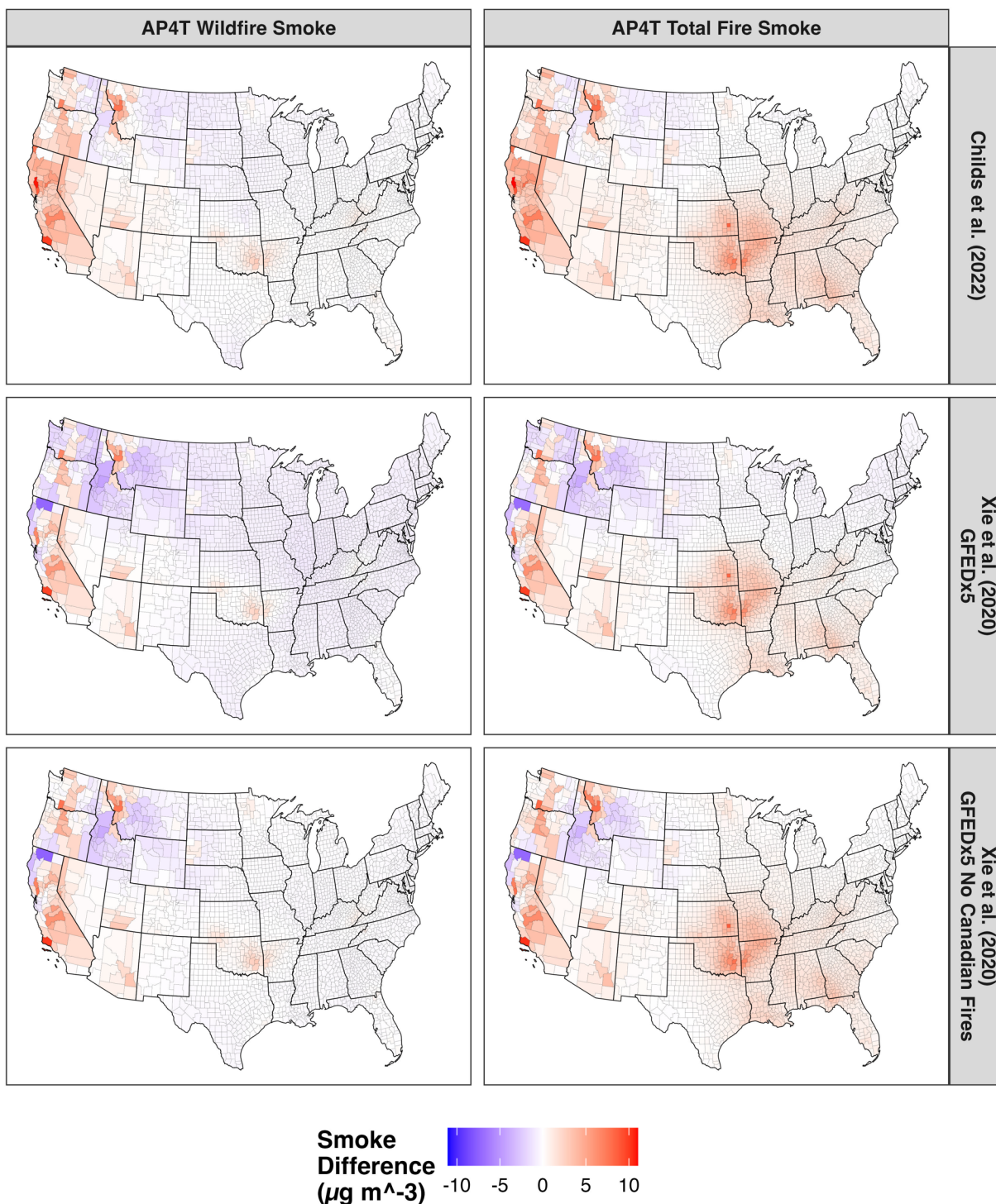
Supplementary Fig. 22 | Smoke PM_{2.5} received from wildfires and prescribed burns modeled in AP4T. Data characterize 2017. Map shows annual average ambient PM_{2.5} concentrations from wildfire (a) and prescribed burn (b) emissions. Scale is transformed via logarithm base 10.

Sources: Concentrations are modeled with AP4T's counterfactual baseline approach by fire type (e.g., all wildfire emissions). Mapping uses the *rgdal* R package [102]. Plotting uses the *ggplot2* R package [103].



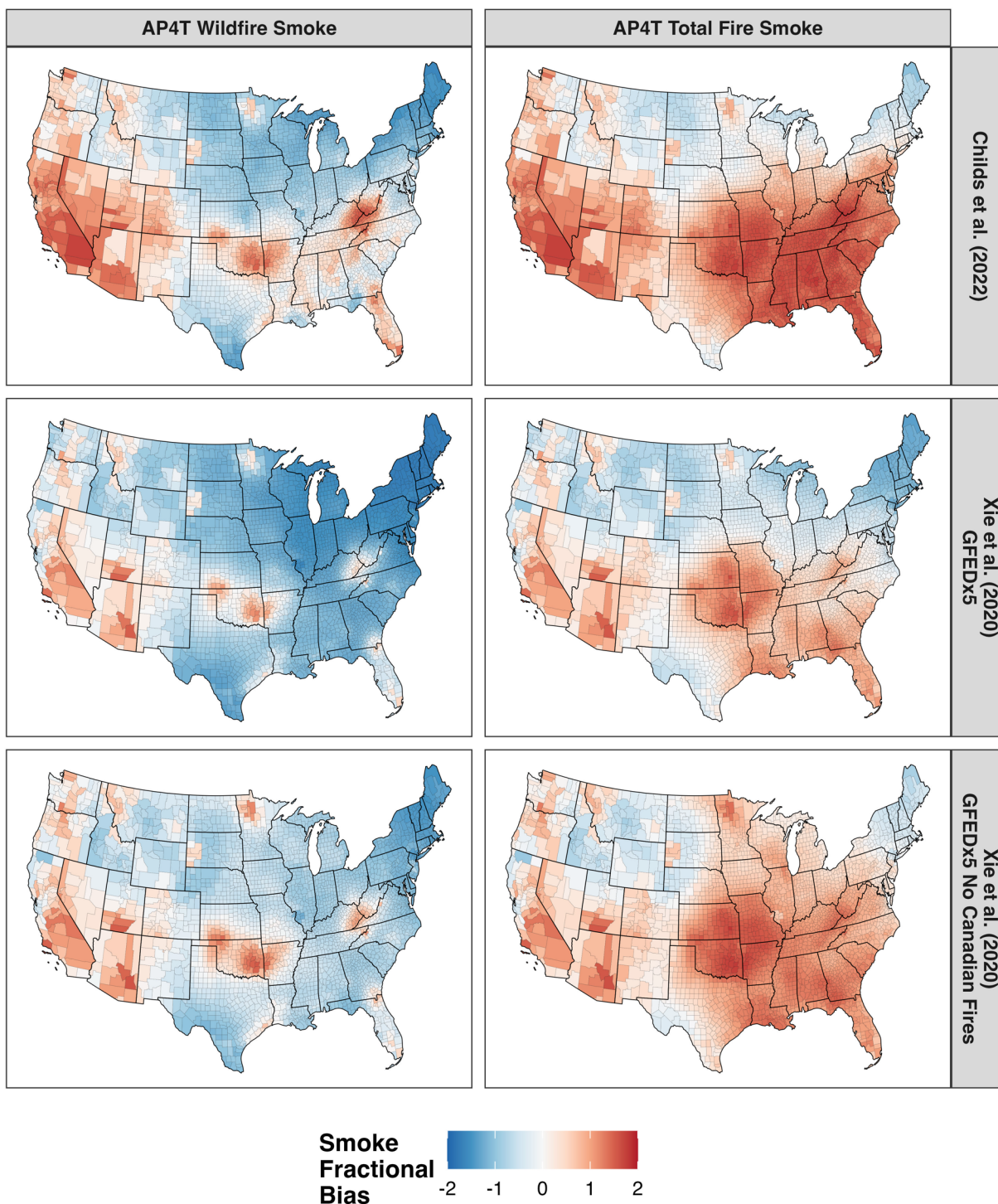
Supplementary Fig. 23 | Fire smoke by county: AP4T, Childs et al., and Xie et al. Data represent 2017. County-level estimates are computed using population-weighted averages across tract-level observations. Scale is transformed via logarithm base 10.

Sources: Smoke $\text{PM}_{2.5}$ estimates for comparison are from Xie et al. (2020) [83], [94] and Childs et al. (2022) [82], [95]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].



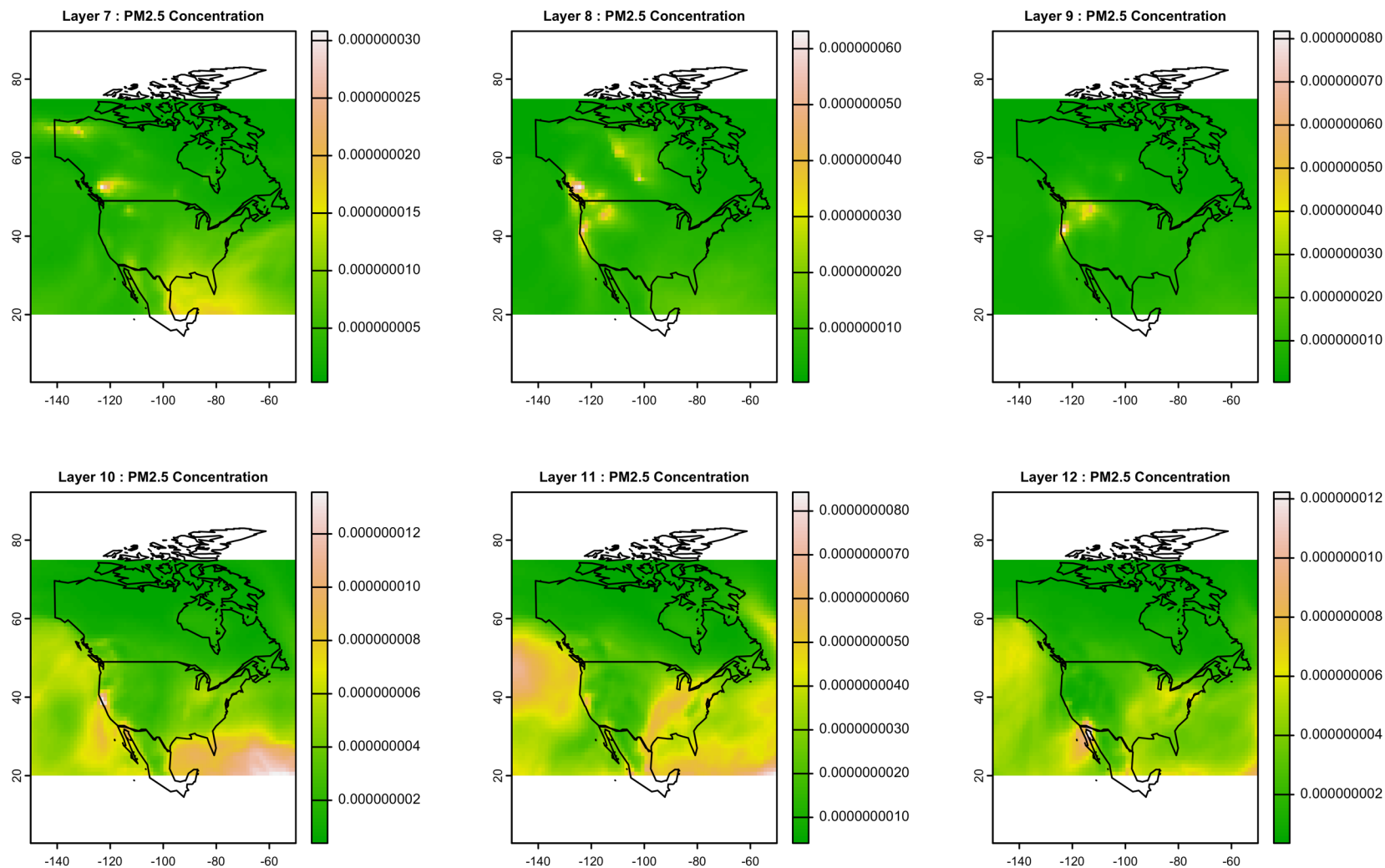
Supplementary Fig. 24 | Fire smoke differences by county: AP4T vs. Childs et al. and Xie et al. Data represent 2017. County-level estimates are computed using population-weighted averages across tract-level observations. Red counties are overestimated by AP4T versus the comparison studies. Blue counties are underestimated by AP4T versus the comparison studies.

Sources: Smoke $\text{PM}_{2.5}$ estimates for comparison are from Xie et al. (2020) [83], [94] and Childs et al. (2022) [82], [95]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].



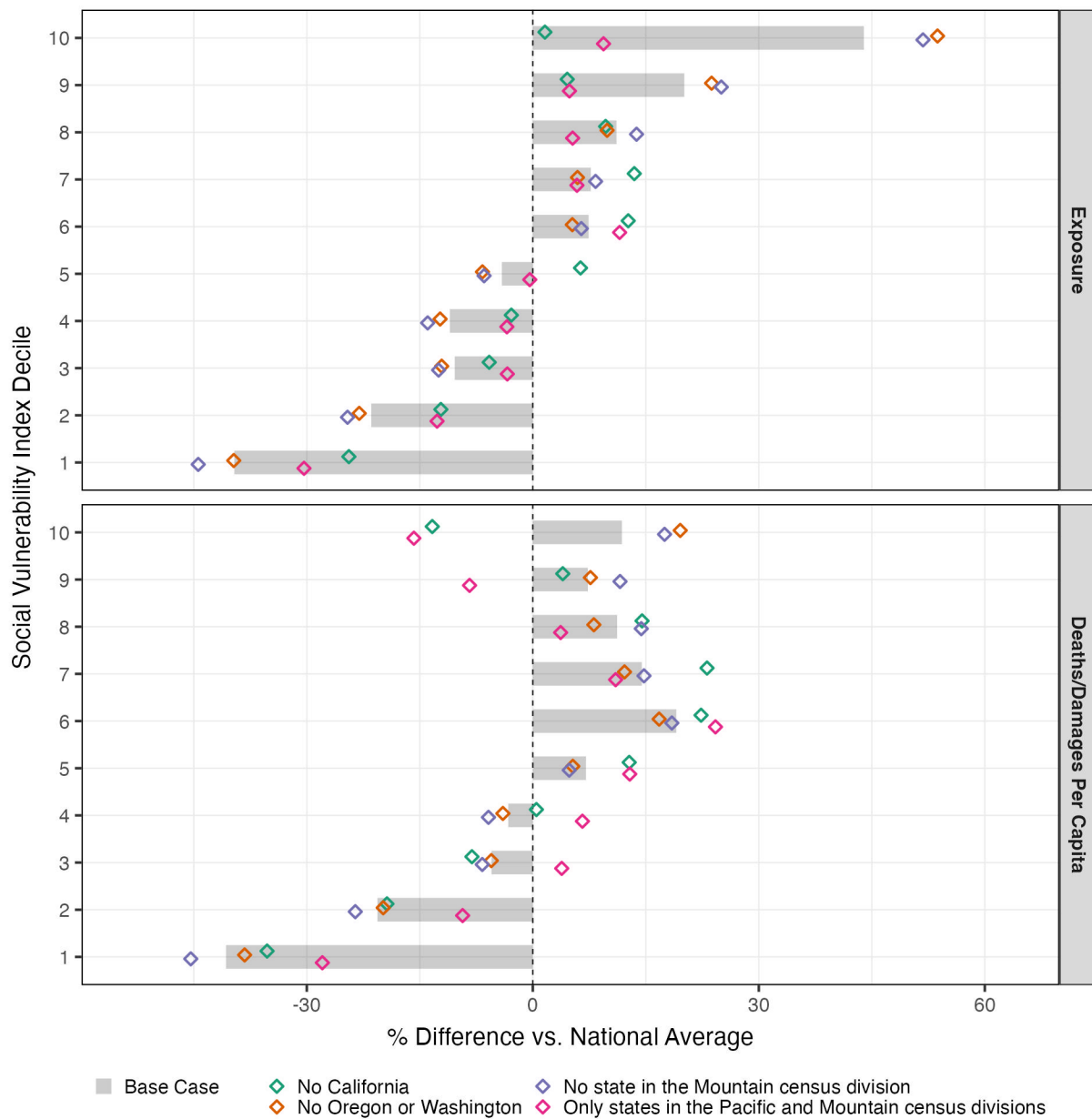
Supplementary Fig. 25 | Fire smoke relative differences by county: AP4T vs. Childs et al. and Xie et al. Data represent 2017. County-level estimates are computed using population-weighted averages across tract-level observations. Relative differences employ fractional biases. Red counties are overestimated by AP4T versus the comparison studies. Blue counties are underestimated by AP4T versus the comparison studies.

Sources: Smoke PM_{2.5} estimates for comparison are from Xie et al. (2020) [83], [94] and Childs et al. (2022) [82], [95]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].



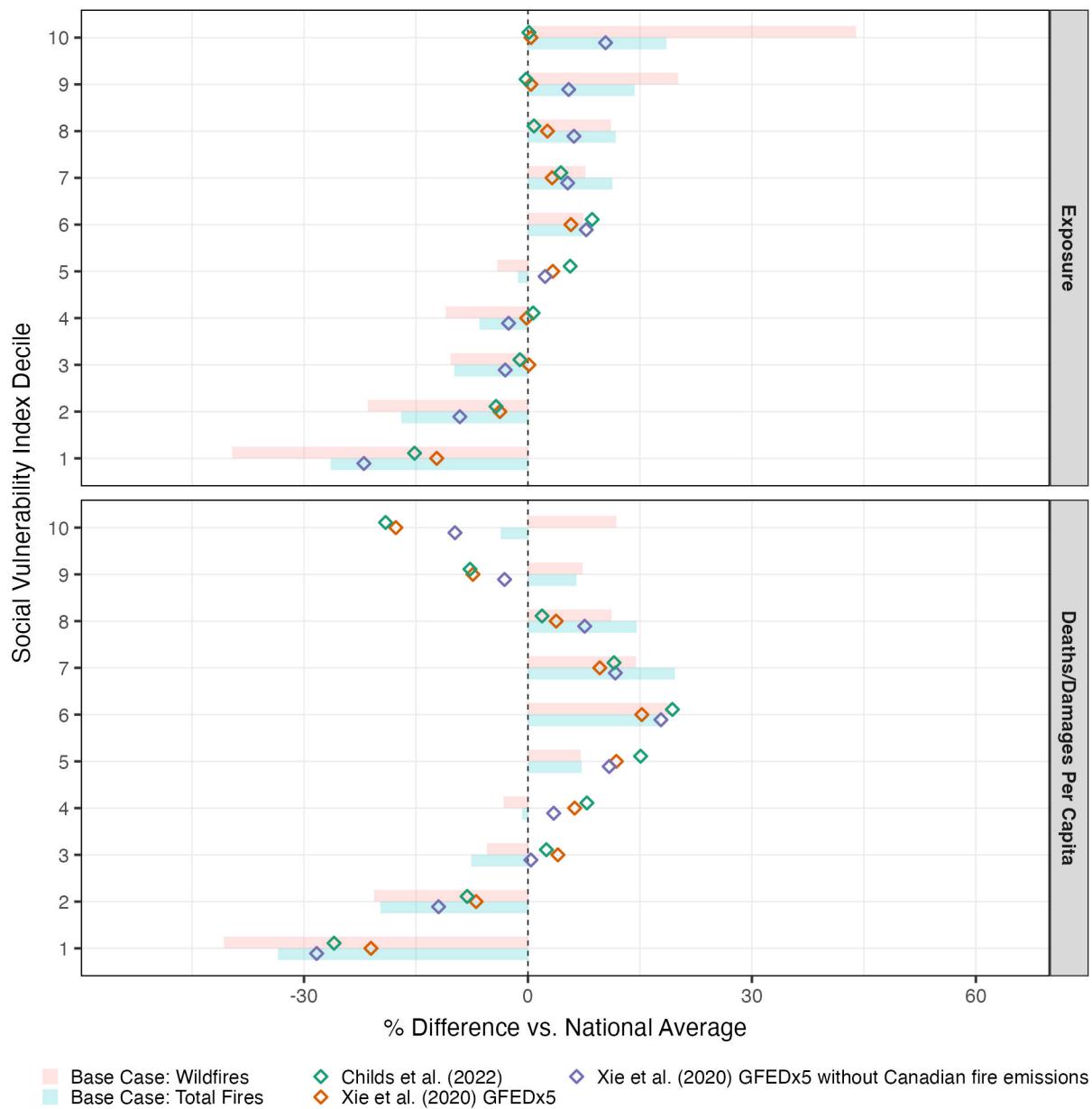
Supplementary Fig. 26 | PM_{2.5} mixing ratios by month from Xie et al.'s GFEDx5 experiment. Data represent 2017. Data are mixing ratios of PM_{2.5} (smoke plus baseline). Months depicted are July (7), August (8), September (9), October (10), November (11), and December (12).

Sources: Xie et al. (2020) [83], [94]. Plotting uses base R.



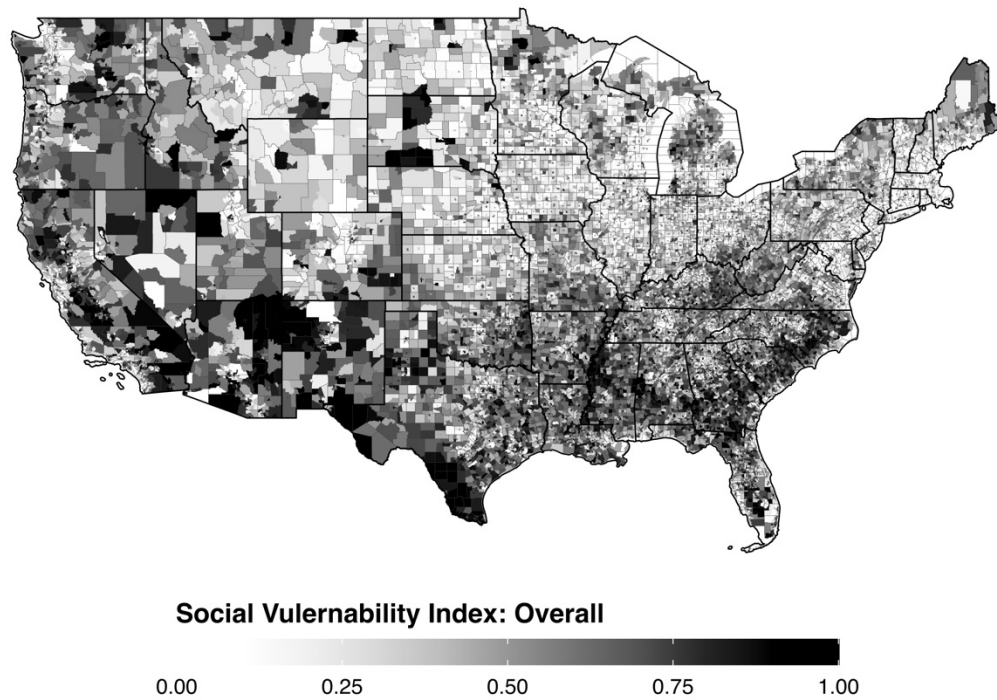
Supplementary Fig. 27 | Sensitivity analysis of exposures and damages from wildfire smoke by SVI decile: Withholding states experiments. Data characterize 2017. Data show percentage differences between population-weighted average exposure (top) and deaths/damages per capita (bottom) for census tracts in overall SVI deciles versus all census tracts. Gray bars consider all census tracts nationally. Green points consider all census tracts except those in California. Orange points consider all census tracts except those in Oregon and Washington. Purple points consider all census tracts except those in the Mountain census division: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. Pink points only consider census tracts in the Pacific and Mountain census divisions. The Pacific census division includes California, Oregon, and Washington.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Exposures and damages are modeled with AP4T's counterfactual baseline approach with wildfire emissions. Plotting uses the *ggplot2* R package [103].



Supplementary Fig. 28 | Sensitivity analysis of exposures and damages from wildfire smoke and total fire smoke by SVI decile: Alternative smoke $PM_{2.5}$ estimates experiments. Data characterize 2017. Data show percentage differences between population-weighted average exposure (top) and deaths/damages per capita (bottom) for census tracts in overall SVI deciles versus all census tracts. Red bars consider wildfire smoke impacts. Green bars consider total fire smoke impacts. Green points use smoke $PM_{2.5}$ data from Childs et al. [82]. Orange points use smoke $PM_{2.5}$ data from Xie et al.'s GFEDx5 experiment [83]. Purple points use smoke $PM_{2.5}$ data from Xie et al.'s GFEDx5 without Canadian fire emissions experiment [83].

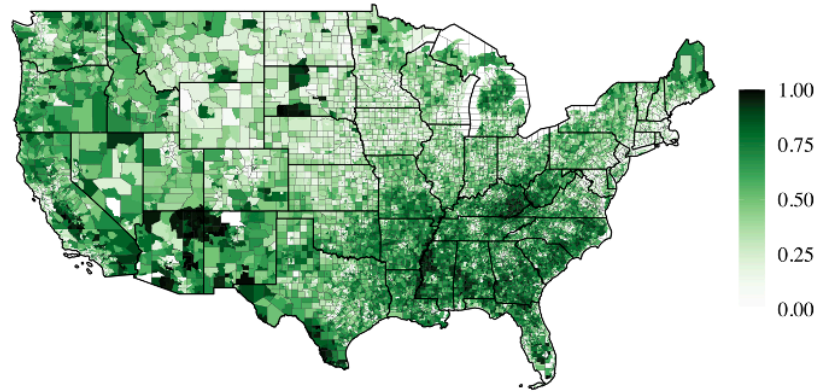
Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Base case exposures and damages are modeled with AP4T's counterfactual baseline approach with wildfire and total fire emissions. Smoke $PM_{2.5}$ estimates for sensitivity analysis are from Xie et al. (2020) [83], [94] and Childs et al. (2022) [82], [95]. Plotting uses the *ggplot2* R package [103].



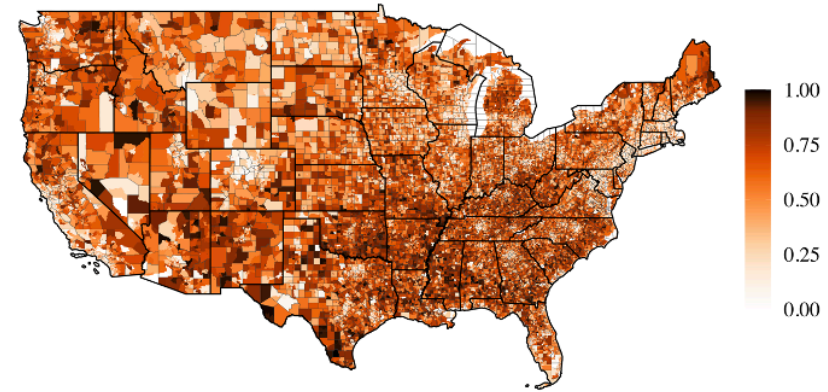
Supplementary Fig. 29 | Overall SVI percentile rank by tract. Data characterize 2017. Black is more vulnerable. White is less vulnerable. The overall SVI is determined using 15 SVVs under four themes (see Table 2 of the main document), where each variable contributes equal weight to the overall SVI percentile rank.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Mapping uses the *rgdal* R package [102]. Plotting uses the *ggplot2* R package [103].

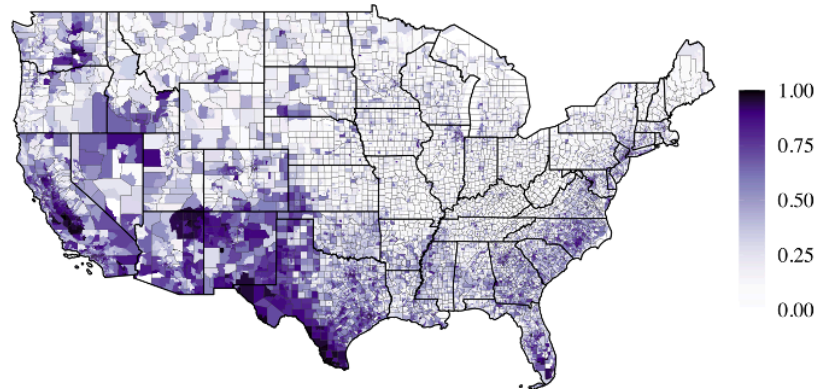
a. Socioeconomic Status



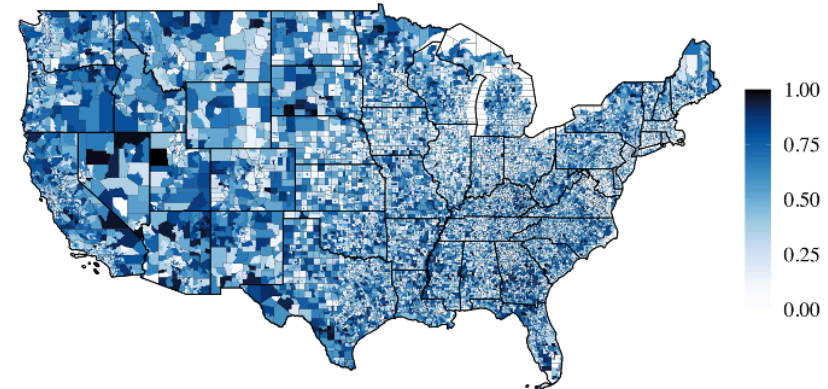
b. Household Composition & Disability



c. Minority Status & Language

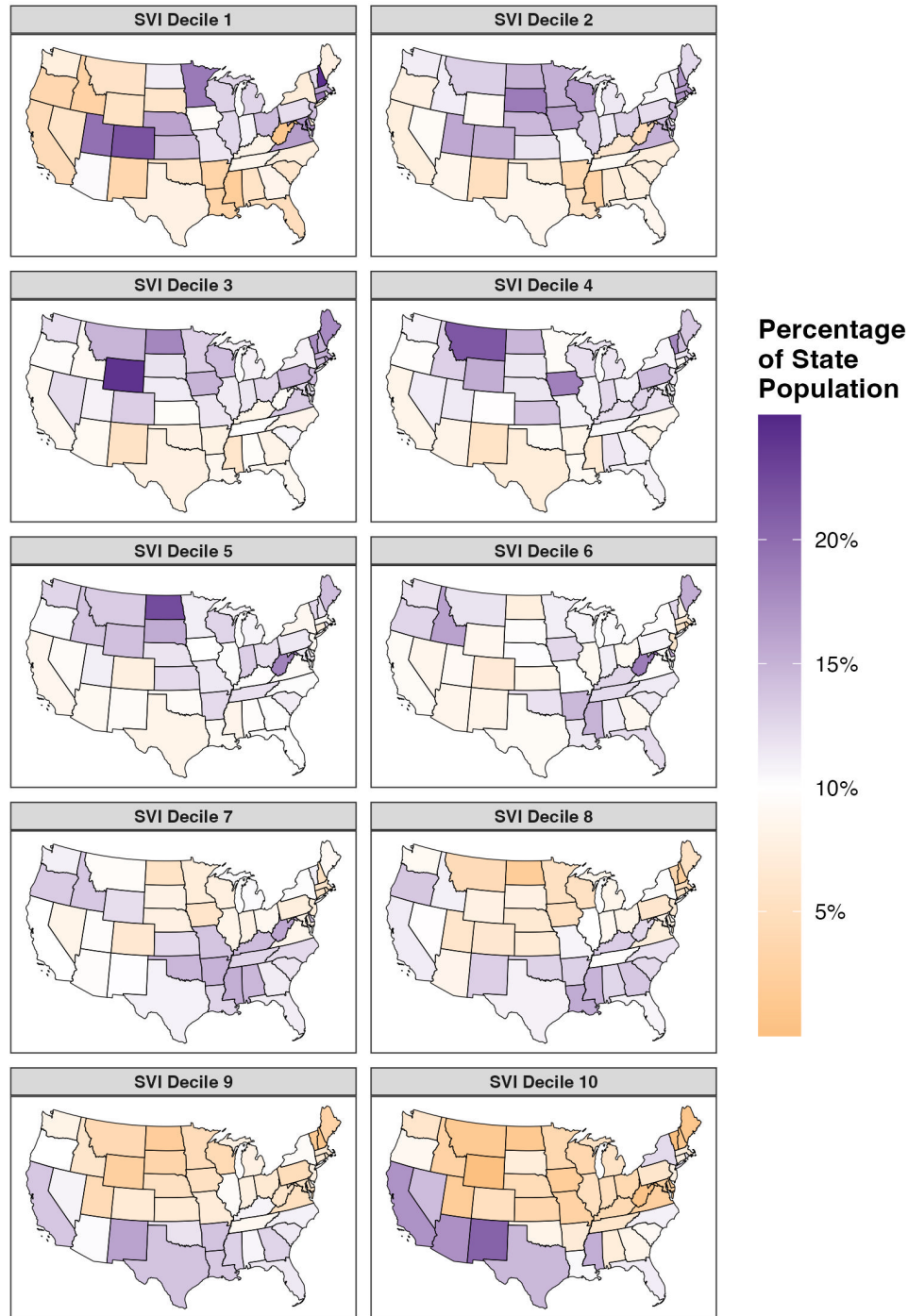


d. Housing Type & Transportation



Supplementary Fig. 30 | Themed SVI percentile ranks by tract. Data characterize 2017. (a) shows Theme 1's SVI (for Socioeconomic Status) by tract; green is more vulnerable, and white is less vulnerable. (b) shows Theme 2's SVI (for Household Composition & Disability) by tract; orange is more vulnerable, and white is less vulnerable. (c) shows Theme 3's SVI (for Minority Status & Language) by tract; purple is more vulnerable, and white is less vulnerable. (d) shows Theme 4's SVI (for Housing Type & Transportation) by tract; blue is more vulnerable, and white is less vulnerable. See Table 2 of the main document for SVVs contributing to each themed SVI.

Sources: SVI is from the CDC [69] developed using methodology from Flanagan et al. (2011) [70]. Mapping uses the *rgdal* R package [102]. Plotting uses the *ggplot2* R package [103].



Supplementary Fig. 31 | State population percentage by overall SVI decile. Data represent 2017. Tracts are divided into deciles from least (1) to most (10) vulnerable using overall SVI percentile ranks. Panels divide populations by SVI decile. White represents 10% of a state’s population, an equitable representation of the SVI decile. Purple represents > 10%, an overrepresentation of the SVI decile. Orange represents < 10%, an underrepresentation of the SVI decile. See Table 2 of the main document for the SVVs comprising the SVI.

Sources: SVI data are from the CDC [69] based on methodology from Flanagan et al. (2011) [70]. Population data are from the U.S. Census Bureau [54]. Mapping uses the *usmap* R package [104]. Plotting uses the *ggplot2* R package [103].

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