Carbon dioxide removal could perpetuate community-scale inequalities of U.S. air pollution in net-zero scenarios

Candelaria Bergero[1*], Jing Cheng[2*], Qiang Zhang[3], Yang Ou[4,5], Haewon McJeon[6], Destenie Nock[7], Inês Azevedo[8], Steven J. Davis[2*]

[1] *Department of Earth System Science, University of California, Irvine, Irvine, CA 92697*
[2] *Department of Earth System Science, Stanford University, Stanford, CA 94305*
[3] *Department of Earth System Science, Tsinghua University*
[4] *College of Environmental Sciences and Engineering, Peking University*
[5] *Institute of Carbon Neutrality, Peking University, Beijing, China*
[6] *Graduate School of Green Growth & Sustainability, Korea Advanced Institute of Science and Technology, Daejeon, Korea 34141*
[7] *Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA 15213*
[8] *Department of Energy Science & Engineering, Stanford University, Stanford, CA 94305*

*corresponding authors: candelaria.bergero@uci.edu, chengj10@stanford.edu, sjdavis@stanford.edu

Pathways to net-zero reduce GHG emissions and improve air quality, but the magnitude and distribution of these improvements will depend on specific mitigation decisions, such as the amount of carbon dioxide removals (CDR). Here, we combine a series of models and datasets to analyze community-scale $PM_{2.5}$ impacts across the contiguous U.S. of net-zero scenarios with different levels of CDR. Both the high- and low-CDR scenarios avoid many $PM_{2.5}$-related deaths compared to a reference scenario, decreasing from around 200,000 to 160,000 and 130,000 deaths in 2050 in the high- and low-CDR scenarios, respectively. However, the low-CDR pathway leads to lower residual emissions and brings larger health benefits that disproportionately affect non-white and low-income groups. Our results thus suggest that in the absence of concerted transition planning, large-scale CDR deployment could be at odds with the equal distribution of climate mitigation-related health benefits in the U.S.

Pursuant to the Paris Agreement goal of limiting the increase in global mean temperatures to well-below 2°C, and ideally 1.5°C, the U.S. Long Term Strategy aims to reach net-zero GHG emissions by 2050 by transforming the energy sector (i.e. fuel switching and higher efficiencies), reducing non-CO_2 emissions, and removing carbon from the atmosphere[1,2]. In turn, achieving net-zero GHG emissions would drastically reduce fuel combustion needs and associated emissions of criteria air pollutants (e.g. particulate matter)—and thus improve human health[3,4]. However, the magnitude and spatial distribution of such health benefits depend on which specific sources of emissions are eliminated and where those sources are located.

Among the factors that affect the degree to which emissions sources are eliminated in net-zero emissions scenarios is the scale of carbon dioxide removal (CDR) approaches such as afforestation/reforestation (AR), capturing biogenic carbon emissions during combustion of biomass (BECCS), or direct air capture (DAC)[5,6]. Prior to and at the time of net-zero emissions, CDR deployed in net-zero scenarios offsets residual GHG emissions from difficult-to-abate sectors (e.g. industry, aviation, agriculture, etc.)[7–10]. Insofar as those residual sources of GHG emissions also emit criteria air pollutants, more CDR deployed will correspond to greater air pollution and adverse health impacts. Indeed, a recent study found that using CDR to offset (as opposed to directly reducing) global emissions could lead to tens of millions of premature deaths due to $PM_{2.5}$ and ozone this century[11]. Thus, although the overall health benefits of reaching net-zero GHG emissions will be substantial, use of CDR may reduce those benefits if it enables polluting infrastructure to continue to operate by offsetting its GHG emissions (though not its air pollution).

Moreover, the spatial distribution of health benefits will be sensitive to where sources of residual emissions are located. In the U.S.—where air pollution still accounts for 100,000-200,000 deaths per year[12], minority and low-income communities have long been disproportionately impacted[13–27]. Thus, insofar as residual sources of emissions are a subset of current sources, use of CDR could also perpetuate inequalities of air pollution exposure and related health damages. As a result, some policies and policymakers are prioritizing a net-zero energy transition that considers social justice and redresses such historical inequalities. For example, the Justice40 Initiative[28,29] sets a goal that 40% of the benefits of federal investments in climate, energy, and sustainable housing should accrue to "disadvantaged communities that are marginalized, underserved, and overburdened by pollution"[30]—including the nearly $1 trillion dollars of future energy- and climate-related investments in the Inflation Reduction Act of 2022 and the Bipartisan Infrastructure Law of 2021[31].

Yet uncertainties in the availability and cost of both CDR and lower-emitting alternatives for difficult-to-abate sectors lead to large variations in the scale of CDR used in net-zero scenarios[32,33]. For example, in net-zero scenarios produced for the U.S. Fifth National Climate Assessment, use of CDR in the country spans a range of 0.8-2.9 $GtCO_2$ removed from the atmosphere by 2050[34]. And the plausible range might be even wider if the models which produce these scenarios fail to capture the full potential range of relevant technological costs[35,36]. But despite policies that intend to prioritize a just distribution of the benefits related to reaching net-zero emissions, the implications of CDR on the distribution of local air quality and health benefits have not yet been quantitatively assessed. Here, we use a combination of integrated assessment, chemical transport, and epidemiological models to evaluate community-level U.S. health benefits in net-zero emissions scenarios that deploy different scales of CDR.

First, we develop three scenarios of the U.S. energy transition using a regional version of an integrated assessment model (GCAM): a reference scenario and low- and high-CDR scenarios that both reach net-zero GHG emissions in the U.S. by 2050 but with 1.3 and 2.4 $GtCO_2$ removed from the atmosphere in that year, respectively (see Supplementary Tables 1-2 for details). We then create gridded estimates of criteria pollutant emissions in each scenario by allocating the state-level emissions produced by GCAM according to the sector-specific distribution of current emissions in the National Emissions Inventory[37] as well as announced and assumed retirement priorities for power plants[38]. Importantly, we do not project changes in the location of emissions except where scenarios imply the retirement of specific electricity-related generators. Next, we model changes in $PM_{2.5}$ concentrations in 2050 using the WRF-CMAQ[39] air quality model, quantifying the changes at a 9-km scale over the contiguous U.S., and at a 1-km scale for each of the 15 most-populated metropolitan statistical areas in the U.S. (together home to >107 million people; Supplementary Table 3). Lastly, we use the U.S. Environmental Protection Agency's (EPA) BenMAP-CE epidemiological model and block group socioeconomic data from the U.S. Census to estimate reductions in $PM_{2.5}$-related deaths in net-zero scenarios and analyze the distribution of these health benefits among communities with regard to race-ethnicity and household median income. Details of our data sources and analytic approach are in the Methods (and Extended Data Fig. 1).

Projected trends in U.S. energy and emissions

Of roughly 70 exajoules (EJ) of primary energy consumed in the contiguous U.S. in 2020, fossil fuels supplied 88% (38% natural gas, 32% oil, and 18% coal), biomass and nuclear provided 4% each, hydropower and wind 2% each, and solar just 1%, with little changes to mid-century (Fig. 1a). In the high-CDR scenario, primary energy consumption grows to 85 EJ in 2050, with fossil fuels supplying 42% of that total (25% natural gas, 12% oil, and 5% coal), biomass 31%, solar and wind increasing to 11% each, nuclear 4%, and hydropower 1% (Fig. 1b). In the low-CDR scenario, primary energy consumption decreases until 2035 then returns to 2020 levels by 2050 (71 EJ), with fossil fuels supplying 23% (15% natural gas, 8% oil, and almost no coal), biomass, wind and solar providing 22%, 21%, and 20%, respectively, nuclear increasing to 12%, and hydropower at 1% (Fig.

1c, and Supplementary Fig. 1). Because offsets are more limited in the low-CDR scenario, fossil fuel use in 2050 is less than half that of the high-CDR scenario (17 EJ versus 36 EJ).

Reflecting the trajectories in energy sources, net annual GHG emissions in the reference scenario remain almost constant at 6 $GtCO_2eq$ per year (Fig. 1d), whereas by definition net annual GHG emissions decrease to zero in 2050 in both of the net-zero scenarios (Fig. 1e-f). By 2050, most of the modeled carbon removal in the high-CDR scenario occurs in the energy sector (1.1 $GtCO_2$ per year from BECCS-refining, and 0.4 $GtCO_2$ per year each from DAC and BECCS-electricity), with AR representing another 0.5 $GtCO_2$ per year (Fig. 1e). In the low-CDR scenario, BECCS-refining and AR each remove 0.6 $GtCO_2$ per year, BECCS-electricity is small (0.05 $GtCO_2$ per year), and there is almost no carbon removal by DAC (Fig. 1f).

Annual primary $PM_{2.5}$ emissions also remain almost constant in the reference scenario, declining only slightly from 1.28 Mt in 2020 to 1.25 Mt in 2050 (Fig. 1g). In contrast, $PM_{2.5}$ emissions decrease in both of the net-zero scenarios, to 1.06 Mt per year in 2050 in the high-CDR scenario and to 0.7 Mt per year in 2050 in the low-CDR scenario (Fig. 1h-i). In all cases, the largest contributor of $PM_{2.5}$ emissions is industry, which accounts for 59% (0.62 Mt) of 2050 emissions in the high-CDR scenario and 70% (0.49 Mt) in the low-CDR scenario. In the high-CDR scenario, industry is followed by BECCS-electricity (19%, or 0.2 Mt), buildings (8%, 0.09 Mt), other energy (including urban processes, 8%, 0.09 Mt), transportation (5%, 0.05 Mt), and refining (1%, 0.01 Mt), while in the low-CDR scenario industry is followed by other energy (including urban processes, 12%, 0.08 Mt), buildings (10%, 0.07), transportation (5%, 0.04 Mt), BECCS-electricity (2%, 0.01 Mt), with other sectors having a small share (Fig. 1h-i). Supplementary Figures 2-4 show analogous state-level results, with Texas, California, and Illinois having the highest $PM_{2.5}$ emissions in the country, and industry still representing the largest share.

Nationwide air pollution and related deaths

Figure 2a-c show projected $PM_{2.5}$ concentrations in 2050 under our three different scenarios. The spatial patterns of $PM_{2.5}$ pollution reflect the distribution of sources as well as topography and meteorology. $PM_{2.5}$ concentrations decrease substantially by 2050 in net-zero scenarios compared to the reference scenario (Fig. 2a-c; cf. 2019 levels in Extended Data Fig. 2). In 2050, projected annual average population-weighted $PM_{2.5}$ concentration in the contiguous U.S. is 5.72 and 4.55 $\mu g/m^3$ in the high- and low-CDR scenarios, respectively, compared to 7.38 $\mu g/m^3$ in the reference scenario (Fig. 2a-c). Similarly, in 2050 the EPA's average annual National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$ of 9 ug/m^3 is exceeded over areas of only 6,783 km^2 and 735 km^2 in the high- and low-CDR scenarios, respectively, compared to 103,949 km^2 in the reference scenario[40].

In turn, projected $PM_{2.5}$-related premature deaths are also substantially lower in the net-zero scenarios than the reference scenario. We estimate 2050 premature adult (>18 years) mortality to be 203,297 (95% confidence interval (CI), 147,344–255,910) in the reference scenario, 159,082 (95% CI 114,986–200,773) in the high-CDR scenario, and 127,498 (95% CI 91,980–161,208) in the low-CDR scenario (Fig. 2d-f). These levels of mortality imply rates of 839 $PM_{2.5}$-related deaths per million adults in the reference scenario in 2050, compared to 656 and 526 deaths per million adults in the high- and low-CDR scenarios, respectively. The Midwest and Eastern U.S., where $PM_{2.5}$ concentrations are highest, also have the highest $PM_{2.5}$-related mortality, with Alabama, West Virginia, Oklahoma, Arkansas, and Louisiana having the highest death rates in all three scenarios in 2050 (e.g. >860 deaths per million people each state in the high-CDR scenario alone, for difference between scenarios see Extended Data Fig. 3).

City-scale air pollution and related deaths

Our low-CDR scenario leads to much lower concentrations of $PM_{2.5}$ in most populous U.S. metropolitan statistical areas (hereinafter referred to as cities) than in the high-CDR scenario (Extended Data Fig. 4-6). Differences in population-weighted $PM_{2.5}$ concentrations and related mortality vary across the cities, with 2050 $PM_{2.5}$ exposure as high as 7.94 $\mu g/m^3$ in Los Angeles to as low as 4.18 $\mu g/m^3$ in Seattle in the high-CDR scenario (Supplementary Table 4). Moreover, Figure 3 shows city-scale patterns of avoided $PM_{2.5}$-related deaths in the low-CDR compared to the high-CDR scenario. As with regional differences, these avoided deaths are spatially heterogenous due to, for example, the location of emission sources, population densities, and topography. Among the 15 most populous cities shown, those with the greatest number of annual avoided deaths (high-CDR minus low-CDR) per unit of population in 2050 include Philadelphia (PA), Chicago (IL), Detroit (MI), Los Angeles (CA), Houston (TX), Miami (FL), Dallas (TX), and Riverside (CA)—each with >100 avoided deaths per million people per year.

In addition to the differences among cities, the deaths avoided within cities are spatially heterogenous also due to, for example, the location of sources, population densities, and topography. The number of deaths avoided in 2050 in the low-CDR scenario in some areas of New York (NY), Chicago (IL), and San Francisco (CA) are as high as 5.5, 4.1 and 3.2 per km^2, respectively, compared to other areas in the same city (Fig. 3).

Community-scale distribution of air pollution and related deaths

While half of the most populous cities see over 100 avoided deaths per million people per year in the low-CDR scenario in 2050, the spatial differences in avoided $PM_{2.5}$-related deaths are unequally distributed among income and racial-ethnic groups. Areas with greater median incomes and greater shares of non-Hispanic whites (hereinafter "whites") have systematically lower population-weighted exposure to $PM_{2.5}$ pollution and in turn lower mortality rates. Across the 15 cities, in both the low- and high-CDR scenarios, areas with median income higher than the 66th percentile of the relevant city's population experience 1.7% less $PM_{2.5}$ pollution (rightmost blue bars in Fig. 4a and 4c) and about 25% less deaths than the city mean (rightmost orange bars in Fig. 4b and 4d). Areas with greater shares of whites experience around 3% less $PM_{2.5}$ pollution (rightmost red bars in Fig. 4a and 4c) and about 17% less deaths than the city mean (rightmost purple bars in Fig. 4b and 4d, Supplementary Table 5-8).

Yet although both our low- and high-CDR scenarios are characterized by disproportional exposure to $PM_{2.5}$ and $PM_{2.5}$-related deaths among low-income and minority groups, we find that such inequalities are reduced in the low-CDR scenario (Figure 5). Figure 5a and 5b compare population-weighted pollution exposure and deaths, respectively, in areas where cities' population is >60% white (y-axes) and <30% white (x-axes), whereas 5c and 5d compare areas where household median income is above the 66th percentile for that city (y-axes) and below the 33rd percentile (x-axes). Pollution levels and related deaths are consistently greater in the areas with fewer whites and lower household income (i.e. all circles fall below the dashed equality line), but the inequality is routinely greater in the high-CDR scenario: the slope of the line segments connecting each cities' low- and high-CDR values (closed and open circles, respectively) is always lower than the dashed equality line, which means that changes between the two scenarios are larger along the x-axes than on the y-axes (see Supplementary Table 9 for values). For example, in New York city there is a decrease in population-weighted mortality of 0.51 between the high- and low-CDR scenarios in areas where population is >60% white (y-axis), whereas the decrease is 1.15 for areas where population is <30% white (x-axis)– i.e. the decrease in mortality exposure is higher in areas with a higher share of minorities (Fig. 5b, Supplementary Table 10-11, Extended Data Fig. 7-8 show results for all the cities).

Discussion and Conclusions

Our analysis of two net-zero GHG emissions scenarios shows that both substantially reduce $PM_{2.5}$ pollution and related health impacts in the contiguous U.S. by 2050 compared to a reference scenario. However, the net-zero scenario that constrains the deployment of CDR (i.e. low-CDR) entails lower gross emissions of GHGs and $PM_{2.5}$, and thus greater human health benefits: we estimate 33,328 (95% CI 23,909–42,368) deaths are avoided nationwide in 2050 under our low-CDR scenario compared to the high-CDR scenario (Extended Data Fig. 3). But more importantly, our high-resolution modeling reveals that the distribution of additional health benefits in the low-CDR scenario also tends to reduce income and racial-ethnic inequalities in $PM_{2.5}$-related mortality within major U.S. cities.

Such trade-offs between CDR and environmental inequality represent a potential conflict of priorities within the Inflation Reduction Act of 2022 (the IRA). Together with the Bipartisan Infrastructure Law of 2021, the IRA allocates roughly $12 billion to support engineered CDR (e.g., $3.2 billion to support direct air capture[41]), even as the law prioritizes benefits for low-income and disadvantaged communities (e.g., sections 13901, 60103, 60106, and especially section 60201 on environmental and climate justice block grants)[42]. Our findings reinforce the need for a coordinated and strategic transition planning[43]: CDR and environmental justice are not mutually exclusive, but they may be at odds if each is pursued in isolation.

Yet more coordinated planning will also need to grapple with the countervailing implications for energy system costs[44,45]. In our scenarios, limiting availability of CDR (i.e. the low-CDR scenario) corresponds to nearly a doubling in the marginal cost of abatement in 2050 compared to the unrestricted (high-CDR) scenario—and 12-22% higher household electricity prices depending on the U.S. state (Supplementary Figs. 5-6). Such prices are also a major social justice concern insofar as they disproportionally affect lower income households[46,47]. While CDR deployment lowers the costs of mitigation in our scenarios (Supplementary Table 12), which is consistent with previous studies[48,49], CDR deployment also increases the costs of pollution by $387 billion (based on VSL, Supplementary Table 13), as $PM_{2.5}$ mortality costs are exogenous to GCAM.

Our results are subject to several caveats and limitations. Most importantly, our scenarios assume pollution point sources in the electricity sector will be retired in accordance with announced schedules[50] and then oldest first (consistent with historical patterns)[51]. Insofar as new emitting generation is deployed by GCAM, we assume it will be sited in the same locations as still-existing plants burning the same fuels (distributed in proportion to existing capacities; also consistent with historical patterns[52,53]). Although we believe these assumptions are reasonable under business-as-usual infrastructure planning processes, improved transition plans could instead prioritize retirements and siting of new infrastructure strategically to equalize the distribution of impacts across urban populations—or even to disproportionally concentrate health benefits accruing to non-white and low-income groups[54]. We also focus on the long-term $PM_{2.5}$ effects under the current climate, and thus likely underestimate future climate change impacts on air pollution-related deaths[55,56]. Moreover, our low-CDR scenario still removes 1.3 $GtCO_2$ from the atmosphere by 2050 in the U.S., which may reflect techno-economic analysis optimism followed by an over-reliance of integrated assessment models on relatively easy-to-model CDR instead of alternative (but in many cases nascent) industrial and agricultural processes and materials. Future studies may build on our approach to prioritize emissions reductions (e.g., infrastructure retirement schedules) with the greatest potential to reduce air pollution-related inequalities[57–60], or analyze energy security and employment opportunities under different energy pathways[46].

Nonetheless, our work robustly evaluates the implications of different net-zero pathways on $PM_{2.5}$-related health impacts within major U.S. cities and nationwide. While our findings bolster the growing consensus that climate mitigation will have large benefits to public health, they also reveal the potential for CDR deployment to sustain community-scale inequalities in the health impacts of the U.S. energy system—which disproportionately harms low-income and non-white groups. Although large-scale use of CDR may ultimately be needed to meet high-ambition climate goals, our results make clear that CDR—or any mitigation pathway or energy technology—can have important and perhaps unexpected trade-offs for communities. A more just energy transition will only be achieved if these tradeoffs are carefully analyzed and incorporated in the decision-making process.

Methods

We quantify the community-specific $PM_{2.5}$ air pollution and health-related impacts of one reference scenario and two net-zero scenarios in the United States in five steps. First, we run an integrated assessment model (GCAM) to estimate future emissions from the energy sector. Second, we downscale state level emissions to a resolution consistent with the Emissions & Generation Resource Integrated Database (eGRID) and the National Emissions Inventory (NEI). Third, we run WRF-CMAQ to estimate ambient $PM_{2.5}$ concentrations in each scenario to 2050. Fourth, we run BenMAP to quantify premature mortality, and the costs associated with death from our scenarios. Finally, we identify the demographic and economic characteristics of people living in each pixel with census data at the census block group level. Extended Data Figure 1 illustrates the steps of our research; the sections below detail each step. All code and data related to this research are publicly available at GitHub (https://github.com/CandeBergero/CDR_PM2.5_distribution_paper) and at Zenodo (10.5281/zenodo.13863764).

Step 1: estimate future energy and emissions (GCAM)

The Global Change Analysis Model (GCAM) is an integrated, multisector model that explores human and Earth system dynamics. GCAM represents the interactions between different systems: energy, water, agriculture and land-use, the economy, and the climate. The main role of this model is to shed light on system interactions and to provide scientific insights on different "what-ifs" scenarios. GCAM represents 32 geopolitical regions, 235 hydrologic basins and 384 land regions. The temporal scale is every 5 years, running from 1990-2100. The model is calibrated historically to 2015, and years since then are modeled periods. For more detailed explanations, refer to[61,62].

GCAM is used for the IPCC scenarios[62] and it has been used in the White House 2021 Long-term Strategy[1].

We use the regional version of GCAM (version 6.0) for the U.S. that runs 31 global geopolitical regions and provides greater spatial definition for the United States, modeling 50 states and the District of Columbia. Each state follows population and economic growth assumptions consistent with the Shared Socioeconomic Pathway 2 (SSP2)[63]. Power generation and emissions are calibrated historically. The GHG emissions included in the model are CO_2, CH_4, N_2O, CF_4, C_2F_6, SF_6, and several HFCs (HFC23, HFC32, HFC43-10mee, HFC125, HFC134a, HFC143a, HFC152a, HFC227ea, HFC236fa, HFC245fa, HFC365mfc). Future emissions are determined by the evolution of the drivers (energy consumption, land-use, population), technology mix, and abatement measures. The air pollutants included in the model for the U.S. are BC, OC, CO, NH_3, NMVOC, NO_x, PM_{10}, $PM_{2.5}$, and SO_2. Air pollutants are modeled at the state level for each fuel and technology using emission factors consistent with the NEI for electricity generation, buildings, transportation, industrial energy use, industrial processes, urban processes, cement, and refining. National totals for historical years are scaled to Community Emissions Data System (CEDS) values to be consistent with the global GCAM model. Given that CEDS does not have $PM_{2.5}$ and PM_{10} emissions, these two pollutants are not scaled, and thus the NEI values are used. Future emissions (2020-2100) follow emission factors for each vintage and fuel-technology-pollutant combination and reflect different air pollution policies, such as New Source Performance Standards from the Environmental Protection Agency (EPA) in the electricity sector, federal regulations on wood heaters for the residential sector, and others (for more details refer to[64]).

We use GCAM because of its cross-sectoral system representation. We model one reference business-as-usual scenario and two net-zero scenarios varying the amount of carbon dioxide removals (CDR) allowed (high and low). By limiting carbon removals, the model finds different market structures to solve for the net-zero emissions constraint, including higher decarbonization of other end-use sectors (buildings, transportation, and industry), earlier/later fossil power plant retirements, and small demand reductions when alternative technologies are not available. We focus on emissions from the energy system from all relevant pollution sectors: electricity generation, industrial activity, transportation, resource production, and buildings[65]. Emissions from these sources are tracked at a state level in 5-year intervals from 2015-2050.

For the reference scenario we model a default GCAM v6.0 scenario, without modifying any assumption. The reference scenario follows historical trends where GDP and population continue growing, thus increasing the demand of services. The historical electrification of end-use sectors continues, which leads to an increase in total electricity generation. The reference scenario also has state-specific assumptions about coal and nuclear retirements, and state-specific assumptions on hydro generation based on recent trends. Natural gas electricity generation grows into the future, following historical trends, displacing coal. This scenario includes the Clean Air Act section 111 (b), which limits CO_2 emissions from new steam-generating electricity and for base-load natural gas plants. This reference scenario also assumes no new development of coal-fired power plants without CCS. There is electricity trade between states. Refining follows historical trends and thus can only happen in states where there is refining historically. Biomass refining can only be developed in states where the feedstocks are available. For further information about reference scenario assumptions refer to[66].

The two net-zero scenarios follow the United States' NDC for 2030 of 50% reduction below 2005 GHG emissions, followed by a net-zero GHG target by 2050. The model solves for this GHG constraint by applying a shadow carbon price in the economy that forces net-zero emissions by mid-century (Supplementary Fig. 5). To avoid leakages in this global model we include a net-zero CO_2 emissions constraint for the rest of the world by 2060. We have additionally reduced the emission factors for electricity generation technologies with carbon capture and storage (CCS) for

SO_2, NOx, $PM_{2.5}$, and PM_{10} following technical report No. 14 from the European Environment Agency[67] (see Supplementary Table 14), which were previously assumed in GCAM to be the same as the non-CCS technology counterparts.

In both scenarios there is anthropogenic carbon dioxide removal (CDR) from bioenergy with CCS (BECCS) in refining, electricity generation, and hydrogen production, from direct air capture (DAC), and from afforestation/reforestation (AR). The two net-zero scenarios differ in their amount of CDR: there is an unrestricted scenario which leads to higher amounts of CDR and there is a restricted scenario which leads to lower amounts of CDR. To restrict CDR, we have artificially inflated the cost of carbon storage in GCAM (Supplementary Table 2). The three scenarios are listed in Supplementary Table 1. We run these scenarios from 2015 (last historical year in GCAM) to 2050 (net-zero target year). We downscale future emissions for 2050 and for all the energy sectors.

Step 2: downscale future emissions (eGRID and NEI)

Given GCAM modeling details and data availability, we use two approaches for downscaling emissions: one for electricity generation, and another one for other energy sectors.

2.1. Electricity generation

Based on plant-by-plant details from GCAM for the U.S. electricity sector and eGRID database, we downscale electricity at a point-source level (i.e. power plant) following retirement and addition quotas from GCAM. We downscale GCAM outputs based on 2020 eGRID data at the generator level. GCAM models electricity generation at the state level in each model period (i.e. every 5 years) by fuel and technology. eGRID has current electricity generation in the U.S. at each power plant by fuel and technology. From the 30,193 generation sources in eGRID 2020 dataset[68], we filter for 10,707 that represent combustion fuels (coal, gas, oil, and biomass), that are operating or planned to operate and that have positive generation (see Supplementary Fig. 7). These generators serve as our baseline.

From GCAM we calculate the gross electricity generation additions (i.e., addition quota) and retirements (i.e., retirement quota) in each state by scenario, fuel, and technology by 2050 (net-zero target year) compared to 2020 (eGRID data). Given that GCAM is not calibrated to eGRID, we scale GCAM quotas to eGRID generation by state, fuel, and technology. This gives us a total amount of generation to be added and to be retired in each state by scenario, fuel, and technology. Once we have the final scaled addition and retirement quotas, we establish a retiring and addition schedule as follows:

1. We first retire generators following the energy information agency's (EIA) retirement schedule[50]. Note that we do not allow over-retirements, and we only retire generators until the GCAM retirement quota is met.
2. If this was not enough, meaning GCAM retirement quota was not met after following EIA retirement schedule, then we start retiring generators based on age, retiring older generators first. This is consistent with the findings of Mills et al.[69]
3. If GCAM retirement quota is larger than existing generation, we subtract this from the addition quota, so that the net-generation is not affected.

Once the retirement quota is met, we proceed to work with GCAM addition quotas.

4. We first max out existing generators in that state of the same fuel and technology assuming a potential maximum capacity factor of 85%.

5. If this was not enough to meet the addition quota, then we build new generators in existing plants that have the same technology based on a weighted distribution, so that larger power plants receive larger generators and smaller power plants receive smaller generators. This is consistent with previous studies[52,53].

The previous steps give us total electricity generation at a generator and plant level by scenario, fuel, and technology by 2050. We then apply emission factors from GCAM by state, fuel, technology, pollutant, and period and we get total emissions for nine different pollutants: BC, CO, NH_3, NOx, NMVOC, OC, $PM_{2.5}$, PM_{10}, and SO_2 (see Supplementary Fig. 8 for a state example for $PM_{2.5}$). These 2050 point-source electricity emissions are adjusted to a 2019 baseline following the EPA air pollutant emissions trends[70]. We use 2019 as the base-year case, instead of 2020, because the global pandemic disrupted emission trends. These are the electricity emissions used to drive the WRF-CMAQ air quality simulations.

2.2. Other energy sectors

Other energy sectors in GCAM include industry, transportation, refining, resource production, buildings (commercial and residential), and urban. Given that GCAM does not have detailed technology information in these energy sectors, we simulate the emission change into the future (i.e., 2050) for a given sector compared to 2020 and apply this factor to the EPA's NEI 2020 dataset[71] to estimate total emissions in 2050.

We match 51 non-point sectors and 84 facility types in NEI to sectors in GCAM and exclude emissions from power plants. It is noted that we keep emissions from 6 non-point sectors (i.e., agriculture and livestock dust, road dust, biogenic, prescribed fires, and wildfires) and 3 facility types (i.e., crematory animal, crematory human, military base) constant with the base-year level, as they are not included in GCAM and are outside the scope for this study. Additionally, the changes in emissions from transportation are applied to NEI in 2017, as opposed to 2020, because of the impact of the 2020 global pandemic on transportation emissions. Finally, these 2050 emissions are also scaled to a 2019 baseline following values based on EPA air pollutant emissions trends[70] and used to drive the WRF-CMAQ air quality simulations.

Step 3: model $PM_{2.5}$ concentrations (WRF-CMAQ)

In the third step, we employ the Weather Research and Forecasting (WRF, version 4.0.1) and the Community Multiscale Air Quality (CMAQ, version 5.2.1) to estimate changes in long-term $PM_{2.5}$ air quality under different scenarios. We focus on $PM_{2.5}$ because of its large impacts on populations, therefore the possibility of bringing the most benefits[43,72].

We design double-nested simulations, with the first domain covering the contiguous U.S. at a 9-km scale, and 12 nested domains covering the 15 most populous metropolitan statistical areas in U.S. at a 1-km scale (Supplementary Fig. 9, Supplementary Table 15). The vertical resolution is 23 sigma levels from surface to tropopause (about 100 mb) for WRF simulations, and 14 sigma levels for CMAQ model. We conduct a total of four groups of experiments, including one base-year case (i.e., 2019) and three future 2050 emission scenarios (i.e., reference, net-zero high-CDR, and net-zero low-CDR). All the simulations are conducted throughout the whole year and with a one-month spin-up. Additionally, we run 36 simulations at a 1-km resolution for the 15 cities of interest (12 base-year case 2019; 12 net-zero high-CDR scenario in 2050; and 12 net-zero low-CDR scenario in 2050).

We use NCEP final analysis data to drive WRF simulations and provide meteorological inputs fixed in 2019 for all simulations[73]. Historical anthropogenic emissions for U.S. are obtained from NEI 2020 and are scaled to 2019 level according to EPA air pollutant annual emission trends. As noted earlier, we used 2019 as a base-year case as opposed to 2020 because the global pandemic disrupted emission trends. Future emission trends (i.e., 2050) are provided by GCAM downscaling process (see *Step 2: downscale future emissions* for details). Historical and future anthropogenic emissions for other bordering countries in the first 9-km domain are derived from CEDS[74] and CMIP[75] databases, respectively, and scaled following GCAM regional values for future years. Natural source emissions, including dust, open biomass burning, and biogenic emissions are also incorporated and fixed in 2019 level. Besides, the chemical initial and boundary conditions for the first domain are interpolated from the dynamic outputs of GEOS-Chem model, which are driven by future gridded CMIP6 emissions. Detailed model configurations, including meteorological and chemical schemes, anthropogenic and natural emission sources, chemical initial and boundary conditions are listed in Supplementary Table 16.

We evaluate our base-year $PM_{2.5}$ simulations with in-situ observations, which were collected from Air Quality System (AQS) monitoring network, maintained by U.S. EPA. The evaluations of annual $PM_{2.5}$ simulations for contiguous U.S. (Supplementary Fig. 10) and 15 most populated cities (Supplementary Fig. 11) suggested a reliable performance of our air quality modeling system. Additionally, we apply a high-resolution and high-quality ground-level $PM_{2.5}$ dataset (GlobalHigh$PM_{2.5}$)[76], which was developed with big data (i.e., ground measurement, satellite retrieval, atmospheric reanalysis and simulations) to systematically reduce WRF-CMAQ simulation uncertainties. Eq. 1 denotes the calibration process, where *i* and *j* represent the specific simulation case and year, respectively; *C* and C_{SIM} refer to the calibrated and original simulated $PM_{2.5}$ concentrations, respectively.

$$C_{i,j} = C_{GlobalHighPM2.5_{2019}} \times \frac{C_{SIM_{i,j}}}{C_{SIM_{base,2019}}} \tag{1}$$

Step 4: model $PM_{2.5}$-related mortality (BenMAP)

In the fourth step, we use the Benefits Mapping and Analysis Program–Community Edition (BenMAP-CE, version 1.5) to estimate the burden to human health of total air pollution from each scenario in the contiguous U.S. at a 9-km resolution and in the 15 most populated metropolitan statistical areas at a 1-km resolution. BenMAP-CE is an epidemiological model developed by the EPA to estimate the number and economic value of air pollution-related deaths and illness. The model uses health impact functions derived from the published epidemiology literature, considering air quality changes, population, baseline incidence rates, and an effect estimate. BenMAP calculates the health impact based on the following function:

$$\Delta Y = \left(1 - e^{-\beta * \Delta AQ}\right) * Yo * Pop \tag{2}$$

Where ΔY is the estimated health impact attributed to air pollution, β is the beta coefficient from an epidemiologic study, ΔAQ is a defined change in air quality, Yo is the baseline rate for the health effect of interest, Pop is the population exposed to air pollution. The reductions in premature mortality are expressed total deaths and in monetary terms based on the "Value of a Statistical Life" (VSL). VSL is the aggregate dollar amount that people would be willing to pay for a reduction in their individual risk of dying in a given year[77,78].

The $PM_{2.5}$ pollution data is provided by WRF-CMAQ, as explained in *step 3*, while the population data is from the American Community Survey (ACS) from the U.S. Census Bureau from 2019 (specifically table ACSDT5Y2019.B01003). The population data was rescaled to the desired resolutions (9-km grids for the contiguous U.S. and 1-km grids for each city analysis). For health baseline incidence we use BenMAP 2015 and 2020 values and linearly extrapolate for 2019, and then rescale these 2019 values from the county level to our 9-km and 1-km grids based on a weighted average per pixel based on overlap area. For our health analysis we use the health impact function from Pope et al.[79] included in BenMAP. The authors in this study examined the relationship between long-term $PM_{2.5}$ exposure and mortality in the contiguous U.S. for 1,599,329 adults aged 18-84 who were interviewed by the National Health Interview Surveys between 1986 and 2014. For the economic valuation, we use EPA Standard Valuation Functions on a current undiscounted VSL of $8.7 million (2015 USD), which represents the mean of a distribution fitted to 26 VSL estimates and is used by the EPA in Regulatory Impact Analyses[80].

We run three main BenMAP scenarios for the 9-km resolution WRF-CMAQ results (reference scenario in 2050; net-zero high-CDR scenario in 2050; and net-zero low-CDR scenario in 2050), and include four additional runs in the Extended Data Figures 2 and 3 (base-year case 2019; reference scenario in 2050 vs net-zero high-CDR scenario in 2050; reference scenario in 2050 vs net-zero low-CDR scenario in 2050; and net-zero high-CDR scenario in 2050 vs net-zero low-CDR scenario in 2050). For the 1-km resolution results, we run 15 main BenMAP scenarios, one per city, to see the difference between net-zero high-CDR and net-zero low-CDR scenarios in 2050, and run BenMAP 45 more times to represent base-year 2019, net-zero high-CDR, and net-zero low-CDR mortality for each city to help interpret results and estimate population-weighted mortality.

Step 5: assess distribution

In the fifth step we identify the race-ethnicity and median household income for people living in each pixel at a 1-km scale for each of the 15 cities analyzed. To identify demographic information, we use data from the Census Bureau, specifically from the ACS. The ACS is a nationwide survey that collects and produces information on social, economic, housing, and demographic characteristics in the U.S. every year. The survey is conducted by the U.S. Census Bureau to gather information at a community level that helps determine how $675 billion in federal and state funds are distributed every year. About 3.5 million U.S. households (1 in 38) per year receives an invitation to participate in the survey, and the participant is required to fill the questionnaire. The household is selected to statistically represent other households in the surrounding community. The U.S. is divided into regions, divisions, states, counties, census tracts, and block groups. The smallest unit available in the ACS is the block group, and it generally contains between 600 and 3,000 people[81]. Other studies have used the ACS to analyze air pollution exposure disparities in the U.S. population and income groups[18], race, age and poverty[19,22].

In this project, we use the 2015-2019 ACS 5-Year Data Products, since this product has smaller population groups and having a fine resolution is important when assessing the distribution of air pollution impacts. The 5-year products are not just an average of 5 years, but rather data pooled over 60 months, weighted to produce estimates controlling for age, race, and Hispanic origin. The 5-year estimate are more robust for analyzing data for small population groups. We focus on demographic and socioeconomic variables, including race-ethnicity (table ACSDT5Y2019.B03002) and median household income (table ACSDT5Y2019.B19013). We use data at the block group level, and when data is missing for income because of privacy issues we use data at higher census levels. We grouped race-ethnicity into the following: "Hispanic or Latino", "non-Hispanic whites", "non-Hispanic Black or African American", and "Other", which includes non-Hispanic Native Hawaiian and Other Pacific Islander alone, non-Hispanic some other race alone, and non-Hispanic two or more races. To simplify our analysis, we then group our data into three bins for race-ethnicity, and three bins for median household income. The race-ethnicity bins relate to the percent of non-Hispanic whites in each group: 0-30% non-Hispanic white, 31-60% non-Hispanic white, 61-100% non-Hispanic white. The income bins are created based on income percentiles in each city: 0-33rd percentile, 33rd percentile plus one USD to the 66th percentile, and

66th percentile plus one USD and higher. Supplementary Figure 12 shows the racial distribution of each city and Supplementary Table 17 contains the median household income cutoff point.

In our analysis we rescale census block group data to calculate the amount of people by race-ethnicity in each pixel and the median household income, using R. For population we assume an equal distribution across the pixel, and for income we calculated the weighted mean for the pixel based on the area of overlap. We then calculate the population-weighted $PM_{2.5}$ and population weighted mortality, similar to[18,24,26], as follows:

$$\text{weighted average} = \frac{\sum_{i=1}^{n}(X_i \times W_i)}{\sum_{i=n}^{n} W_i} \tag{3}$$

Where X_i is the $PM_{2.5}$ concentrations or mortality in each pixel and W_i is the population in that pixel. The population weighted value is thus the sum of the product of either $PM_{2.5}$ concentration or mortality in each pixel and the population in that pixel, divided by the total population in the city (for the 1-km analysis). We calculated this for all the population, and then for each race-ethnicity group and income group. The population weighted values thus represent a measure of exposure. For $PM_{2.5}$ concentrations it represents the exposure of people to pollution, while for mortality it represents the population's exposure to death. We then define "excess exposure" as the additional exposure as a percentage for a given group compared to the level of the population at a whole. This is the exposure of a group (either race-ethnicity or income) compared to the same metric for the whole population in a given city. Supplementary Figure 13 shows excess exposure in 2019.

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Competing interests: the authors declare no competing interests.

Data and materials availability: We used data from relevant literature as cited in our study. All code used in this study is publicly available at GitHub (https://github.com/CandeBergero/CDR_PM2.5_distribution_paper). All data used in this study is publicly available at Zenodo (10.5281/zenodo.13863764).

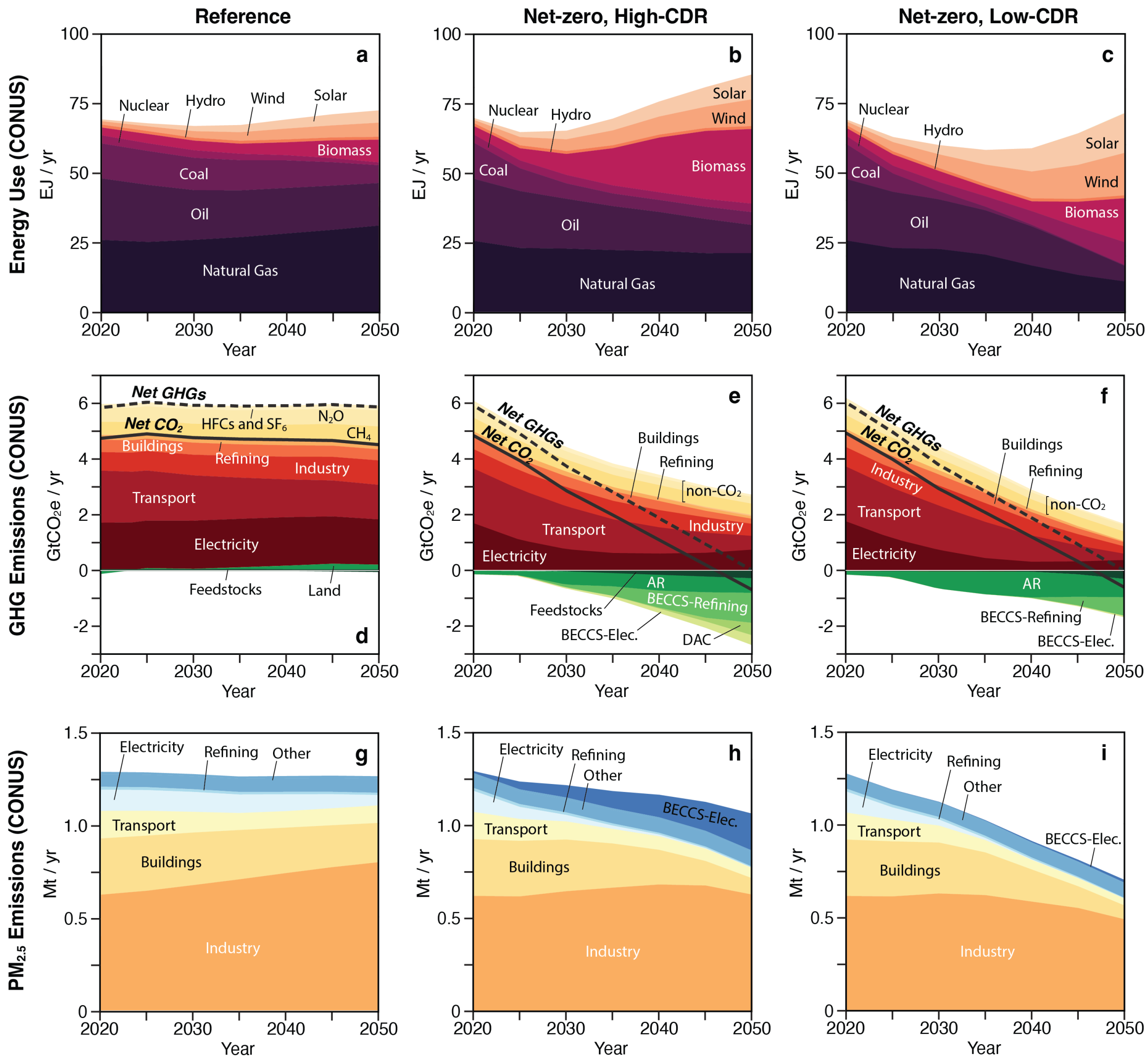

Figure 1 | GCAM modeling results for the U.S. Each row represents a variable and each column a scenario. The top row represents primary energy use in the contiguous U.S. in EJ per year for different sectors (**a-c**). The second row represents GHG emissions in $GtCO_2e$ per year with red colors representing sources for CO_2 and yellow colors representing non-CO_2 emissions (**d-f**). The bottom row represents $PM_{2.5}$ emissions in Mt per year in the three scenarios with colors representing the source for these emissions (**g-i**).

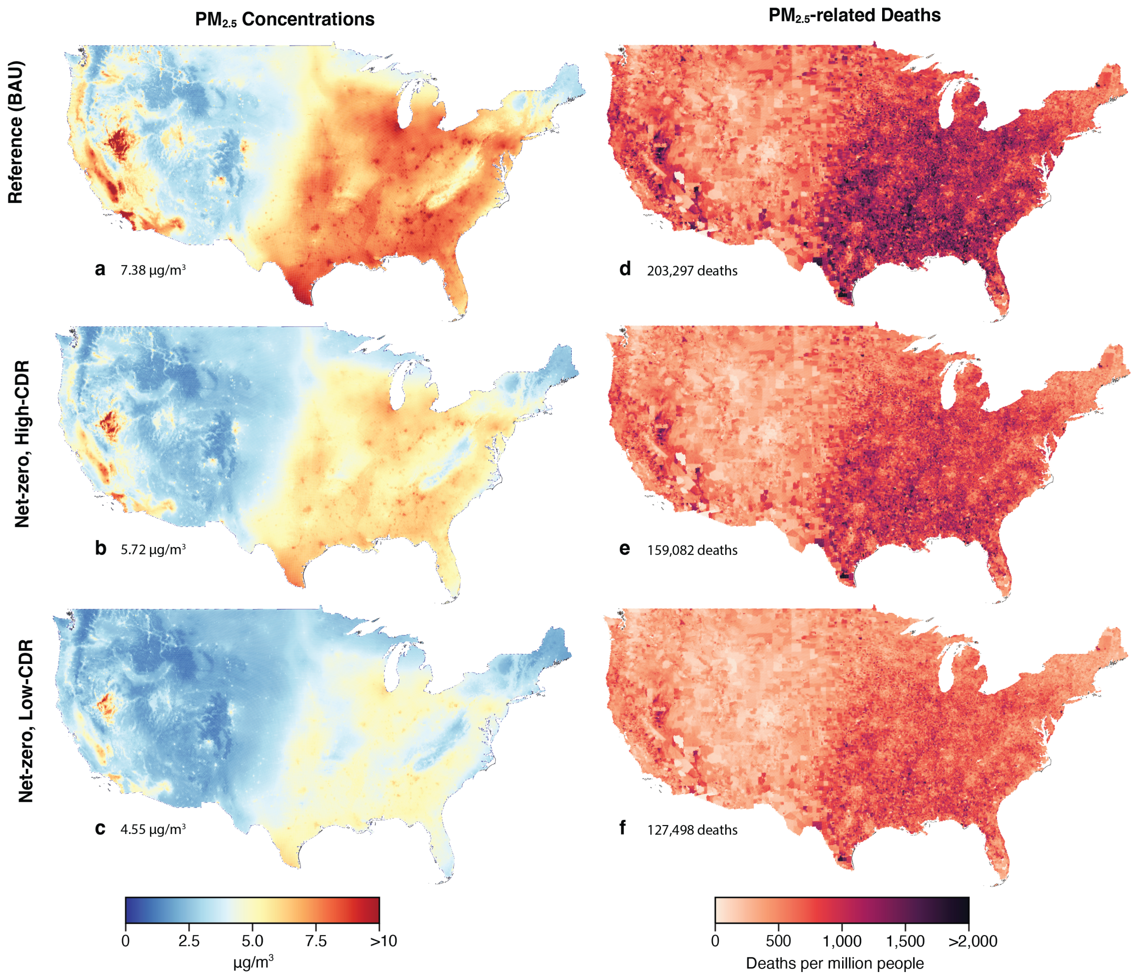

Figure 2 | $PM_{2.5}$ concentrations and related mortality in the contiguous U.S. in 2050. The first column represents yearly mean $PM_{2.5}$ concentrations in μg/m^3 as modeled in WRF-CMAQ in 2050 for our three scenarios at a 9-km scale. Values represent population weighted $PM_{2.5}$ concentration. The color scale turns beige at 5 μg/m^3, representing the Air Quality Guidelines from the World Health Organization, while the standard for the EPA is 9 μg/m^3, when values become red. Yearly mean $PM_{2.5}$ values above these thresholds pose important risks to public health (**a-c**). Following the air pollution concentrations, the right column introduces the related mortality in deaths per million people in each 9-km pixel as estimated in BenMAP-CE. Values represent median estimate in mortality (**d-f**).

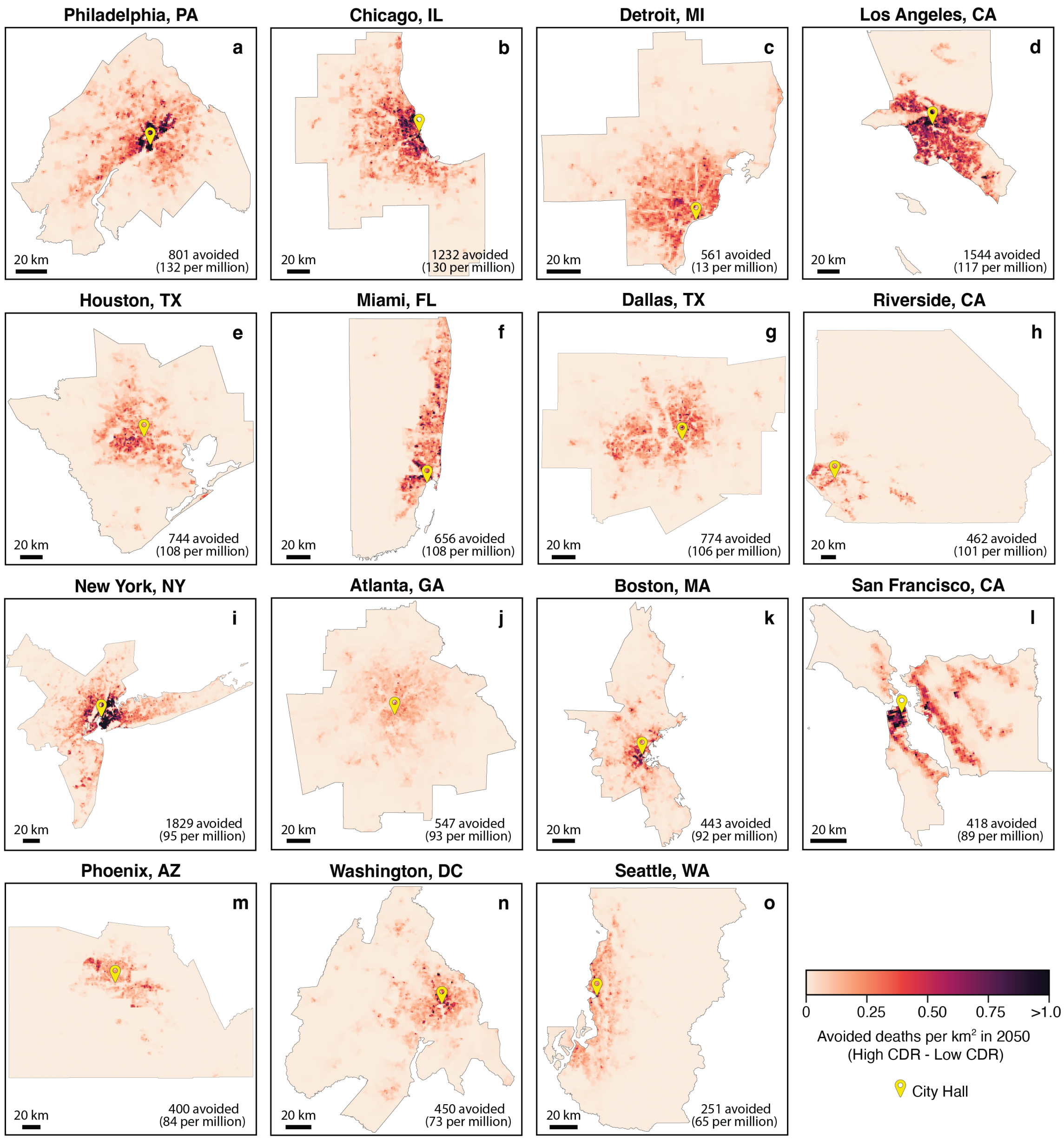

Figure 3 | $PM_{2.5}$-related deaths avoided in 2050 in the 15 most populated U.S. cities by limiting CDR. The figure shows the avoided mortality in the low-CDR scenario compared to the high-CDR scenario in 2050 in the 15 most populated cities in the U.S., sorted from highest to lowest mortality rate (i.e., deaths per million people). Each pixel in the cities represents $1km^2$. The city hall is included for geographical reference.

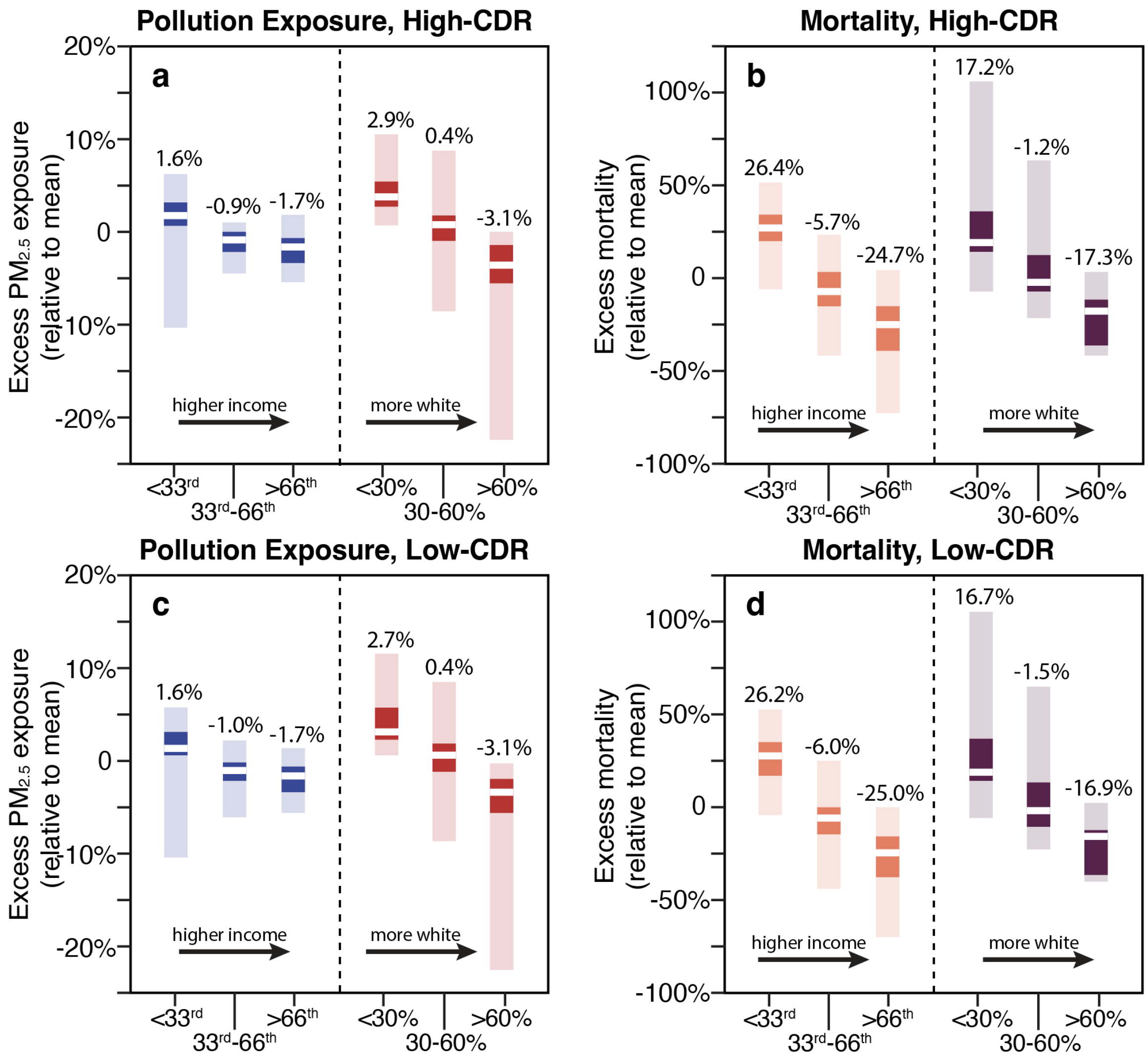

Figure 4 | Distribution of impacts across race- ethnicity and income groups. Excess in pollution exposure and mortality across the 15 most populated cities in the U.S. for high-CDR scenario (**a, b**) and low-CDR scenario (**c, d**). Excess exposure is defined in each group (e.g. areas with <30% whites or below the 33rd median household income percentile) compared to the city's mean. White lines represent the median value across the 15 cities, the darker shade represent the first and third quintiles, while the minimum and maximum values across the cities are represented by the lighter shades in each bar. Median values show that excess exposure increases as the household median income and as the percent of non-Hispanic whites decreases.

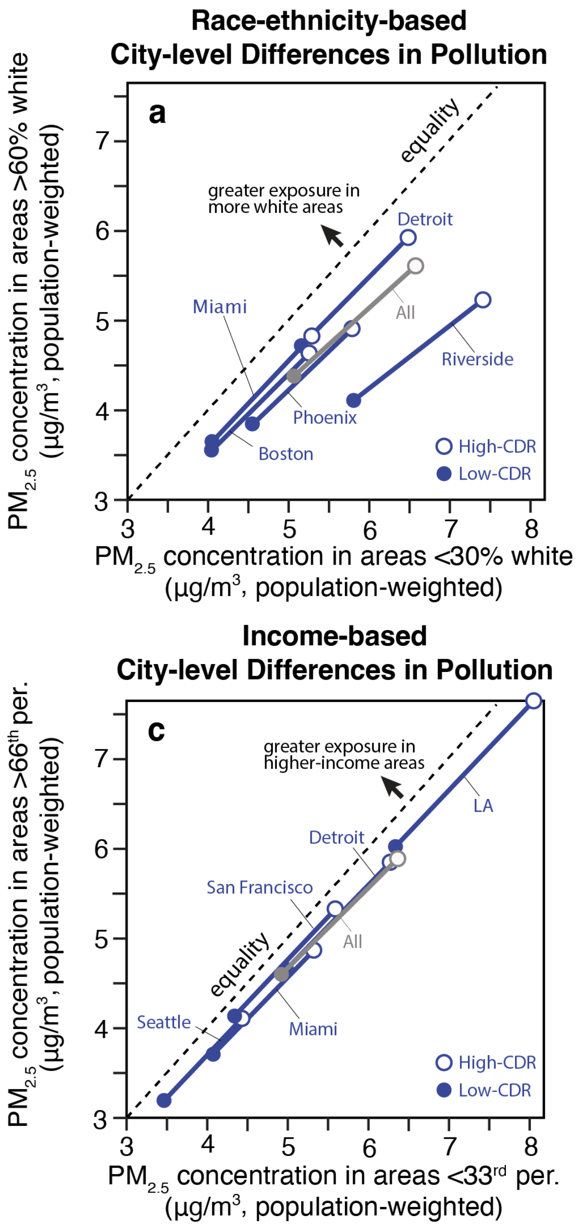

Figure 5 | City-level difference in population-weighted pollution and mortality. Panels **a** and **b** show the decrease in inequalities in the low-CDR scenario compared to the high-CDR scenario in the 5 cities with the lowest slope between the points for pollution exposure and mortality, respectively, in terms of race-ethnicity (comparing areas in a city where population is over 60% white in the y-axes, to those in the same city where population is less than 30% white in the x-axes). Panels **c** and **d** do the same but in terms of household median income (comparing areas in a city where the median household income is above the 66th percentile in the y-axes, to those in the same city where household median income is below the 33rd percentile in the x-axes). Population-weighted values are used to represent exposure in pollution and mortality. Refer to Extended Data Figures 7-8 for all cities.