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LETTER

Phasing out coal power plants based on cumulative air pollution impact and equity objectives in net zero energy system transitions

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Abstract

Transitioning to a net zero economy entails rapidly retiring US coal power plants, a major source of both greenhouse gases and air pollution. Conceptualizations of just transitions often embed climate, socioeconomic, and environmental justice objectives. Here we evaluate the influence of cumulative air pollution impact and equity objectives in the context of coal electric power plant retirement decisions. Operating coal power plants accounted for approximately 11 600 mortalities ($100B in damages) in 2018, disproportionately impacting low income, nonwhite, and rural populations. To evaluate the future phase-out of coal generators, we optimize for alternative climate policy goals, in addition to air pollution objectives related to the distribution of impacts on the basis of income, race, voting patterns, population density, and National Ambient Air Quality Standards classifications. With policy goals to both achieve net zero emissions by mid-century and to minimize cumulative air pollution-related mortality, approximately 134 000 deaths ($1.2T) are avoided from 2020 to 2050 (relative to business-as-usual). We find that the way in which equity objectives are operationalized has a large influence on asset-level retirement decisions and policy design. Phase-out strategies associated with policy objectives to minimize cumulative mortalities across the US population are generally consistent with objectives to minimize impacts on vulnerable subpopulations, but differ from those that target geographically-defined vulnerable communities.

1. Introduction

In order to stabilize the global mean temperature, net emissions of greenhouse gases must approach zero, requiring a fundamental transformation of the US energy system [1, 2]. There is mounting policy and political discourse regarding just transitions as well as embedding environmental justice goals into climate policy [3–5]. The concept of just transitions has evolved to incorporate aspects of energy, environmental, and climate equity and justice, and to include elements related to the distribution of costs, risks, and benefits, such as air pollution and jobs [6–9]. In the broader context of environmental policy and planning in the United States (US), principles of equity and justice have historically been treated as subsidiary, if considered at all, rather than as explicit objectives [10]. Several studies have modeled least-cost technological pathways to achieve deep decarbonization at the macro-energy systems level based on principles of efficiency [11–16], but few studies focus on asset-level transitions based on principles of justice and equity.

Coal combustion in the electric power sector is a major source of anthropogenic greenhouse gas emissions, accounting for approximately 18% of US emissions in 2018 [17]. To achieve net zero emissions targets, many studies show that all coal power capacity must retire by 2030 or earlier [13, 15, 16]. Coal capacity declined by 70% from 1990 to 2019 and at an increasing rate over the past decade (figure 1(h)) [18]. However, coal continues to comprise almost a quarter of US electric power sector generation (as of 2019), with the aging coal power fleet consisting of approximately 300 power plants [19, 20]. Empirical evidence shows that retired plants

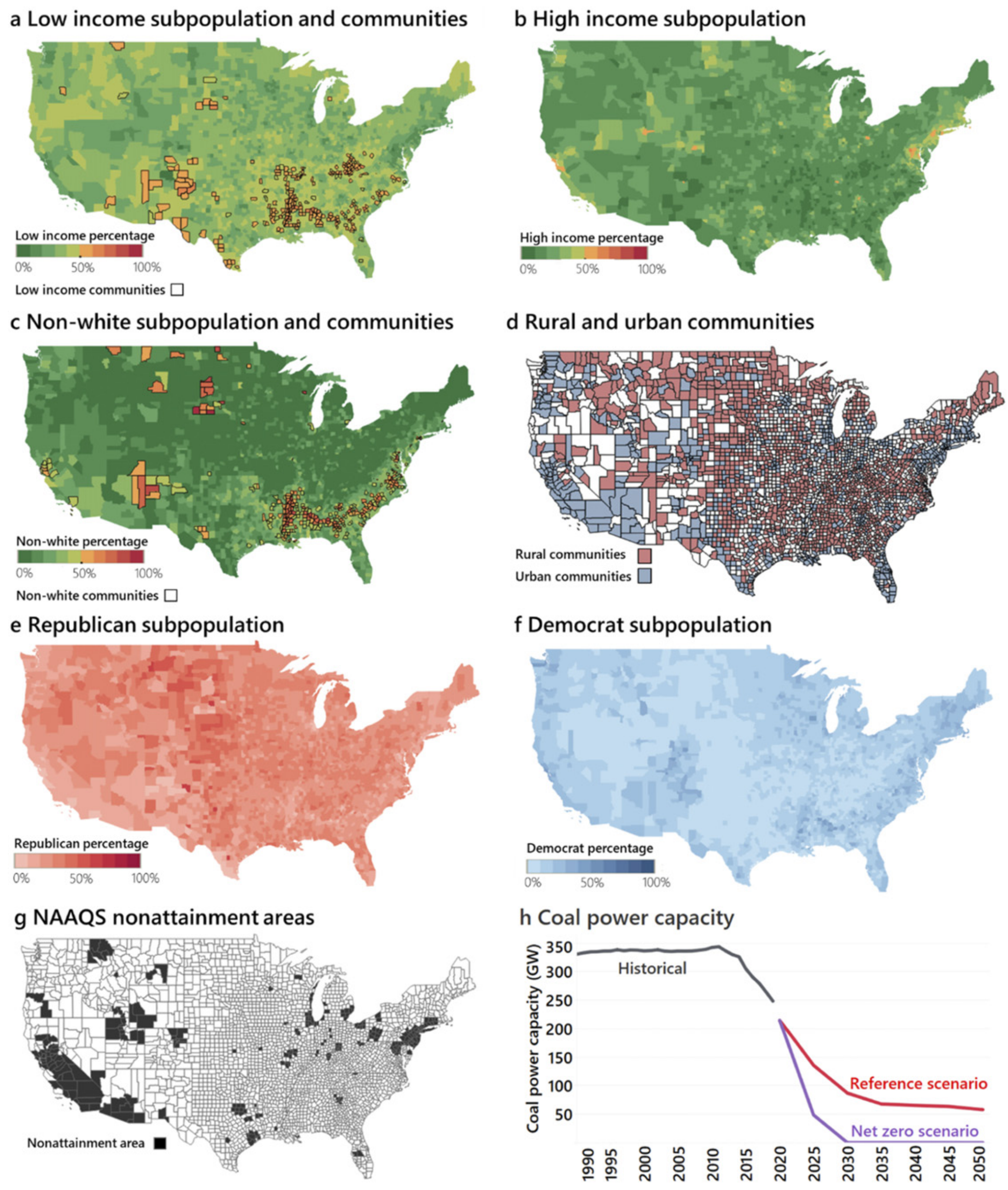

Figure 1. Subpopulations and communities stratified by (a) and (b) income, (c) race, (d) population density, (e) and (f) voting patterns, and (g) NAAQS nonattainment classification. (h) Historical capacity and future capacity constraints by climate policy scenario. Refer to the methods section for details regarding the classification of subpopulations and communities.

tend to be smaller, older, less efficient, and more polluting than operating plants, with sulfur dioxide (SO_2) emissions rates, planning reserve margins, load variation, and vintage functioning as the strongest predictors of asset-level retirements [21, 22]. Future retirement decisions may be influenced by different factors than in the past, especially in the context of deep decarbonization and with an increasing public focus on environmental justice.

The energy system is also a substantial source of air pollution and corresponding adverse health impacts, most significantly premature mortality from cardiopulmonary and respiratory illness, associated with exposure to elevated fine particulate matter ($PM_{2.5}$) concentrations [23–32]. There is a large body of literature attributing health damages to different sectors, showing that coal combustion in the power sector was responsible for 10%–14% of health impacts resulting from emissions of primary $PM_{2.5}$ and secondary $PM_{2.5}$ formed from the atmospheric oxidation of nitrogen oxides (NO_x) and SO_2 emissions [25, 30, 33–35]. There is also evidence that air pollution from the electric power sector may disproportionately impact populations on the basis of socioeconomics and race [10, 25, 34, 35]. Several studies have evaluated the air pollution co-benefits associated with transitioning away from coal generation in the US [36–40], but none have performed an asset-level assessment based on both net zero emissions targets and policy objectives to minimize cumulative air pollution impacts and disparities on the basis of income, race, political geography, population density, and National Ambient Air Quality Standards (NAAQS) nonattainment classification. Here, we evaluate air quality impacts and damages associated with asset-level retirements of coal power generators in the US under different climate and air pollution policy objectives.

2. Methods

The formulation, assumptions, and data are introduced in the following sections and elaborated upon in section 1 of the supplementary information (https://stacks.iop.org/ERIS/2/021004/mmedia) (SI). We develop a historical baseline for 2018 and future projections from 2020 to 2050 of cumulative impacts and the distribution of impacts across subpopulations and communities. We then formulate an optimization model in which cost drivers and air pollution impacts are minimized, in order to evaluate the sequencing of the retirement of coal power generators. We specify a base set of assumptions that are adopted throughout, in addition to performing a sensitivity analysis to account for the main sources of uncertainty that can reasonably be captured.

2.1. Power plant data

We compile data (i.e., coordinates, heat rate, operating year, SO_2 emissions rate, capacity, generation) for 738 generators and 389 power plants reported by the US Energy Information Administration (EIA) and US Environmental Protection Agency (EPA) [19, 41, 42].

2.2. Emissions modeling

We model both historical air pollutant emissions for 2018 as well as future emissions from 2020 to 2050. For historical emissions, we use plant-level SO_2 and NO_x emissions reported by the EIA in 2018 [43]. We also estimate future emissions for each generator, using SO_2 and NO_x emission factors (in units of pounds per million British thermal unit) reported by the EIA for each plant in 2018 or reported in the EPA Emissions & Generation Resource Integrated Database (eGRID) for each generator in 2016 [42, 43]. To derive $PM_{2.5}$ emission factors, we develop a scaling factor that relates $PM_{2.5}$ and NO_x based on emissions for a subset of plants reported in the EPA National Emissions Inventory (NEI) in 2017 [44]; we develop a scaling factor because not all plants are reported in the NEI dataset. We convert emission factors (to units of pounds per kilowatt-hour) based on plant-specific heat rates reported in the EPA eGRID for 2016 [42]. We then estimate future annual, generator-level emissions (in units of metric tons) by coupling generator-level emission factors with regional and time-varying capacity factors that align with different climate policy regimes (as described in the subsequent section on optimization modeling).

2.3. Air quality impact modeling

We combine the emissions estimates with the Air Pollution Emission Experiments and Policy Analysis Model (v.3, AP3), a reduced complexity air quality model that generates estimates of pollution-induced premature mortalities in downwind receptors associated with emissions from source locations [45, 46]. To assess uncertainty in the functional form of the model, in addition to employing the base model AP3, we also evaluate mortalities using source-resolved versions of the Estimating Air pollution Social Impact Using Regression (EASIUR) model [47] and Intervention Model for Air Pollution (InMAP) [48], which are functionally different but provide complementary insight. Mortality estimates are also sensitive to the relationship between pollutant concentration and health response; therefore, we perform a sensitivity analysis whereby we vary the concentration-response (C-R) relationship based on the Harvard Six Cities (H6C) (the base modeling assumption) and American Cancer Society (ACS) studies [26, 28].

We adjust mortality estimates over time based on future population projections. We use 5 years, county-level population projections from the EPA’s Integrated Climate and Land Use Scenarios (ICLUS) project. ICLUS includes demographic and spatial allocation models, consistent with the Intergovernmental Panel on Climate Change Shared Socioeconomic Pathways and Representative Concentration Pathways to project population, demographics, and land use change to 2100 [49]. We use the B2 scenario projections, which represents a regionally-oriented world of moderate population growth, moderate fertility rates, low international and domestic migration, and solving regional environmental and economic problems.

We evaluate historical mortality and mortality rates associated with coal power plant emissions stratified by household income level (i.e., $<$\$20 000, \$20 000 to $<$\$35 000, \$35 000 to $<$\$50 000, \$50 000 to $<$\$100 000, $\geqslant$\$100 000), poverty level (i.e., above, below poverty level), race and ethnicity (i.e., non-white, black or African American, American Indian, Asian, white, Hispanic or Latino), US presidential election voting patterns from 2016 (i.e., Democrat, Republican, other party, non-voting), population density (i.e., rural, urban, mixed), and National Ambient Air Quality Standard (NAAQS) classification (i.e., nonattainment,

attainment). We use county-level demographic data from the US Census Bureau's American Community Survey for 2018, data classifying counties as not meeting NAAQS for $PM_{2.5}$, PM_{10}, SO_2, and/or ozone for 2019 reported by the EPA, and county-level voting data for the 2016 US Presidential Election from the MIT Election Data and Science Lab [50–52].

We also estimate future total mortality and mortality rates for subpopulations and communities stratified by demographic, political, and environmental attributes, as depicted in figures 1(a)–(g). Specifically, with respect to income, we estimate the (1) total mortality of the low income subpopulation defined as all households with an income less than \$30 000, (2) total mortality of low income communities defined as the top ten percentile of counties with respect to the percentage of the population that is low income (i.e., 49% or greater), and (3) mortality rates of low income and high income (i.e., $\geqslant$\$100 000) subpopulations. Similarly, with respect to race, we estimate the (1) total mortality of non-white subpopulations, (2) total mortality of non-white communities defined as the top ten percentile of counties with respect to the percentage of the population that is non-white (i.e., 42% or greater), and (3) mortality rates of non-white and white subpopulations. With respect to population density, we estimate (1) total mortality on rural communities (defined as the counties in which two-thirds or more of the population is classified as rural) and (2) mortality rates of rural communities as well as urban communities (defined as the counties in which two-third or more of the population is classified as rural or urban, respectively). We estimate mortality rates for Republican and Democrat subpopulations based on 2016 US presidential county-level voting patterns. We also estimate total mortality in 2019 NAAQS nonattainment counties. While county-level changes in population density is adjusted for over time, county-level changes in demographics, income, voting patterns, and NAAQS nonattainment are not accounted for over time.

2.4. Air quality damage estimation

To develop monetized impact estimates, we multiply mortality by the value of a statistical life (VSL), a commonly used measure of the willingness-to-pay for small changes in mortality risk. We treat VSL parametrically, assuming a base value of \$8.9M and range of \$850 000 to \$23M (in units of 2019 USD); these values align with the mean and 95% confidence interval (CI) associated with a probabilistic VSL that follows a Weibull distribution, consistent with the approach used by the EPA [53]. We do not adjust VSL based on future wage inflation or deflation. We alternatively assume a discount rate of 0% (base assumption), 2%, 3%, or 7%.

2.5. Optimization modeling

To assess alternative future pathways for coal power generation in the United States, we apply the multi-objective energy & equity (MOEE) model, an adaptable macro-energy system planning optimization architecture that incorporates cumulative impact and social equity objectives. See Mayfield *et al* (forthcoming) for additional details regarding the MOEE model. This model leverages the previously described data and emissions, air quality, and damage modeling. To represent different future climate and air pollution policy regimes, we formulate linear programs with different objective functions, simulated inputs, and constraint sets. These climate and air quality policy regimes are agnostic with respect to the explicit policy instrument or mechanism. The model selects the timing, location, and order of coal generator retirements from 2020 to 2050. Further information regarding the mathematical formulation is provided in supplemental information (SI) section 1. The optimization models are solved using the general algebraic modeling system.

Climate policy scenarios. We model two future climate policy scenarios: (1) the entire energy system develops assuming that existing regulations remain as enacted throughout the period of analysis, generally consistent with the EIA Annual Energy Outlook reference case projection for coal (reference scenario), and (2) the entire energy system transitions to achieve an economy-wide net zero emissions target by mid-century (net zero scenario). These climate policy scenarios are formulated as annual, regional capacity constraints and capacity factors, as shown in figure 1(h). Capacity constraints are parameterized based on output from the *Net Zero America* (NZA) study, which implements a macro-energy system optimization model to select alternative techno-economic pathways, each of which meet a linearly decreasing net-zero emissions constraint over time and are cost-minimized subject to a range of end-use demand electrification and renewable deployment assumptions [15, 16]. In other words, the net zero scenario capacity constraints are consistent with the broader US energy system transition. Retirement of all coal capacity by 2030 consistent with net zero targets entails a decline rate [23 gigawatts per year (GW/yr)] that is similar to the peak historical rate of decline in 2015 (21 GW/yr), but higher than the retirement rate based on the EIA projections (10 GW/yr) that assume relevant laws and regulations are unchanged.

Cost objectives. SI table 2 specifies four types of cost objectives that align with different historical drivers of coal power plant retirements. The objective function is to minimize aggregate costs, age, heat rate, or SO_2 emissions rate across all generators. We use generator-specific age, heat rate, and SO_2 emissions rate data reported by the EIA [19]. We develop generator-specific marginal capital and operations & maintenance costs based on the formulation used in the National Energy Modeling System, which is a function of plant vintage, capacity, and air pollution abatement equipment [21].

Air quality objectives. We specify nineteen types of air pollution objectives related to cumulative mortality and the distribution of mortality (refer to SI table 2). We minimize cumulative deaths for the entire US population. Alternatively to reflect the distribution of air pollution impacts, we minimize deaths across subpopulations and communities or minimize the difference in mortality rates between subpopulations and communities on the basis of income, race, political geography, population density, and existing environmental burdens.

3. Historical air pollution impacts and equity

Other studies have estimated air pollution impacts from coal power generation and have found evidence of racial and socioeconomic disparities in the distribution of impacts [25, 34, 35]. Here, we expand upon previous studies by modeling additional dimensions of air pollution equity and the political geography of air pollution. We further estimate historical air pollution impacts to provide a consistent baseline by which to compare and derive future estimates under different air pollution and climate policies.

The baseline air pollution impacts associated with coal power generation in 2018 amount to approximately 11 600 premature mortalities. This is equivalent to monetized impacts of $100B, with a 95% CI range from $10B to $270B which reflects the vast uncertainty in the VSL. For comparison, other recent studies estimate that coal power generation resulted in $120B damages in 2011 and 9400 premature mortalities in 2014 [25, 35].

Figure 2(a) depicts the spatial distribution of capacity and historical impacts, and SI figure 3 shows the spatial distribution of damages (as a percentage of aggregate county-level income). Coal power plant capacity is distributed across 46 states and 285 counties, whereas air pollution impacts are dispersed across all counties in the contiguous 48 states. We assess the spatial Gini coefficient (η), which is an aggregate measure of the spatial equity across the system in which each county is compared to all other counties; it ranges in value from 0 for a completely equal distribution to 1 for complete inequity. We find high spatial inequities with respect to electric power capacity ($\eta = 0.96$), with 90% of capacity concentrated in 5% of counties. There are also spatial inequities with respect to air pollution ($\eta = 0.72$), with 60% of deaths concentrated in 10% of counties. For context, estimated spatial inequities of coal generation-related air pollution impacts exceed that of household income inequality in the US ($\eta = 0.49$ for 2018) and air pollution impacts across the natural gas supply chain in the Appalachian basin ($\eta = 0.69$) (10, 50). There are large county-level variations in impacts in 2018. There are fewer than one model premature mortality in approximately half of the counties in the contiguous US However, in the populous Harris County, Texas, where Houston is located and where 43% of the population is nonwhite and 38% of the population is low income, there are approximately 310 mortalities. Similarly, in Cook County, Illinois, where Chicago is located and 37% of the population is nonwhite and 38% is low income, there are approximately 290 modeled premature mortalities. As shown in SI figures 2 and 3, to further assess the spatial distribution of impacts, we estimate air pollution-induced mortally rates (m) (in units of premature mortality per 100 000 people) and air pollution-induced damages as a percentage of aggregate county-level income. There are large spatial variations in the mortality rates and damages in 2018, with the highest mortality and damage rates in the Appalachian basin where the annual mortality rates are on the order of 10 to 20 deaths per 100 000 people or annual damages represent 5 to 8% of total income in many counties.

To assess the distribution of impacts based on demographic, political, and environmental attributes, figure 2(b) shows air pollution-induced mortalities rates, and SI table 3 shows total mortality and attribution or percent distribution of mortalities across populations. Most mortality is attributed to SO_2 emissions (76%), whereas NO_x (18%) and $PM_{2.5}$ (6%) emissions represent smaller shares. Air pollution impacts are regressive, such that the lowest income group has the highest mortality rate ($m = 3.87$) and the highest income group has the lowest mortality rate ($m = 3.22$). Moreover, SI figure 4 shows a trend of increasing county-level income corresponding to decreasing air quality damages (normalized by income), which further demonstrates the impact of coal-related air pollution and associated higher health burden on lower income communities. There is not a discernable difference in mortalities rates for populations above ($m = 3.58$) and below the poverty line ($m = 3.68$). The mortality rate for the black or African American population ($m = 3.88$) is marginally higher (3%) than the mortality rate for the white population ($m = 3.78$) and marginally higher (8%) than the average mortality rate across the entire US population ($m = 3.60$). We also show that mortality rates are lower than average for Hispanic or Latino ($m = 2.30$) populations. Underlying these mortality rate estimates are government-reported demographic and socioeconomic statistics that may undercount undocumented persons, and therefore, mortality rates may not capture the extent of the disproportionate impacts on certain populations. With respect to population density, mortality rates are much higher (93%) in rural ($m = 5.97$) than urban ($m = 3.09$) communities, given that most coal capacity is sited away from densely populated areas.

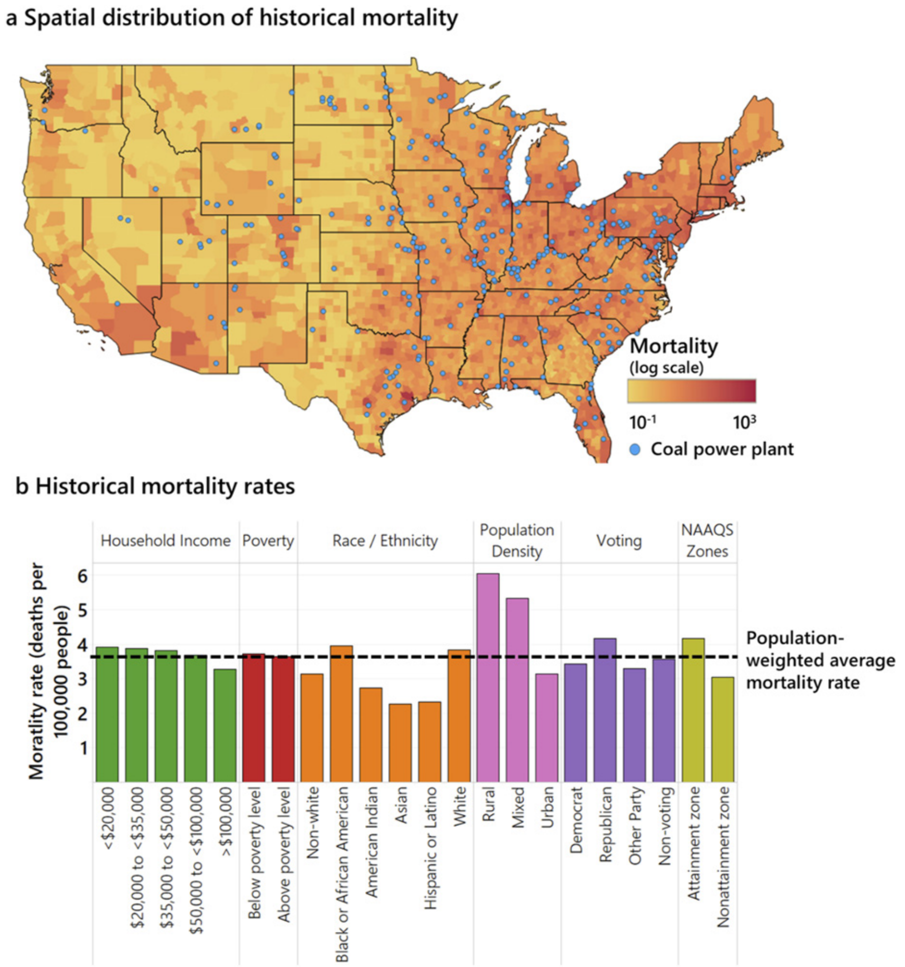

Figure 2. 2018 air pollution impacts and equity implications associated with coal electric power plant emissions. (a) Spatial distribution of historical mortalities. (b) Historical mortality rates by subpopulation. Air pollution impacts are based on modeling using AP3.

The mortality rates are lower in NAAQS nonattainment areas ($m = 3.01$), which tend to be more densely populated areas with multiple emission sources. There is also a political stratification of mortality rates, with those voting for the Republican presidential candidate in 2016 having a relative higher (17%–27%) mortality rate ($m = 4.11$) than those voting for the Democratic candidate ($m = 3.38$), voting for a third-party candidate ($m = 3.24$), or not voting ($m = 3.51$).

Overall, the historical baseline distribution of air pollution impacts informs which dimensions of equity to focus future air pollution policy, in addition to identifying the assets to retire more rapidly based on different equity objectives.

4. Future air pollution impacts and equity

Other studies have estimated air pollution co-benefits and interactions with climate objectives associated with future coal electric power declines. This work is distinct from previous studies in the following ways: (1) evaluates the time-series and cumulative air pollution impacts rather than a snapshot in time, (2) sequences the retirement of generators accounting for asset-level specificity and heterogeneity, (3) models net zero scenarios by instilling coal capacity constraints that account for US energy system-level dynamics, and (4) evaluates air pollution equity and political geography objectives in addition to traditional efficiency objectives that have the potential to drive generator retirements.

Figure 3(a) shows annual air pollution-related deaths associated with different coal retirement pathways, showing a distinction between sequencing retirements on the basis of minimizing costs versus deaths under different climate policies. As depicted in figure 3(b), under the reference (or business-as-usual) climate policy scenario and assuming generators retire based on cost drivers, there are approximately 159 000 air pollution-related deaths ($1.41T) from 2020 to 2050. Absent a net zero emissions goal, where the sequencing of coal

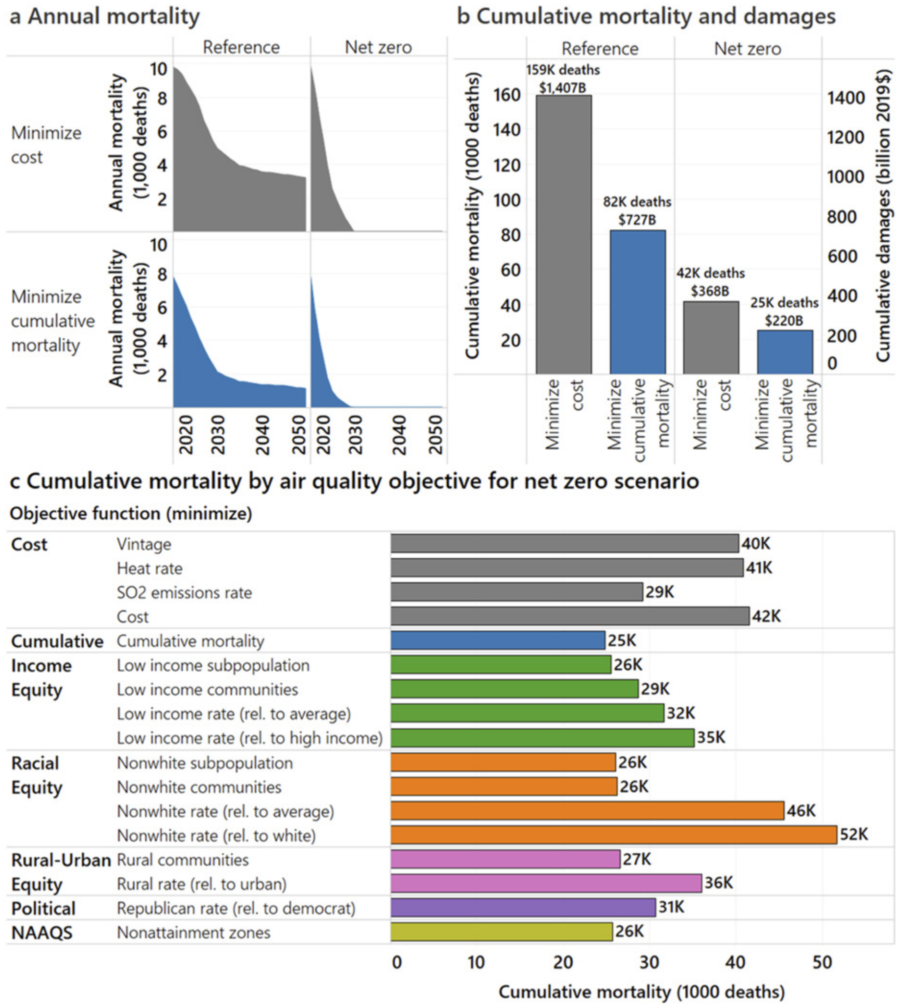

Figure 3. Comparison of air pollution impacts under net zero and business-as-usual constraints as well as cost and cumulative air pollution objectives. (a) 2020–2050 cumulative mortality and damages, (b) 2020–2050 net mortality and damages (relative to cost minimizing, business-as-usual scenario), and (c) annual mortality. All values under baseline air quality model, concentration-response relationship, VSL, and discount rate assumptions.

retirements is based on minimizing air pollution-related deaths rather than minimizing costs, approximately 82 000 deaths ($730B) result, representing a net reduction of 77 000 deaths ($680B). There is even a greater reduction in cumulative mortality following a net zero emissions climate scenario in which all coal electric power capacity retires by 2030. In a net zero energy system transitions, approximately 117 000 deaths ($1.04T) are avoided assuming the sequencing of coal retirements is based on minimizing costs, and approximately 134 000 deaths ($1.19T) are avoided assuming the sequencing is based on minimizing cumulative mortality.

Figure 4 depicts uncertainty associated with the air quality model functional form, C-R relationship, VSL, and discount rate. We perform a single factor sensitivity analysis, which isolates the marginal effect of different sources of uncertainty, but does not capture compounding uncertainties. We use three air quality models to reflect differences in model functional form, showing there is relatively minimal variation between cumulative impacts; however, there may be spatial variation that is not otherwise captured in comparisons of cumulative estimates, and chemical transport mechanisms are likely the source of uncertainty, in addition to changing demographics, that may influence the sequencing of retirements on the basis on different dimensions of equity. There is some variation with respect to the C-R relationship, in which estimates based on the Harvard Six Cities study [26] are on the order of 2.5X those based on the ACS study [28]. There are additional uncertainties related to VSL and discount rates, reflecting a range of normative preferences. The largest source of uncertainty is the VSL with a 95% CI that spans three orders of magnitude. There are many other sources of uncertainty that are not reflected in these estimates, which will require additional fundamental model development. There is uncertainty in the current spatial distribution of inequities, which are compounded by future uncertainties in time-variant factors such as changing atmospheric chemistry and population dynamics that may influence the nature of future inequities and may be induced by large-scale transitions in the energy system.

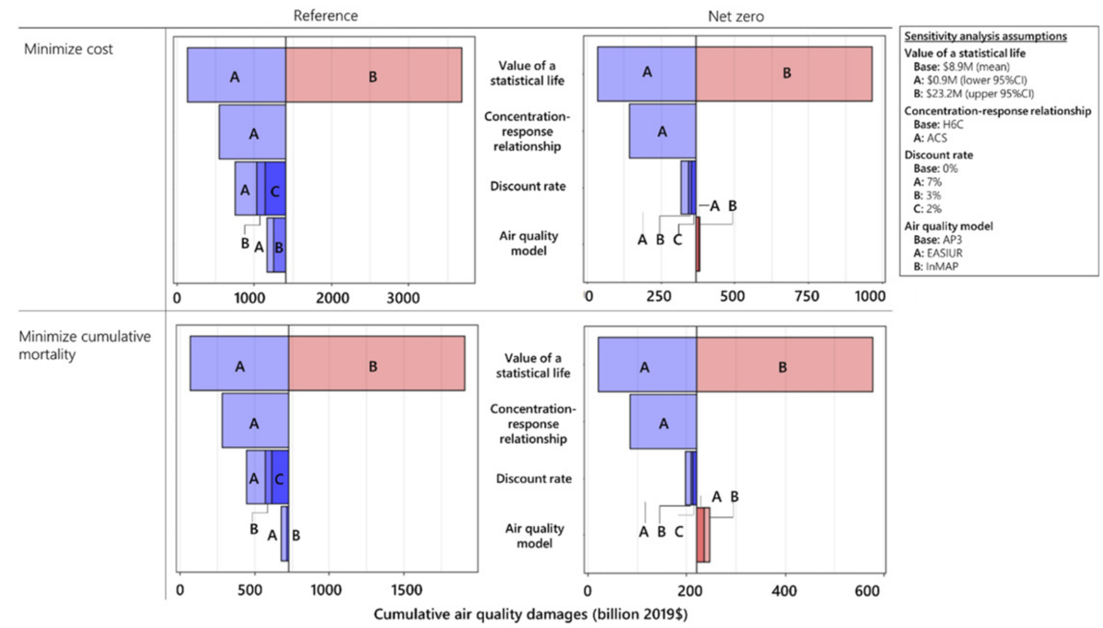

Figure 4. Sensitivity of future air pollution damages under net zero and business-as-usual constraints as well as cost and cumulative air pollution objectives. Includes sensitivity of damages to assumptions related to the value of a statistical life, concentration-response relationship, discount rate, and air quality model.

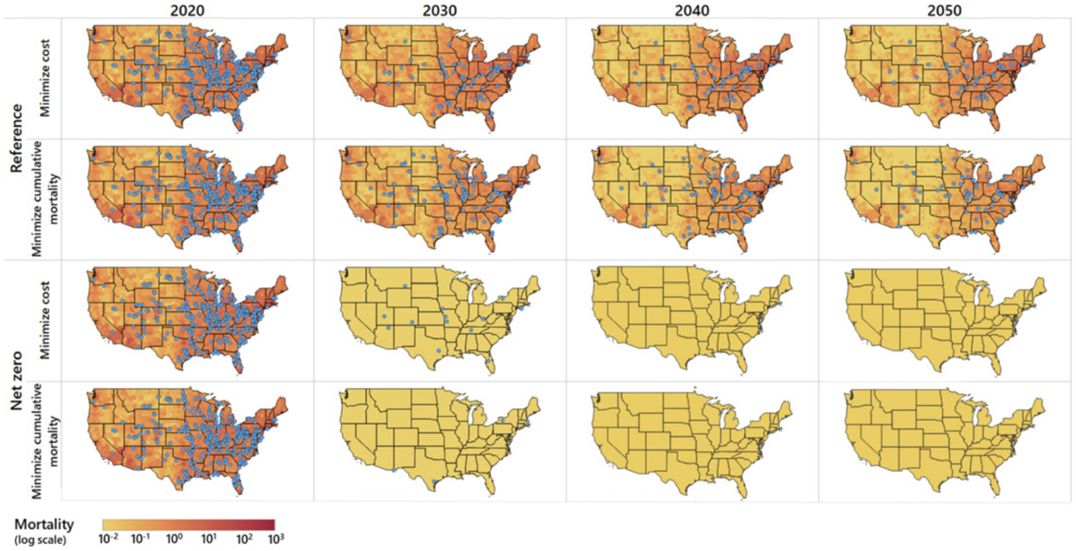

Figure 5. Spatial distribution of air pollution impacts over time.

Figure 5 and SI figure 6 illustrate the spatial distribution of impacts under alternative air pollution and climate policies. Closure of coal generators are depicted over time, showing variation in generator-level sequencing between policy scenarios. Following a climate and/or air quality policy regime, there are large reductions in impacts for most counties observable within the first five years (2021–2015); for example, in Harris County, Texas, in 2025, premature mortalities are reduced by ∼80% (relative to 2021) if closures are driven by air pollution goals absent a net zero emissions goal, and reduced by more than 90% with a net zero emissions goal.

In addition, we explore objectives that focus on minimizing the distribution of air pollution impacts across subpopulations and communities, rather than minimizing cumulative impacts across the entire population. Figure 3(c) depicts cumulative mortalities associated with alternative equity objectives related to income, race, voting patterns, population density, and NAAQS nonattainment status. We find that equity objectives that focus on minimizing impacts on specific subpopulations (e.g., minimizing mortalities across the entire low income or nonwhite subpopulation) loosely align with an objective focused on minimizing cumulative impacts across the entire population. Similarly, minimizing cumulative mortalities is almost analogous to minimizing

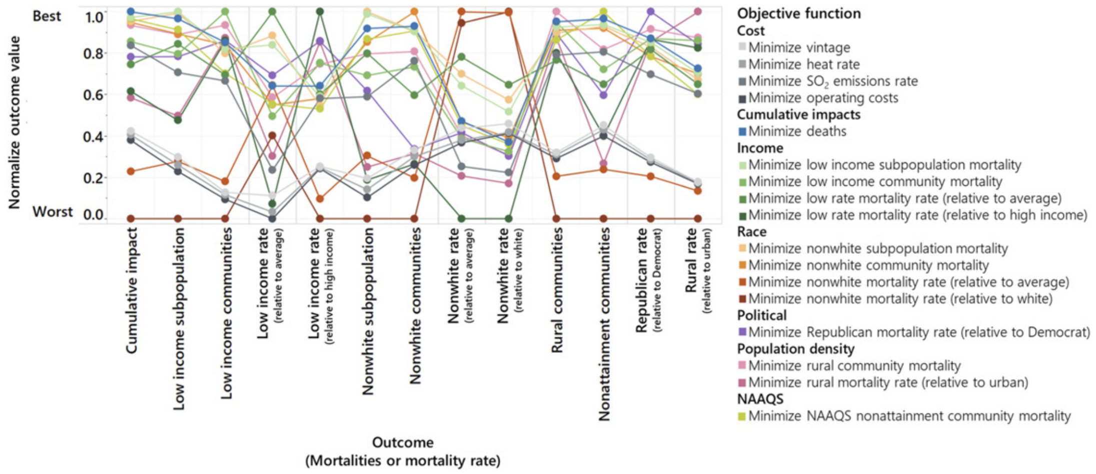

Figure 6. Air pollution equity by objective.

impacts in NAAQS nonattainment areas, given that both objectives prioritize closure of generators proximate to more densely populated areas. However, there is a notable difference in objectives that minimize impacts on subpopulations versus specific communities (i.e., minimizing mortalities within counties in which a large share of the population is low income or nonwhite), where the latter objective preferentially retires generators proximate to specific counties. There is an even a greater difference between objectives that seek to minimize the relative risk (e.g., minimizing the difference in mortality rates between low and high income subpopulations) rather than minimizing impacts on subpopulations or communities. Generator-level data on the sequencing of retirements under each objective and climate policy are provided in workbook provided in SI.

Figure 6 shows the relative ordering of objectives across different normalized equity metrics, where a value of 1 represents the best possible equity outcome and 0 represents the worst outcome (within the range of outcomes modeled); this provides an indication of the tradeoffs and synergies between equity objectives, as well as the relative dominance of some equity objectives over others. Given the compounding nature of many forms of inequity and intersectionality of attributes, we observe some synergies between objectives across different attributes, including nonwhite and low income, low income and rural, and Republican and rural communities and/or subpopulations. The way in which equity is operationalized also influences sequencing of coal plant closures, public health outcomes, and the underlying policy mechanisms needed to achieve certain outcomes. For example, alternative formulations of minimizing air pollution inequities on the basis of race have vastly different outcomes for nonwhite subpopulations and communities. Minimizing the difference between the nonwhite and average mortality rates results in one of the highest total mortality outcomes for nonwhite subpopulations. These results suggest that clarifying and articulating values and preferences associated equity is essential in order to better operationalize objectives as they relate to both computational modeling and policy evaluation & design.

5. Discussion and policy implications

Alternative climate and air pollution impact and equity policies related to the coal power sector can lead to different public health outcomes. Whereas most studies evaluate annual benefits corresponding to 'overnight' changes in infrastructure, considering the rate and trajectories of a transition, the flow of benefits over time, and the spatial distribution of benefits has meaningful implications for infrastructure planning and policy evaluation and design. Cumulative benefits can convey near-term benefits to encourage public support for climate and air pollution policies as well as support long-term policy designs that consider the persistence of impacts from continued operations of existing facilities and siting new long-lived, polluting infrastructure.

Retiring coal power by 2030 as part of a net zero energy system transition generates substantial public health benefits, even without explicit air pollution policy objectives. There is substantial near-term benefit from a net zero transition (38 000 avoided mortalities form 2020–2030), but most of the benefits accrue over the long-term (79 000 avoided mortalities from 2030–2050). Without a net zero policy goal, substantial benefits also accrue from sequencing retirements based on air pollution impacts rather than cost drivers, while maintaining an appropriate level of firm capacity at the regional level to ensure grid reliability. If regulatory action with respect to climate change is unlikely or delayed, there may be more incentive from a public health perspective to further regulate criteria air pollutant emissions across the system or target emission reductions for facilities that present a relatively high public health risk for vulnerable populations. Since SO_2 emission rates play a large role in both economic and air quality objectives, making emission standards and abatement requirements more stringent, especially for power plants that disproportionately impact vulnerable populations, may serve as a strategic lever to more rapidly retire power plants, absent an explicit climate policy. This work also shows how the coal power sector will continue to rapidly transform, even absent additional regulation, with a shrinking set of potentially regulated facilities that have common attributes (i.e., newer, larger) that may allow for them to operate and persist within the system without countervailing regulation.

Health impacts from coal power plants disproportionately impact low income, nonwhite, and rural subpopulations, and given that coal power plants are long-lived, with an average vintage of 45 years old for existing generators (as of 2019), air pollution inequities are persistent. Given the compounding effects of COVID-19 and air pollution, in addition to the broader political landscape as it relates to racial injustice, there is growing salience and public support for policies in which social equity and justice are objectives (rather than outcomes) of a decision-making process. Here, we show that policy objectives that minimize cumulative air pollution impacts for the entire population generally align with objectives that seek to minimize impacts on vulnerable subpopulations, but do not necessarily align with policies that target specific vulnerable communities. Social equity as it relates to infrastructure transitions is inherently multi-dimensional, and this analysis can be extended to consider the rest of coal value chain including mining, in addition to the distribution of other costs (e.g., job loss) and benefits (e.g., reduced morbidity, water quality improvements) associated with closure and reclamation of coal sites. The general approach presented in this study can be applied in other geographies with a large coal electric power fleet and exposed population (e.g., India, South Africa) and to other sectors. This study also highlights the need to integrate social sciences that evaluate normative preferences regarding equity goals and tradeoffs, which can be operationalized in computational decision support tools and policies.

While this study provides an example of how to leverage and develop integrated computational tools to support just infrastructure transitions, there is a need to further interrogate and improve computational tools, so that they are suitable for regulatory decision-making related to spatial inequities and long-term cumulative impacts. There is uncertainty in the current spatial distribution of inequities, which are compounded by uncertainties in time-variant factors, such as changing atmospheric chemistry and population dynamics, that may influence the nature of future inequities but also may be induced by large-scale energy system transitions.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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