Methods for Analyzing the Air Quality and Health Impacts of U.S. Appliance Standards

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1. Background

Fossil-fuel residential appliances and the energy generated in power plants to power electric appliances emit many pollutants that are harmful to human health. These pollutants include volatile organic compounds (VOCs) and Criteria Air Pollutants, [1] which are regulated by the United States Environmental Protection Agency (EPA) (e.g., fine particulate matter ($PM_{2.5}$), nitrogen oxides (NO_x), sulfur dioxide (SO_2)).

When inhaled, these air pollutants can cause a range of negative respiratory, cardiovascular, and neurological health impacts when inhaled.[2] Certain populations, such as children, the elderly, and those with underlying health conditions (e.g., asthma), are more susceptible to the impacts of air pollution.[3] Further, certain communities in the United States, such as low-income communities and communities of color, tend to experience a disproportionate share of environmental burdens[4] and are therefore more likely to experience adverse health outcomes from air pollution.

In this report, we estimate the impacts of emissions from the residential sector in the United States on outdoor $PM_{2.5}$ and $PM_{2.5}$-related mortality (**Section 2**). We used residential emissions input files provided by CLASP[5] and the Intervention Model for Air Pollution (InMAP), a reduced-form model. We estimate the impacts of two emissions scenarios: (1) the "actual" scenario, which captures emissions from the residential sector for the year 2017 and (2) the "counterfactual" scenario, which captures the emissions from the residential sector in the absence of energy efficiency standards. Additionally, we summarized the methods used to allocate InMAP's outdoor $PM_{2.5}$ and $PM_{2.5}$-related mortality estimates to U.S. census tracts by race and ethnicity in order to facilitate the further understanding of impacts on disadvantaged communities, as defined by the Justice40 initiative (**Section 3**).[6]

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[1]United States Environmental Protection Agency. (2023, June). Criteria Air Pollutants.
[2]Murray, C. J., Aravkin, A. Y., Zheng, P., Abbafati, C., Abbas, K. M., Abbasi-Kangevari, M., ... & Borzouei, S. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), 1223-1249.
[3]United States Environmental Protection Agency. (2023, June). Research on Health Effects from Air Pollution.
[4]United States Environmental Protection Agency. (2023, June). Power plants and Neighboring Communities.
[5] Boucher, L. (2024). How National Appliance Standards Can Help Deliver Justice40 and Improve Public Health. *CLASP.*
[6]U.S. Department of Energy's Office of Economic Impact and Diversity. (2023, July). Justice40 Initiative.

2. Modeling Health Impacts

2.1 InMAP Background

We used InMAP[7] 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 U.S. (excluding Alaska and Hawaii).[8,9,10] 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 calculations that 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)[11] than other reduced-form models, which typically provide information at the county level. InMAP also includes racial demographic information, which enables users to assess which demographic groups may see the greatest health impacts or benefits from the modeled emissions scenario.

2.2 InMAP Inputs

Our InMAP models were driven by the input data described in detail below. As a supplement to this document, we have provided all of the InMAP input and output files.

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[7] Tessum, C. W., Hill, J. D., & Marshall, J. D. (2017). InMAP: A model for air pollution interventions. PloS One, 12(4), e0176131.
[8] Thakrar, S. K., Balasubramanian, S., Adams, P. J., Azevedo, I. M., Muller, N. Z., Pandis, S. N., ... & Hill, J. D. (2020). Reducing mortality from air pollution in the United States by targeting specific emission sources. *Environmental Science & Technology Letters*, *7*(9), 639-645.
[9] Tessum, C. W., Apte, J. S., Goodkind, A. L., Muller, N. Z., Mullins, K. A., Paolella, D. A., ... & Hill, J. D. (2019). Inequity in consumption of goods and services adds to racial–ethnic disparities in air pollution exposure. *Proceedings of the National Academy of Sciences*, *116*(13), 6001-6006.
[10] Goodkind, A. L., Tessum, C. W., Coggins, J. S., Hill, J. D., & Marshall, J. D. (2019). 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*(18), 8775-8780.
[11] Paolella, D. A., Tessum, C. W., Adams, P. J., Apte, J. S., Chambliss, S., Hill, J., ... & Marshall, J. D. (2018). Effect of model spatial resolution on estimates of fine particulate matter exposure and exposure disparities in the United States. *Environmental Science & Technology Letters*, *5*(7), 436-441.

Emissions Scenarios: We ran eight InMAP model runs detailed in **Table 1**. For our InMAP model runs, we were provided emissions shapefiles from CLASP[12] that included two distinct emissions scenarios:

1. **Actual**: 2017 emissions attributed to residential appliances and equipment.
2. **Counterfactual**: 2017 emissions from residential 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
1	**Actual**	**Power sector**	Census Tracts	Lepeule et al., 2012
2			InMAP Grid	Krewski et al., 2009
3		**Appliances**	Census Tracts	Lepeule et al., 2012
4			InMAP Grid	Krewski et al., 2009
5	**Counterfactual**	**Power sector**	Census Tracts	Lepeule et al., 2012
6			InMAP Grid	Krewski et al., 2009
7		**Appliances**	Census Tracts	Lepeule et al., 2012
8			InMAP Grid	Krewski et al., 2009

The emissions from the "actual" scenario are from the National Emissions Inventory (NEI) for the year 2017.[13] The emissions from the "counterfactual" scenario were provided by the Appliance Standards Awareness Project (ASAP).[14] Both scenarios included two shapefiles that provided emissions data in short tons (i.e., US ton) 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

[12] Boucher, L. (2024). How National Appliance Standards Can Help Deliver Justice40 and Improve Public Health. *CLASP.*
[13] United States Environmental Protection Agency. (2023, June). National Emissions Inventory (NEI).
[14] Boucher, L. (2024). How National Appliance Standards Can Help Deliver Justice40 and Improve Public Health. *CLASP.*

two InMAP simulations to capture the impacts of the power sector and residential appliances separately. The files provided by CLASP 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 μg 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.[15] The first RR estimate was from Krewski et al.[16] which had a coefficient of 1.06. The second RR estimate was from Leupeule et al.[17] which had a coefficient of 1.14. Given the uncertainty in the concentration-response function,[18] 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.[19] 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

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

[16]Krewski, D., Jerrett, M., Burnett, R. T., Ma, R., Hughes, E., Shi, Y., . . . Tempalski, B. (2009). Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality. *Res Rep Health Eff Inst*(140), 5-114; discussion 115-136.

[17]Lepeule, J., Laden, F., Dockery, D., & Schwartz, J. (2012). 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*(7), 965-970.

[18]Ford, B., & Heald, C. L. (2016). Exploring the uncertainty associated with satellite-based estimates of premature mortality due to exposure to fine particulate matter. *Atmospheric Chemistry and Physics*, *16*(5), 3499-3523.

[19]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.

Community Survey, which covers a five-year time span from 2011-2015. The demographic data shapefile included a number of 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.[20]

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 three percent discount rate values 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.

2.3 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.[21] Output variables from InMAP include the annual-average outdoor $PM_{2.5}$ concentration attributable to the residential sector and $PM_{2.5}$-related mortalities (see below).

$PM_{2.5}$-Related Mortality: The $PM_{2.5}$-related mortality estimates from the eight InMAP model scenarios that we ran are provided in **Table 2**. We note that these estimates were calculated before the InMAP output files were allocated to each census tract (**Section 3**). Comparing the "actual" and "counterfactual" scenarios, we find residential appliance standards will save 1,920-4,370 lives per year, depending on the concentration-response function used. While the exact mortality estimates differ between this and previous studies due to a wide range of

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[20] Kodros, J. K., Carter, E., Brauer, M., Volckens, J., Bilsback, K. R., L'Orange, C., ... & Pierce, J. R. (2018). Quantifying the contribution to uncertainty in mortality attributed to household, ambient, and joint exposure to $PM_{2.5}$ from residential solid fuel use. *GeoHealth*, *2*(1), 25-39.
[21] Tessum, C. W., Hill, J. D., & Marshall, J. D. (2017). InMAP: A model for air pollution interventions. PloS One, 12(4), e0176131.

factors (e.g., model resolution, chemistry, demographic information, concentration-response function), our mortality estimates are similar to previous estimates of mortality from the residential sector.[22]

Table 2. Annual mortality rates from residential appliances and power generation. Estimates are calculated using InMAP-grid shapefiles.

Scenario	Emissions	Mortality⁺ *"Low" estimate* Incidences	Mortality* *"High" estimate* Incidences	Monetary Impact⁺ *"Low" estimate*	Monetary Impact* *"High" estimate*
Actual	**Power sector**	10,060	22,740	$96 billion	$216 billion
	Appliances	1,530	3,440	$14 billion	$33 billion
	Total	11,590	26,180	$110 billion	$249 billion
Counterfactual	**Power sector**	11,930	26,980	$113 billion	$256 billion
	Appliances	1,580	3,570	$15 billion	$34 billion
	Total	13,510	30,550	$128 billion	$290 billion
	Total Difference	1,930	4,370	$18 billion	$42 billion

⁺Krewski et al., 2009; *Lepeule et al., 2012

Race and Ethnicity-Specific Mortality: The InMAP model has the capability of estimating $PM_{2.5}$-related health impacts by race and ethnicity, because of the relatively high resolution of the model (up to 1 km). In **Table 3**, we provide a summary of mortality impacts by race and ethnicity (before the model outputs are summarized by census tract).

Emissions from the power sector led to higher mortality rates for Black and White people compared to the overall population, with Black people having a 1.2 times higher mortality rate and White people having a 1.1 times higher mortality rate than the overall population. Black, Latino, and Asian people had higher mortality rates than the overall population for emissions from residential appliances. Asian people had the highest mortality rates which were 1.6 times higher than the overall population. Disproportionate health impacts between

[22] Thakrar, S. K., Balasubramanian, S., Adams, P. J., Azevedo, I. M., Muller, N. Z., Pandis, S. N., ... & Hill, J. D. (2020). Reducing mortality from air pollution in the United States by targeting specific emission sources. *Environmental Science & Technology Letters*, *7*(9), 639-645.

different racial and ethnic groups are well-documented in the peer-reviewed literature for both the residential and power sector.[23]

Table 3. Annual per capita mortality by race and ethnicity. Estimates are calculated using InMAP-grid shapefiles and the Leupeule et al.[24] concentration-response function.

Scenario	Emissions	Black *$ per capita*	Latino *$ per capita*	Native *$ per capita*	Asian *$ per capita*	White *$ per capita*	Overall *$ per capita*
Actual	**Power sector**	827	454	558	435	747	687
	Appliances	154	114	48	163	87	104
Counterfactual	**Power sector**	982	538	662	516	887	815
	Appliances	160	118	49	169	90	108

2.4 Limitations of InMAP

InMAP uses simplified, rather than full chemistry and physics, 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.[25] It is important to note, however, that the $PM_{2.5}$ concentrations modeled by InMAP represent marginal rather than absolute impacts of emissions and cannot be compared directly to the National Ambient Air Quality Standards (NAAQS) or ambient air quality monitors.

InMAP is also 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 U.S. EPA.[26] InMAP also does not capture the health impacts of

[23]Tessum, C. W., Paolella, D. A., Chambliss, S. E., Apte, J. S., Hill, J. D., & Marshall, J. D. (2021). $PM_{2.5}$ polluters disproportionately and systemically affect people of color in the United States. *Science Advances*, *7*(18), eabf4491.
[24]Lepeule, J., Laden, F., Dockery, D., & Schwartz, J. (2012). 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*(7), 965-970.
[25]Gilmore, E. A., Heo, J., Muller, N. Z., Tessum, C. W., Hill, J. D., Marshall, J. D., & Adams, P. J. (2019). An inter-comparison of the social costs of air quality from reduced-complexity models. *Environmental Research Letters*, *14*(7), 074016.
[26]United States Environmental Protection Agency. (2023, June). Hazardous Air Pollutants.

ozone, which is the second leading source of air pollution-related health impacts, after $PM_{2.5}$.[27,28] Further, previous studies have found that residential gas stoves are a source of both VOCs (including HAPs)[29] and NO_x,[30] which have direct health impacts and may react in the atmosphere to form ozone. As a result, the health impacts calculated with InMAP likely underestimate the total health impact of emissions from the residential sector in the U.S.

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 populated-weighted exposure,[31] 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.

3. Interpolated Modeled Outcomes

3.1 Data Aggregation Background

We mapped the outputs from the InMAP grid to U.S. census tracts to compare the impacts of emissions from residential appliances and the emissions from power generation for residential appliances on disadvantaged communities, as defined by the Justice40 initiative.[32] We used population weighting to distributed the changes in $PM_{2.5}$ concentrations and $PM_{2.5}$-related mortalities. Below, we describe the inputs and methods used in our gridding process.

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[27] Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, 525(7569), 367-371.
[28] Murray, C. J., Aravkin, A. Y., Zheng, P., Abbafati, C., Abbas, K. M., Abbasi-Kangevari, M., ... & Borzouei, S. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *396*(10258), 1223-1249.
[29] Lebel, E. D., Michanowicz, D. R., Bilsback, K. R., Hill, L. A. L., Goldman, J. S., Domen, J. K., ... & Shonkoff, S. B. (2022). Composition, Emissions, and Air Quality Impacts of Hazardous Air Pollutants in Unburned Natural Gas from Residential Stoves in California. *Environmental Science & Technology*, *56*(22), 15828-15838.
[30] Lebel, E. D., Finnegan, C. J., Ouyang, Z., & Jackson, R. B. (2022). Methane and NO_x emissions from natural gas stoves, cooktops, and ovens in residential homes. *Environmental Science & Technology*, *56*(4), 2529-2539.
[31] Paolella, D. A., Tessum, C. W., Adams, P. J., Apte, J. S., Chambliss, S., Hill, J., ... & Marshall, J. D. (2018). Effect of model spatial resolution on estimates of fine particulate matter exposure and exposure disparities in the United States. *Environmental Science & Technology Letters*, *5*(7), 436-441.
[32] U.S. Department of Energy's Office of Economic Impact and Diversity. (2023, July). Justice40 Initiative.

3.2 Interpolation Inputs

InMAP Outputs: Our interpolation used the output files from InMAP 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 2.2** 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.

3.3 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 U.S. 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 allocated 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 2.2**.

We produced four files through our interpolation analysis:

1. **emis_actual_pp_high_allocated_census_tract.shp:** for the "actual" scenario with power sector emissions,
2. **emis_actual_res_high_allocated_census_tract.shp:** for the "actual" scenario with residential appliance emissions,
3. **emis_counterfactual_pp_high_allocated_census_tract.shp:** for the "counterfactual" scenario with power sector emissions, and
4. **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 earlier in **Section 2.4**, 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.[33] 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.

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