clasp Efficient Appliances for People & the Planet

Annex A: Methodology

How National Appliance & Equipment Energy Conservation Standards Can Help Improve Public Health and Advance Justice40 Initiative Goals

11 MARCH 2024

AUTHORS

Lauren Boucher, CLASP

CONTRIBUTORS

Dr. Kelsey Bilsback, PSE Healthy Energy

Jeremy Domen, PSE Healthy Energy

CONTACT

info@clasp.ngo

CITATION AND COPYRIGHT

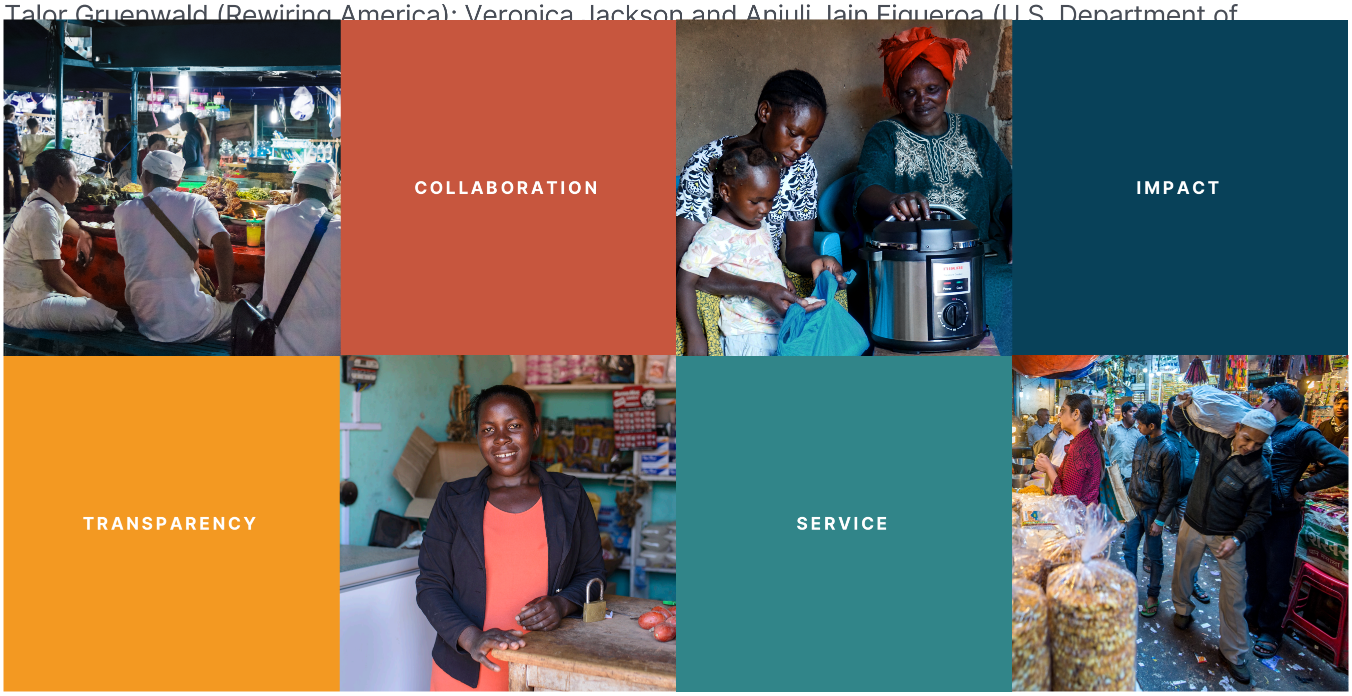
Lauren Boucher, How National Appliance and Equipment Energy Conservation Standards Can Help Improve Public Health and Advance Justice40 Initiative Goals, CLASP, March 2024, https://www.clasp.ngo/research/all/how-national-appliance-and-equipment-energy-conservation-standards-can-improve-public-health-and-advance-justice40-initiative-goals/

ABOUT

This document describes the methodology used to estimate the impact national appliance and equipment standards adopted over a 30-year period in the United States have had on PM2.5-related mortality. The findings of this analysis are presented in the issue brief, [How National Appliance and Equipment Energy Conservation Standards Can Help Improve Public Health and Advance Justice40 Initiative Goals.]

ACKNOWLEDGEMENTS

We would like to gratefully acknowledge the following individuals for their insights, guidance, and technical support in the development and/or review and execution of this project: Aimee Bell-Pasht, Lowell Ungar (ACEEE), Andrew deLaski, Joanna Mauer, and Madeline Parker (ASAP), Matt Malinowski, Ari Reeves, Alexia Ross, and Corinne Schneider (CLASP); Joe Vukovich and Jackie Wong (NRDC). We would also like to thank the following people for their thoughtful review, guidance, and feedback on this report: Eric Ruben and Nancy Metayer (Energy Solutions); Berneta Hayes (National Consumer Law Center); Mikyla Reta, Sabrina Johnson, Batoul Al-Sadi, and Olivia. Walker (Natural Resources Defense Council); Anilla Cherian (NYSERDA); Talor Gruenwald (Rewiring America); Veronica Jackson and Anjuli Jain Figueroa (U.S. Department of



1. Modeling Health Impacts

1.1 INMAP BACKGROUND

We used InMAP[1] version 1.9.0 to estimate the impact of residential emissions on $PM_{2.5}$ and $PM_{2.5}$-related mortality. InMAP has been peer-reviewed and is widely used in the scientific literature to estimate air quality and health impacts in the contiguous US (excluding Alaska and Hawaii).[2,3,4] InMAP is a marginal change model, meaning it is designed to be used to evaluate the impacts of *changes* in atmospheric $PM_{2.5}$ concentrations rather than the total atmospheric concentrations. InMAP estimates the marginal changes in annual average outdoor $PM_{2.5}$ using information about emissions and a series of scientific calculations. These calculations account for the evolution of emissions in the atmosphere–including atmospheric transport, chemistry, and deposition. InMAP can also be configured to use epidemiological relationships to estimate $PM_{2.5}$-related health impacts, e.g., mortality. InMAP includes both the air quality impacts of $PM_{2.5}$ and the impacts of $PM_{2.5}$ precursors—NO_x, SO_x, NH_3, and VOCs—which are emitted directly and then react chemically in the atmosphere to form $PM_{2.5}$.

InMAP provides greater spatial granularity (up to 1 km grid) than other reduced-form models, which typically provide information at the county level.[5] InMAP includes racial demographic information, which enables the user to assess which demographic groups may see the greatest health impacts or benefits from the modeled emissions scenario.

1.2 INMAP INPUTS

InMAP was driven by a series of input data that are described in detail below. As a supplement to this document, we have provided all InMAP input and output files.

Emissions Scenarios: We ran eight InMAP model runs that are detailed in **Table 1**. For our InMAP model runs, we used two distinct emissions scenarios:

1. **Actual**: 2017 emissions attributed to appliances and equipment (residential fossil fuel appliances and electric appliances).
2. **Counterfactual**: 2017 emissions from appliances and equipment in the absence of appliance energy efficiency standards.

Table 1. Summary of InMAP model runs.

Scenario	Emissions	Spatial Allocation	Concentration-Response Function
Actual	**Power sector**	Census Tracts	Lepeule et al., 2012
		InMAP Grid	Krewski et al., 2009
	Appliances	Census Tracts	Lepeule et al., 2012
		InMAP Grid	Krewski et al., 2009
Counterfactual	**Power sector**	Census Tracts	Lepeule et al., 2012
		InMAP Grid	Krewski et al., 2009
	Appliances	Census Tracts	Lepeule et al., 2012
		InMAP Grid	Krewski et al., 2009

The emissions from the "actual" scenario are from the National Emissions Inventory (NEI) for the year 2017.[6] To construct the counterfactual scenario, CLASP used state-level energy savings estimates provided by the Appliance Standards Awareness Program (ASAP) for the year 2017 based on standards adopted over a 30-year period to estimate the percentage increase in electricity demand in 2017 if those standards had not been adopted. To meet this additional demand, new power plants would likely be needed and/or older power plants would prolong retirement. Rather than model the changes in installed capacity needed to support this additional demand, we uniformly scaled 2017 NEI emissions data proportionate to the estimated increase in electricity demand based on the energy savings estimated provided by ASAP. This choice may have resulted in an overestimation in emissions from baseload electricity generation and an underestimation from peaking electricity generation. Additionally, this decision assumes that the emissions in the counterfactual scenario follow the same geographic distribution as they do in the actual scenario and does not consider the location of new facilities that would be needed to meet the added demand. We applied a similar approach when estimating emissions in the counterfactual scenario for residential fossil fuel appliances. The emissions estimates in the counterfactual scenario reflect the emissions factors the NEI used to estimate residential emissions in 2017. These emissions factors are more conservative than what one could expect in a scenario without standards.

Both scenarios included two shapefiles that provided emissions data in short tons per year. The first shapefile for each scenario contained elevated power-sector emissions data that were attributable to the residential sector (elevated_emissions.shp and elevated_emissions_counterfactual.shp) and the second shapefile contained ground-level emissions data from residential appliances allocated to U.S. census tracts (emis_res_gas_2017.shp and emis_res_gas_2017_counterfactual.shp). For the actual and counterfactual scenarios, we ran two InMAP simulations to capture the impacts of the power sector and residential appliances separately. The files included "NA" values for some emissions, which were introduced when the emissions files were created in R. To run InMAP, any “NA” emissions values were replaced with zeros.

Health Impact Function: The equation used to calculate the $PM_{2.5}$-related mortality from emissions that are attributable to the residential sector is given below:

$$\Delta \text{Mortality} = \text{Pop}(\exp^{\beta \cdot \Delta X} - 1)Y_0$$

In this equation, the change in mortality is calculated using the population (Pop), the baseline mortality rate (Y_0), and the concentration-response function, which includes the change in concentration of annual-average $PM_{2.5}$ (ΔX) and a beta coefficient (β). β is determined using relative risk (RR) associated with a 10 $\mu g\ m^{-3}$ increase in annual-average outdoor $PM_{2.5}$. β has the following functional form:

$$\beta = \ln(RR) / 10\ \mu g\ m^{-3}$$

where the RR estimate is derived from the epidemiological literature. We used the two RR estimates (**Table 1**) that are also used in the U.S. Environmental Protection Agency’s Co-Benefits Risk Assessment Health Impacts Screening and Mapping Tool.[7] The first RR estimate was from Krewski et al.,[8] which had a coefficient of 1.06. The second RR estimate was from Leupeule et al.,[9] which had a coefficient of 1.14. Given the uncertainty in the concentration-response function,[10] we used these two calculations to represent a “low” and “high” estimate, respectively, providing an estimated mortality rate range.

Demographic Data: Our InMAP model runs used baseline all-cause mortality rates for the entire U.S. population from the Centers for Disease Control and Prevention for the year 2013.[11] The mortality rates were for all genders and age groups at the county level. We also used census-block-group level population, race, and ethnicity data from the 2015 American Community Survey, which covers a five-year span from 2011-2015. The demographic data shapefile included several census block groups with invalid geometries that were fixed using the “fix geometries” function in QGIS. While we expect there to be some changes in baseline mortality and population between the time the demographic data was collected (2013 and 2015, respectively) and the year that was used for emissions estimates (2017), this discrepancy likely has a much smaller impact on our $PM_{2.5}$-related mortality calculation compared to the uncertainty in the calculations used by InMAP to estimate $PM_{2.5}$ and the uncertainty in the concentration-response function.[12]

Monetary Impacts: We calculated the monetary value of the mortality impacts by multiplying the mortalities estimates calculated using InMAP by the value of a statistical life for a 2017 income level. We estimated the 2017 income level dollar amount by linearly interpolating the 3% discount rate values used for the years 2016, 2023, and 2028 used in the U.S. Environmental Protection Agency’s Co-Benefits Risk Assessment Health Impacts Screening and Mapping Tool. We used a value of approximately $9.5 million in 2017 dollars.

1.3 INMAP OUTPUTS

InMAP Output Files: Our InMAP runs produced eight output shapefiles, four for the “actual” and four for the “counterfactual” scenarios, respectively (**Table 1**). The outputs from InMAP are provided on a variable rectangular grid, which is optimized to focus computational resources toward understanding exposures and health impacts. Thus, grid cells tend to be larger in rural and remote areas and smaller in densely populated regions. The size of the horizontal grid depends on the local population density and pollutant concentrations.[13] Output variables from InMAP include the annual-average outdoor $PM_{2.5}$ concentration attributable to the residential sector and $PM_{2.5}$-related mortalities.

1.4 LIMITATIONS OF INMAP

InMAP is a reduced-form model, meaning that it uses simplified calculations to estimate atmospheric $PM_{2.5}$ concentrations, compared to state-of-the-science chemical-transport models that model the atmospheric processes more explicitly. Recent studies have demonstrated that reduced-form models, including InMAP, provide significant computational advantages with only a minor loss in fidelity.[14] Given that InMAP is a reduced-form model, we also note that the $PM_{2.5}$ concentrations modeled by InMAP represent the marginal impacts of emissions rather than the absolute impacts, meaning that InMAP outputs cannot be compared directly to the National Ambient Air Quality Standards (NAAQS) or ambient air quality monitors.

The health impacts calculated with InMAP likely underestimate the total health impacts of emissions from the residential sector in the US. InMAP is limited to quantifying the health impacts of sources that emit $PM_{2.5}$ and $PM_{2.5}$ precursors and does not include the impacts of a range of other air pollutants. For example, InMAP does not include the direct impacts of VOCs, many of which are identified as hazardous air pollutants (HAPs) by the US EPA. InMAP also does not capture the health impacts of ozone, which is the second leading source of air pollution-related health impacts, after $PM_{2.5}$.[15],[16] Further, previous studies have found that residential gas stoves are a source of both VOCs (including HAPs)[17] and NO_x,[18] which have direct health impacts and may react in the atmosphere to form ozone.

Despite emissions consistently being lower in the “actual” case as compared to the “counterfactual” case, mortality is not always lower for all areas in the “actual” case. Part of the discrepancy is due to differences in the InMAP output grid resolution (i.e., grid density or the number of rectangular grid subdivisions) between scenarios. The spatial resolution of the InMAP grid can significantly impact model-estimated population-weighted exposure,[19] as emissions and population tend to be spatially correlated. Lower total mortality in the counterfactual scenario can occur in areas where the spatial resolution of the InMAP grid differs between the actual and counterfactual scenarios.

2. Interpolated Modeled Outcomes

2.1 INTERPOLATION BACKGROUND

After running InMAP, we mapped the outputs from the InMAP grid to U.S. census tracts to support the further elucidation of the impacts of emissions from residential appliances and the emissions stemming from power generation for residential appliances on disadvantaged communities, as defined by the Justice40 initiative.[20] We used the two concentration-response functions (**Table 1**) to demonstrate uncertainty in mortality estimates, but we conducted the spatial allocation for the simulations that used the Lepeule et al.[21] concentration-response function only. We distributed the changes in $PM_{2.5}$ concentrations and $PM_{2.5}$-related mortalities due to emissions from appliances and the power sector by census tract weighting by population. Below, we describe the inputs and methods used in our gridding process.

2.2 INTERPOLATION INPUTS

InMAP Outputs: Our interpolation used the output files from InMAP: emis_actual_pp_high.shp, emis_actual_res_high.shp, emis_counterfactual_pp_high.shp, and emis_counterfactual_res_high.shp for the "actual" and "counterfactual" scenarios for the power sector (pp) and appliances (res), respectively.

Demographic Data: Our interpolation required population data aggregated by race or ethnicity and census subdivisions. For consistency, we relied on the same census block group demographic data for both the InMAP model runs and for the interpolation of outdoor $PM_{2.5}$ concentrations and $PM_{2.5}$-related mortality. (See "Demographic Data" under **Section 1.2** for details.) Using demographic data on the block-group level provides additional accuracy when interpolating values as it more accurately reflects population distribution compared to census-tract level data.

2.3 POPULATION-WEIGHTING METHODS

Population-Weighted $PM_{2.5}$-Related Mortality: We allocated the estimated $PM_{2.5}$-related mortality by race and ethnicity to the US census tracts. We did this by weighting the total and race-and-ethnicity-specific mortality outputs from InMAP by the total and race-and-ethnicity-specific census-block-group population data. We weighted the mortality outcomes using population data rather than mortality data because race and ethnicity-specific population data are available readily at a higher spatial resolution (census-block-group level rather than county-level), which allowed us to better capture small-scale differences in race and ethnicity.

We used both QGIS and R to allocate $PM_{2.5}$-related mortality. Shapefiles were reprojected to the same coordinate reference system (CRS) and the intersection between InMAP grids and census-block groups were calculated using the "intersection (multiple)" and "add geometries" functions in QGIS. The resulting shapefile contained census block groups split along InMAP grid boundaries. We used R to calculate the percentage of each census block-group that was within each InMAP grid and the associated population each census block-group fraction contributed to the total and race-and-ethnicity-specific InMAP grid population. This method assumes that the population distribution within a census block group is uniform. Using population data on the census block group level for the population weighting allows for greater accuracy when allocating mortality and monetary impacts, compared to census tract level data.

Total and race- and-ethnicity-specific InMAP mortality was then allocated to each census block-group fraction based on population, and the overall total and race- and-ethnicity-specific mortality were summed for each census block-group. The resulting shapefile was joined with the census-block-group shapefile using the GISJOIN column and scrutinized in QGIS. We then summed $PM_{2.5}$-related mortality on the census-tract level and merged census block-group geometries into tracts using the GISJOIN column in R and QGIS.

We calculated the monetary value of the mortality impacts by multiplying the allocated mortality estimates by the value of a statistical life for a 2017 income level as described in **Section 1.2**.

We produced four files through our interpolation analysis:

- **emis_actual_pp_high_allocated_census_tract.shp:** for the "actual" scenario with power sector emissions,
- **emis_actual_res_high_allocated_census_tract.shp:** for the "actual" scenario with residential appliance emissions,
- **emis_counterfactual_pp_high_allocated_census_tract.shp:** for the "counterfactual" scenario with power sector emissions, and

- **emis_counterfactual_res_high_allocated_census_tract.shp:** for the "counterfactual" scenario with residential appliance emissions.

Because InMAP only outputs $PM_{2.5}$-related mortality in populated regions within the contiguous U.S., we can check for $PM_{2.5}$-related mortality conservation between the InMAP output and the interpolated mortality. For the actual and counterfactual cases for the power sector and appliance scenarios, allocated total and race-and-ethnicity-specific mortality were conserved. As discussed in **Section 1.4**, there are a few census tracts where the "actual" case had higher mortality compared to the "counterfactual" case, partially due to differences in the InMAP output grid resolution (i.e., grid density or the number of rectangular grid subdivisions) between scenarios.

Population-Weighted $PM_{2.5}$: To allocate the $PM_{2.5}$ air concentrations to the census-tract level, we weighted the $PM_{2.5}$ concentration outputs from InMAP by the total population, following the same approach that we did for $PM_{2.5}$-related mortality. We chose a population-weighting approach for $PM_{2.5}$ over an area-weighing approach because the population-weighting approach is commonly used by entities, such as the World Health Organization, as an indicator for exposure.[22] We note that because InMAP is a *marginal* air quality model, these outdoor $PM_{2.5}$ concentrations represent only the $PM_{2.5}$ attributable to the residential sector (rather than the absolute concentration of $PM_{2.5}$ in the atmosphere). The results of the population-weighted $PM_{2.5}$ allocation are included in the output files of the population-weighted $PM_{2.5}$-related mortality allocation. We note that, unlike $PM_{2.5}$-related mortality, InMAP does output $PM_{2.5}$ air concentrations over unpopulated regions, bodies of water, and regions outside of census shapefiles (*e.g.,* nearby parts of Canada and Mexico). Therefore, we cannot check the overall conservation of total $PM_{2.5}$. However, we expect the accuracy of the allocated results to be similar to those for population-weighted $PM_{2.5}$-related mortality.

3. Defining Disadvantaged Communities

To add the current Justice40 community designations to the files produced during our interpolation analysis,[1] we used Version 1.0 of the Climate and Economic Justice Screening Tool's Communities list data to merge the interpolated results with Justice40 disadvantaged community designations by census tract.[23] We used the variable titled, "Identified as disadvantaged" to indicate whether a census tract would be counted as a disadvantaged community.

4. Quantifying Health Benefits

Our analysis explored the impact of national appliance and equipment standards on $PM_{2.5}$ related benefits. To assess this health benefit, we took the difference in modeled $PM_{2.5}$-related mortality between the actual and counterfactual scenarios for each census tract. We then summed the difference for each census tract to determine the total number of premature $PM_{2.5}$-related deaths national appliance and equipment standards prevented in 2017.

To assess how the avoided $PM_{2.5}$-related deaths were distributed across Justice40 disadvantaged communities, we summed the difference in $PM_{2.5}$ mortality in each scenario for all census tracts

[1] emis_actual_pp_high_allocated_census_tract.shp, emis_actual_res_high_allocated_census_tract.shp, emis_counterfactual_pp_high_allocated_census_tract.shp, and emis_counterfactual_res_high_allocated_census_tract.shp

identified as disadvantaged by Version 1.0 of the Climate and Economic Justice Screening Tool's Communities data list to find the total number of avoided $PM_{2.5}$-related deaths attributed to national appliance standards. We then took the sum of all avoided $PM_{2.5}$-related deaths and divided that by the sum of all $PM_{2.5}$-related deaths to find the proportion of avoided $PM_{2.5}$-related deaths observed in Justice40 disadvantaged communities.

InMAP enables users to model $PM_{2.5}$-related mortality among different racial and ethnic groups. To assess how the avoided $PM_{2.5}$-related deaths were distributed, we used the preexisting baseline mortality data within input to estimate the $PM_{2.5}$-related deaths across five different demographic groups: White, non-Latino adults; Black adults, non-white Latino adults, Native American adults, and Asian adults. We then summed the difference of $PM_{2.5}$-related deaths in the two scenarios for each of those five demographic groups. To estimate the distribution of health benefits we took the sum of all avoided $PM_{2.5}$-related deaths for each groups and divided that by the sum of all $PM_{2.5}$-related deaths to find the proportion of avoided $PM_{2.5}$-related deaths observed in different racial and ethnic groups in the United States.[2]

[2] 2017 population data were sourced from the U.S. Census Bureau's American Community Survey's Five-Year Data for the years 2013-2017.

Endnotes

[1] Tessum, Christopher W., Jason D. Hill, and Julian D. Marshall. “InMAP: A Model for Air Pollution Interventions.” PLOS ONE 12, no. 4 (April 19, 2017): e0176131. https://doi.org/10.1371/journal.pone.0176131.

[2] Thakrar, Sumil K., Srinidhi Balasubramanian, Peter J. Adams, Inês M. L. Azevedo, Nicholas Z. Muller, Spyros N. Pandis, Stephen Polasky, et al. “Reducing Mortality from Air Pollution in the United States by Targeting Specific Emission Sources.” Environmental Science & Technology Letters 7, no. 9 (September 8, 2020): 639–45. https://doi.org/10.1021/acs.estlett.0c00424.

[3] Tessum, Christopher W., Joshua S. Apte, Andrew L. Goodkind, Nicholas Z. Muller, Kimberley A. Mullins, David A. Paolella, Stephen Polasky, et al. “Inequity in Consumption of Goods and Services Adds to Racial–Ethnic Disparities in Air Pollution Exposure.” *Proceedings of the National Academy of Sciences* 116, no. 13 (March 26, 2019): 6001–6. https://doi.org/10.1073/pnas.1818859116.

[4] Goodkind, Andrew L., Christopher W. Tessum, Jay S. Coggins, Jason D. Hill, and Julian D. Marshall. “Fine-Scale Damage Estimates of Particulate Matter Air Pollution Reveal Opportunities for Location-Specific Mitigation of Emissions.” *Proceedings of the National Academy of Sciences* 116, no. 18 (April 30, 2019): 8775–80. https://doi.org/10.1073/pnas.1816102116.

[5] Paolella, David A., Christopher W. Tessum, Peter J. Adams, Joshua S. Apte, Sarah Chambliss, Jason Hill, Nicholas Z. Muller, and Julian D. Marshall. “Effect of Model Spatial Resolution on Estimates of Fine Particulate Matter Exposure and Exposure Disparities in the United States.” *Environmental Science & Technology Letters* 5, no. 7 (July 10, 2018): 436–41. https://doi.org/10.1021/acs.estlett.8b00279.

[6] United States Environmental Protection Agency. (2023, June). National Emissions Inventory (NEI).

[7] United States Environmental Protection Agency. (2023, June). Co-Benefits Risk Assessment Health Impacts Screening and Mapping Tool (COBRA).

[8] Krewski, Daniel, Michael Jerrett, Richard T. Burnett, Renjun Ma, Edward Hughes, Yuanli Shi, Michelle C. Turner, et al. “Extended Follow-up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality.” *Research Report (Health Effects Institute)*, no. 140 (May 2009): 5–114; discussion 115-136.

[9] Krewski, Daniel, Michael Jerrett, Richard T. Burnett, Renjun Ma, Edward Hughes, Yuanli Shi, Michelle C. Turner, et al. “Extended Follow-up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality.” *Research Report (Health Effects Institute)*, no. 140 (May 2009): 5–114; discussion 115-136.

[10] Ford, Bonne, and Colette L. Heald. “Exploring the Uncertainty Associated with Satellite-Based Estimates of Premature Mortality Due to Exposure to Fine Particulate Matter.” *Atmospheric Chemistry and Physics* 16, no. 5 (March 17, 2016): 3499–3523. https://doi.org/10.5194/acp-16-3499-2016.

[11] Centers for Disease Control and Prevention, National Center for Health Statistics. Compressed Mortality File 1999-2015 on CDC WONDER Online Database, released December 2016. Data are from the Compressed Mortality File 1999-2015 Series 20 No. 2U, 2016, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

[12] Kodros, J. K., E. Carter, M. Brauer, J. Volckens, K. R. Bilsback, C. L’Orange, M. Johnson, and J. R. Pierce. “Quantifying the Contribution to Uncertainty in Mortality Attributed to Household, Ambient, and Joint Exposure to PM2.5 From Residential Solid Fuel Use.” *GeoHealth* 2, no. 1 (2018): 25–39. https://doi.org/10.1002/2017GH000115.

[13] Tessum, Christopher W., Jason D. Hill, and Julian D. Marshall. “InMAP: A Model for Air Pollution Interventions.” *PLOS ONE* 12, no. 4 (April 19, 2017): e0176131. https://doi.org/10.1371/journal.pone.0176131.

[14] Gilmore, Elisabeth A., Jinhyok Heo, Nicholas Z. Muller, Christopher W. Tessum, Jason D. Hill, Julian D. Marshall, and Peter J. Adams. “An Inter-Comparison of the Social Costs of Air Quality from Reduced-Complexity Models.” *Environmental Research Letters* 14, no. 7 (July 2019): 074016. https://doi.org/10.1088/1748-9326/ab1ab5.

[15] United States Environmental Protection Agency. (2023, June). Hazardous Air Pollutants.

[16] Lelieveld, J., J. S. Evans, M. Fnais, D. Giannadaki, and A. Pozzer. “The Contribution of Outdoor Air Pollution Sources to Premature Mortality on a Global Scale.” *Nature* 525, no. 7569 (September 2015): 367–71. https://doi.org/10.1038/nature15371.

[17] Lebel, Eric D., Drew R. Michanowicz, Kelsey R. Bilsback, Lee Ann L. Hill, Jackson S. W. Goldman, Jeremy K. Domen, Jessie M. Jaeger, Angélica Ruiz, and Seth B. C. Shonkoff. “Composition, Emissions, and Air Quality Impacts of Hazardous Air Pollutants in Unburned Natural Gas from

Residential Stoves in California." *Environmental Science & Technology* 56, no. 22 (November 15, 2022): 15828–38. https://doi.org/10.1021/acs.est.2c02581.

[18] Lebel, Eric D., Colin J. Finnegan, Zutao Ouyang, and Robert B. Jackson. "Methane and NOx Emissions from Natural Gas Stoves, Cooktops, and Ovens in Residential Homes." *Environmental Science & Technology* 56, no. 4 (February 15, 2022): 2529–39. https://doi.org/10.1021/acs.est.1c04707.

[19] Paolella, David A., Christopher W. Tessum, Peter J. Adams, Joshua S. Apte, Sarah Chambliss, Jason Hill, Nicholas Z. Muller, and Julian D. Marshall. "Effect of Model Spatial Resolution on Estimates of Fine Particulate Matter Exposure and Exposure Disparities in the United States." *Environmental Science & Technology Letters* 5, no. 7 (July 10, 2018): 436–41. https://doi.org/10.1021/acs.estlett.8b00279.

[20] U.S. Department of Energy's Office of Economic Impact and Diversity. (2023, July). Justice40 Initiative.

[21] Lepeule, Johanna, Francine Laden, Douglas Dockery, and Joel Schwartz. "Chronic Exposure to Fine Particles and Mortality: An Extended Follow-up of the Harvard Six Cities Study from 1974 to 2009." *Environmental Health Perspectives* 120, no. 7 (July 2012): 965–70. https://doi.org/10.1289/ehp.1104660

[22] European Health Information Gateway. (2023, June). Population weighted annual mean PM2.5 in cities. World Health Organization, European Region.

[23] Council on Environmental Quality. "Climate and Economic Justice Screening Tool." Climate and Economic Justice Screening Tool, November 22, 2022. https://screeningtool.geoplatform.gov.