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Optimizing Emissions Reductions from the U.S. Power Sector for Climate and Health Benefits

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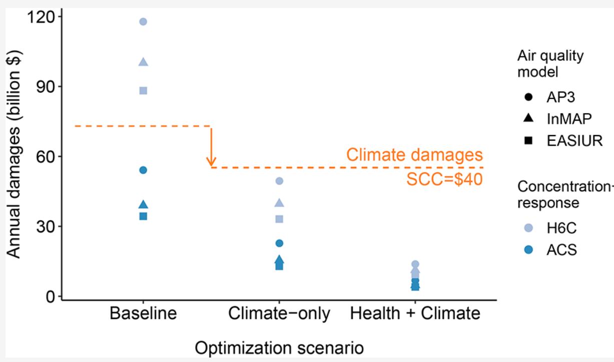
ABSTRACT: Improved air quality and human health are often discussed as "co-benefits" of mitigating climate change, yet they are rarely considered when designing or implementing climate policies. We analyze the implications of integrating health and climate when determining the best locations for replacing power plants with new wind, solar, or natural gas to meet a CO_2 reduction target in the United States. We employ a capacity expansion model with integrated assessment of climate and health damages, comparing portfolios optimized for benefits to climate alone or both health and climate. The model estimates county-level health damages and accounts for uncertainty by using a range of air quality models (AP3, EASIUR, and InMAP) and concentration−response functions (American Cancer Society and Harvard Six Cities). We find that reducing CO_2 by 30% yields \$21−68 billion in annual health benefits, with an additional \$9−36 billion possible when co-optimizing for climate and health benefits. Additional benefits accrue from prioritizing emissions reductions in counties with high population exposure. Total health benefits equal or exceed climate benefits across a wide range of modeling assumptions. Our results demonstrate the value of considering health in climate policy design and the need for interstate cooperation to achieve additional health benefits equitably.



■ INTRODUCTION

More than a third of annual global carbon dioxide (CO_2) emissions come from electric power generation, making it a focus of efforts to mitigate climate change. At the same time, electricity generated from fossil fuels emits co-pollutants—such as sulfur-dioxide (SO_2) and nitrogen oxides (NO_x)—that degrade air quality.[1] Long-term exposure to fine particulate matter ($PM_{2.5}$) produced from SO_2 and NO_x emissions is strongly linked to premature death and other adverse health consequences,[2−4] and the social costs of the health effects attributable to U.S. power sector emissions are estimated at \$60−130 billion annually.[1,5]

A common framework for understanding the linkage between the climate and health impact of emissions is to treat improvements in air quality and health as "co-benefits" that offset costs and offer additional incentives to pursue climate mitigation.[6−8] Various studies have explored these co-benefits for historical changes to the power sector,[9−11] proposed power sector interventions or future pathways[12−17] and the energy sector more broadly,[18−21] finding that health co-benefits often offset much of the cost of mitigation or even exceed climate benefits altogether.[22−24]

Inspite of the linkages between health and climate, few policies have been explicitly designed to optimize for improvements along both dimensions. There is substantial variability in the health impacts from existing fossil fuel plants;[5,25−28] accordingly, the choice of which power plants are replaced by low-emissions alternatives can dramatically alter the health benefits from a given reduction in system-wide emissions[29−31] (see Supporting Information (SI) Section A for a plot of climate and health damages of existing power plants).

Previous research has explored climate and health linkages by comparing different policy options for their benefits. Using a co-benefit framework, Rafaj et al. compare the health benefits of climate mitigation relative to a baseline with no emissions policy.[32] Driscoll et al. demonstrate that the design of a U.S. climate mitigation proposal can affect the resulting health benefits.[33] Other work has considered how health benefits or other environmental externalities might affect power plant operations and capacity expansion planning, often with limited spatial or temporal resolution.[31,34−37] Outside the power sector, research has also looked at how multiple health and

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climate objectives might inform choosing from a range of development or mitigation strategies.[38,39]

Recent work has considered the importance of locational variation in health and climate damages. For instance, Siler-Evans et al. demonstrate how this variability would influence siting new wind and solar U.S.,[40] while Muller highlights the welfare benefits of spatially differentiated emissions regulations.[41] Krieger et al. explore how using proxy metrics for climate and health would affect which locations to prioritize for retiring gas peaking power plant, focusing only on California.[42] However, there has been limited exploration of how a spatially granular co-optimization of climate and health benefits would affect emissions reductions across all U.S. power plants. Rodgers et al. examine how climate and health benefits affect capacity expansion,[43] but focus only on the PJM grid operator territory and employ a surrogate function for health damages due to the complexity of incorporating air quality modeling into an optimization function.

In this study, we explore how the optimal locations for emissions reductions from the U.S. power sector might change with integrated treatment of climate and health benefits estimated at a county-level. We use data on the existing fossil fuel fleet from the Continuous Emissions Monitoring System (CEMS) data set—maintained by U.S Environmental Protection Agency (EPA)—to build a simplified unit retirement model that simulates "overnight" changes, meaning that plants are retired and replaced with new facilities instantaneously.

We use this model to comply with an exogenously specified 30% CO_2 reduction target by minimizing social costs, comparing scenarios which optimize based on minimizing climate damages only or health and climate damages jointly in the objective function and using an ensemble of reduced complexity air quality model to quantify the health impacts of emissions. These reduced form models, which have greatly reduced computational burden relative to full scale air quality models, offer a new means of more easily integrating and co-optimizing for climate and health benefits. By comparing our climate-only and health + climate scenarios, we can better understand how including health might affect the design of emissions reductions from the power sector.

■ METHODS AND MATERIALS

Overview of Modeling Approach. We develop a capacity retirement and expansion model to explore the implications of location when integrating climate and health considerations in emissions reductions. Such optimization models are used to determine the optimal investment in generating capacity given a set of objectives and constraints. Because our focus is on the implication of using health and climate criteria to determine retirements, we assume instantaneous plant replacement and do not assess power system operations.

We limit new capacity builds in our model to three technologies: natural gas combined-cycle (NGCC) plants, wind, and utility-scale solar, which represent the large share of recently installed capacity in the U.S.[44] Although natural gas has limited ability to achieve long-term climate goals, high efficiency NGCC plants emit less half as much CO_2 and far less SO_2 and NO_x than coal, resulting in fewer health consequences.[45] We also consider the impact of upstream emissions from methane leakage in the natural gas supply chain. We constrain the location of new generation capacity to the same county of the plant the new capacity is replacing, thus eliminating the need for additional electricity transmission infrastructure.

Although some of the modeling assumptions abstract away from real siting decisions, our work provides insight on how health benefits might change under different siting scenarios; such results could be used to inform more sophisticated planning processes or could be incorporated into more sophisticated power sector modeling.

Description of Data and Modeling Parameters. The following sections describe the data sources used (1) to represent the existing fossil fuel fleet, (2) to estimate the climate and health damages from emissions, and (3) to construct and operate new generating capacity.

1. Existing Fleet Data. We acquire information on the current power plant fleet from the EPA's Continuous Emissions Monitoring System (CEMS) data, which includes emissions and generation from all fossil fuel units larger than 25 megawatts. We use CEMS 2017 unit-level data on annual emissions of CO_2, SO_2, and NO_x (metric tons), annual gross load (megawatt-hours, MWh), fuel and unit type, and facility location, including coordinates and county-specific FIPS codes. We use this data to calculate average annual emissions rates for each unit, which we then use to approximate the emissions reductions from reduced generation.

Of the approximately 3300 units in the CEMS data for 2017, around 160 are missing information on electric load supplied. For these plants, we estimate the total electric load based on a linear regression of generation by CO_2 emissions by fuel and unit type; details are shown in SI Section A. Any remaining units with missing emissions or CO_2 emissions lower than those feasible for coal or gas units were left out of the analysis.

2. Climate and Health Damages. We focus primarily on total annual emissions of three pollutants in this study: CO_2 for climate change and SO_2 and NO_x for air quality and human health. CO_2 is the leading contributor to climate change, while particulates formed from SO_2 emissions are estimated to contribute to roughly 75% of air pollution mortalities from power plants.[46] In addition to these three pollutants, we also consider the climate impacts of methane (CH_4) leakage from the use of natural gas. To estimate methane leakage, we used approximate heat rate assumptions based on NREL's Annual Technology Baseline (ATB) report to back-calculate the amount of natural gas consumed at all current or newly built plants. We then assume a 3% leakage rate to estimate total methane released and finally convert this to CO_2 equivalent using a 100-year global warming potential (GWP) (see SI Section B for calculation details and sensitivity analysis discussion). Future work might consider the role of other pollutants, such as direct $PM_{2.5}$, volatile organic compounds, and ammonia.

In order to evaluate the climate and health benefits from emissions reductions in an integrated fashion, we need to establish a common metric by which to compare the two. Here, we employ a monetized damage approach. Monetizing the benefits associated with a reduction of risk implies a number of serious issues to consider and subjective decisions to make, such as how to how to discount future climate and health benefits.[47,48] Despite these obstacles, however, such monetization is commonly a part of federal policy making and benefit-cost analysis, and as such, we employ this approach here. To monetize climate and health damages, we follow standard accounting practices used in economics, employing

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Environ. Sci. Technol. 2020, 54, 7513−7523

estimates of the marginal damage (in $ per ton) of an additional ton of pollutant and multiplying them by total emissions to compute total damages from those emissions.

Since CO_2 is a well-mixed pollutant, its marginal impact on climate change does not vary in space. Accordingly, we use a constant estimate of costs per additional ton of CO_2 emitted. We take our baseline estimate of this quantity—the social cost of carbon (SCC)—from the U.S. government's interagency working group, which is approximately $40 per ton (in $2017) when assuming a three percent discount rate.[49] This SCC estimate represents a monetization from a range of climate impacts in the U.S., including changes to net agricultural productivity, property damages from increase flood risk, and the value of ecosystem services due to climate change, among others. The SCC also includes changes to human health from climate change; because these measures largely refer to impacts related to changes to temperature and climate occurring in the future, we distinguish these from the measures of human health that focus on premature mortality from traditional air pollutants in the short term.

For evaluating health damages, we only value reductions in the risk of premature mortality and exclude any benefits from reduced morbidity, improved visibility, or effects on the environment. Previous estimates suggest that, when monetized, mortality accounts for 95% of damages from energy sector air pollution,[1] making this focus appropriate for this work; however, future policy analysis or research may want to broaden the scope to other health or environmental implications. In addition, we focus only on the effects of secondary $PM_{2.5}$ from emissions of SO_2 and NO_x, which tend to dominate health damages from air quality relative to other factors such as ozone.[50]

Unlike the SCC, the marginal damage of pollution is spatially heterogeneous; as such, air quality modeling is needed to understand the damage of different pollutants by location. We use three different integrated assessment models—AP3, EASIUR, and InMAP—to translate emissions into $PM_{2.5}$ concentration and subsequently, health damages.[51−53] Each of these three uses reduced complexity air quality modeling to estimate county-level per ton marginal health damage in monetary units for SO_2 and NO_x emissions across the continental U.S. Each model varies in its approach to approximating chemical transport: AP3 uses Gaussian Plume modeling with rudimentary chemistry, EASIUR employs a regression-based approximation to a full chemical transport model, and InMAP embodies a modeling structure that is simplified temporally and in terms of chemistry and physics.[54] Although these reduced form models are less precise than full scale chemical transport models for assessing air quality impacts, previous work has found that they exhibit comparable performance to more complex models in estimating annual average $PM_{2.5}$ concentrations from emissions and health damages[51,54] (see additional discussion on the performance of these models relative to full chemical transport models in SI Section C).

The modest differences with full-scale air quality models coupled with greatly reduced computation time thus enable a tighter integration of these factors in policy analysis. Furthermore, our use and intercomparison of three distinct models—each of which employs fundamentally different methods for approximating complex atmospheric chemistry[54]—increases the reliability of our results by helping to bound the uncertainty due to differences across air quality modeling approaches.

Each of these air quality models estimate the marginal damage from a ton of emissions by estimating the change to air quality (in annual $PM_{2.5}$ concentration) and subsequent exposed population. The expected health response is then estimated using a concentration−response function. Here, we use two concentration−response functions derived from the American Cancer Society (ACS) and the Harvard Six Cities (H6C) studies[4,55] These two studies bound the health risks derived by a number of epidemiological studies; our baseline analysis primarily employs the ACS study result, which is substantially lower than the H6C and thus may provide a conservative estimate on health risks. To convert health effects to monetized damages, we use an estimate of value of mortality risk reduction, referred to as the value of statistical life (VSL). The VSL used is based on the EPA recommended value of $7.4 million in USD $2006 and updated to $9 million in USD $2017.[56,57]

The models provide county-specific marginal damages for SO_2 and NO_x based on background emissions and concentrations levels from 2005 for EASIUR and InMAP and from 2014 for AP3. Total annual health damages for different emissions scenarios are thus calculated by multiplying emissions by county with their county-specific marginal damages.

We evaluate both climate and health damages (and benefits) on an annual basis, which we compare to annualized mitigation costs from new generation capacity. We explore uncertainty in the estimation of both climate and health damages by performing sensitivity analysis on key inputs to our modeling, including the choice of air quality model and concentration−response function as described above, as well as exploring the use of alternative values for the SCC and VSL.

3. New Generation Capacity. The model builds and operates new natural gas combined cycle, wind, and solar generation capacity to meet load and satisfy the emissions target. We assume that new natural gas plants are dispatchable and can meet the same loads as the thermal loads they replace. Emissions rates for replacement NGCC capacity are the generation-weighted average emissions rates for all combined-cycle units with CEMS data that came online between 2010 and 2017 (see SI Section A).

For wind and solar, we help firm those resources by including a requirement for the co-location of 60 megawatt (MW)/240 MWh of energy storage for every 100 MW of wind or solar capacity installed. We use an estimate of $1500 per kilowatt (kW) of installed storage capacity for the capital cost of lithium-ion storage.[58]

To estimate the required plant capacity (in MW) needed to meet reductions in annual generation by coal, we divide the annual generation (in MWh) needed by the estimated hours of operation. For the natural gas combined cycle plants, we assume an average capacity factor of 56% with a heat rate of 6.46 mmBtu per MWh generated based on estimates from the NREL ATB.[59] We assume that replacement plants are built in capacity increments of 150 MW, based on the median plant size estimate from the EPA NEEDS database.

For wind and solar, we estimate county-level average annual capacity factors based on resource availability for each resource. We use site level wind capacity factor estimates directly from NREL's Wind Toolkit,[60] averaging those values by county. Similarly, we take annually averaged global

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Environ. Sci. Technol. 2020, 54, 7513−7523

horizontal irradiance (GHI) from NREL's 10-km solar radiation database, which is summarized at the county level,[61] and then use linear regression estimates of utility-scale solar capacity factors based on GHI from Lawrence Berkeley National Laboratory to estimate county-level average annual capacity factors for new solar facilities.[62] For both wind and solar, any missing county-level data is assumed to be ineligible for new wind or solar construction. See SI Section D for additional details on these data.

After optimizing for the amount of generation replaced and new capacity installed, we calculate the total annual mitigation cost, defined as the additional costs of the optimization scenario relative to the baseline. This includes annualized capital expenditures from all new capacity as well as the sum of annual fixed operations and maintenance (O&M), variable O&M, and fuel costs. In addition, we subtract from this cost any savings from reduced fixed and variable O&M and reduced fuel costs from any existing coal or natural gas plants that shut down or reduce operations. We use estimates of capital, O&M, and fuel costs from NREL's 2018 ATB, provided in detail in SI Section D.[59] Capital costs are annualized assuming a 20 year useful lifetime and a 7% discount rate. The model optimizes on total system cost, which includes costs from new capacity as well as O&M and fuel costs for existing plants; we assume existing plants have no remaining capital costs.

We conduct a number of sensitivity analyses on our modeling assumptions for new capacity, including using the NREL ATB's upper estimate for price of natural gas, using a version of the model without renewables (i.e., only new natural gas is constructed), and using a formulation of costs that incorporates technology- and location-specific costs. SI Section G provides additional discussion of the sensitivity analysis on cost assumptions.

Optimization Model Formulation. The model uses a linear optimization to minimize damages related to climate damages or both climate and health damages, subject to a constraint on total national CO_2 emissions. The objective of our optimization model is to minimize the sum of annual damages from climate and health—along with annualized mitigation costs—as shown in the equation below:

$$\mathrm{Min}\left(w^* \sum_{p \in NO_x, SO_2} \sum_{j} (MD_{j,p} {}^* E_{j,p}) + SCC^* \sum E_{j,CO2} + TC\right) \tag{1}$$

In this equation, $MD_{j,p}$ is the marginal damage from one ton of pollutant p emitted by generating units in county j [$ per ton] (where $p \in \{SO_2, NO_x\}$), $E_{j,p}$ is the annual emissions of pollutant p by all generating units that are located in county j [tons], SCC is the social cost of carbon [$ per ton CO_2], and TC is the total annualized cost of the system[$] for all existing and new capacity. Mitigation costs for each scenario are calculated by taking the difference in total cost between the baseline and optimization scenario (see Methods above). Total emissions in a county comprise emissions by existing generating units (indexed by i) and emissions from new natural gas units, which are summed by county (indexed by j). Damages and costs are compared on an annual basis. We run scenarios optimizing to minimize the combination of mitigation costs and (1) climate damages (climate-only scenario, w = 0) or (2) health and climate damages combined (health + climate scenario, w = 1).

County-level emissions totals are calculated from the product of each unit's average annual emissions rate—$ER_{i,p}$ for existing units and ER_{NG} for new NGCC facilities [tons per MWh]—with that unit's level of annual generation— x_i^G or x_j^{NG} [in MWh] for existing units or new NGCC units, respectively. Both x_i^G or x_j^{NG} serve as decision variables of the model, along with the amount of generation from wind and solar, x_i^S or x_j^W. This formulation is given by eq 2, where Q represents the subset of units i that are located in county j. Included in the CO_2 emissions rate for natural gas units (both existing and new) is the amount of CO_2-equivalent emissions from methane leakage.

$$E_{j,p} = \sum_{i \in Q} (ER_{i,p} {}^* x_i^G) + ER_{NG,p} {}^* x_j^{NG} \tag{2}$$

In seeking to minimize annual damages and mitigation costs, the model is also constrained to achieve a specified CO_2 emissions reduction target, where T_p is the targeted annual CO_2 emissions after reducing by some percentage compared to the baseline. Because this analysis does not consider the full set of trade-offs between cost of mitigation and climate benefits for deep decarbonization, we specify that annual CO_2 emissions must fall with 0.01% of the emissions target, shown in the equation below, so that the model does not overshoot the CO_2 target. Although the CO_2-equivalent of methane leakage is counted for assessing total climate damages, it is not included when assessing whether the model has achieved the CO_2 reduction. We run our optimization with a CO_2 reduction target of 30% below 2017 annual emissions; we select 30% since it represents the approximate reduction proposed by the U.S. Clean Power Plan.

$$99.99\% {}^* T_{CO_2} \leq \sum_{j} E_{j,CO_2} \leq T_{CO_2} \tag{3}$$

We also constrain the model such that annual generation must be preserved by county for each scenario. This constraint is shown in eq 4 below, where G_j is the annual generation from fossil units in 2017.

$$G_j = \sum_{f \in F} x_j^f + \sum_{i \in Q} x_i^G \tag{4}$$

The maintenance of constant generation within each county as an initial constraint helps alleviate electricity transmission concerns since replacement generation could utilize existing transmission networks, while also ensuring that all scenarios are able to supply the same level of net-load (i.e., the amount of load that remains after removing renewables and nuclear). Existing generating units are also constrained such that their maximum annual output is the amount of generation they provided in 2017. Such a formulation misses the potential for increasing generation from units that for some reason may have under-supplied in 2017 (e.g., a unit may have been offline for maintenance), which may result in our model over-estimating mitigation costs.

We formulate our optimization as a linear problem. The model is coded in Python using the PYOMO optimization package and optimized using the Gurobi solver, version 8.0.1. Additional details on the code and the model formulation—as well as discussion of results using a mixed integer linear programming formulation—can be found in SI Section E.

RESULTS AND DISCUSSION

Benefits from Including Avoided Health Damages. Figure 1 shows estimates of annual climate and health damages

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Environ. Sci. Technol. 2020, 54, 7513−7523

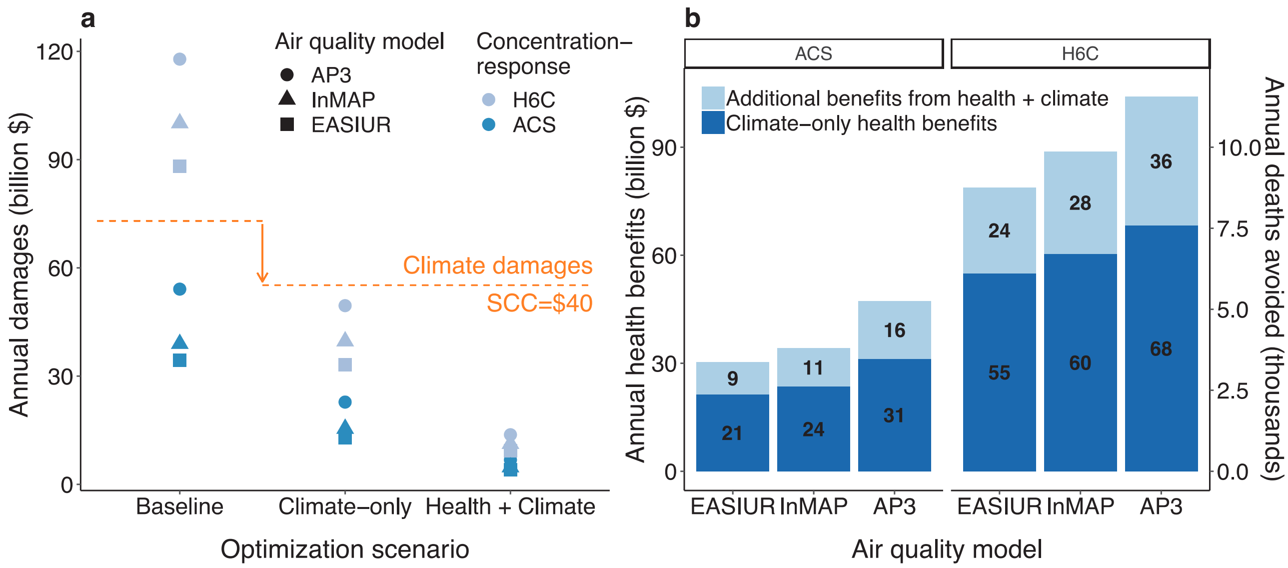

Figure 1. (a) Annual health damages (blue) and climate damages (orange) in billion \$2017. Damages are shown for baseline emissions from the 2017 fossil fuel fleet and after emissions reductions achieved in complying with the CO_2 target according to the two optimization scenarios (climate-only and health + climate). Health damages are shown for a range of air quality models (EASIUR, InMAP, and AP3) and concentration–response function (ACS, H6C), all using a \$9 million VSL. Climate damages are estimated using a SCC of \$40 per ton CO_2 and include the effect of methane leakage. (b) Summary of health benefits (in monetized damages and deaths avoided) from the climate-only and health + climate scenarios relative to the baseline for the different air quality models and concentration–response functions.

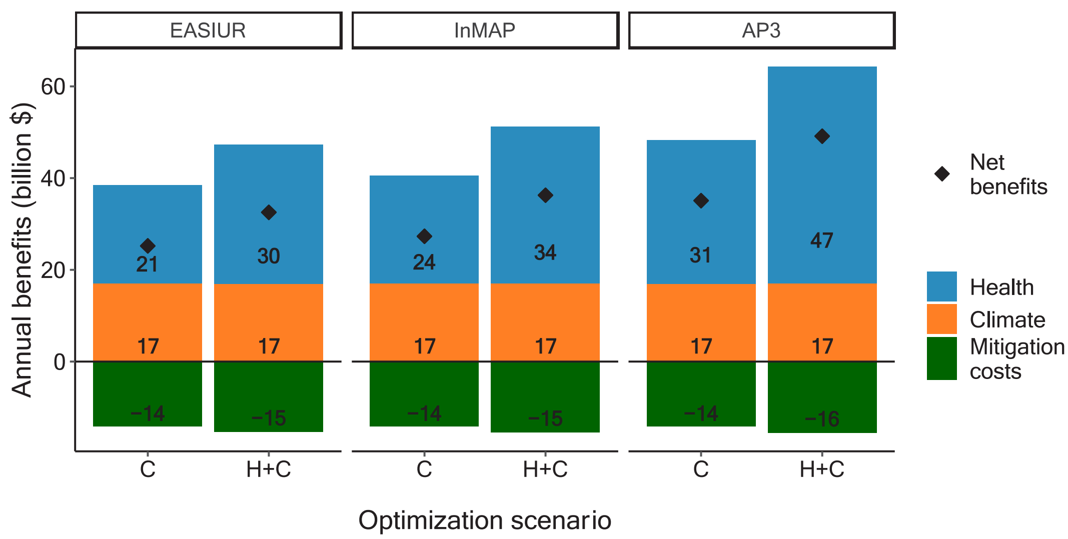

Figure 2. Annual benefits and costs (in billion \$) of each optimization scenario (C: climate-only, H+C: health + climate) relative to the baseline scenario. Damages are shown for climate using a \$40 per ton SCC and for health using each of the three air quality models, a \$9 million VSL, and the ACS concentration–response function. Mitigation costs are the capital and operating costs from new natural gas capacity, annualized assuming a 20-year useful lifetime and a 7% discount rate; see Methods section for additional cost assumptions. Diamonds indicate annual net benefits (avoided climate and health damages less mitigation costs) for each scenario.

in each scenario (Figure 1a), along with annual health benefits from the climate-only and health + climate scenarios (Figure 1b). Even without considering health as a co-objective, achieving a 30% CO_2 reduction target using a climate-only approach yields annual health benefits of \$21–68 billion (2,300–7,500 lives saved each year) relative to the current baseline scenario in which emissions are not reduced. Annual health damages decrease from \$34–120 billion in the baseline scenario to \$13–50 billion in the climate-only scenario, with substantially higher damage and benefit estimates when using the H6C concentration–response relative to the ACS.

When health is explicitly considered as a co-objective, annual health benefits increase to \$30–104 billion (3400–11600 lives saved each year). The range of annual damages falls to \$4–14 billion, and the additional health benefits the health + climate approach are \$9–36 billion annually (900–3900 lives saved). Because the location of CO_2 emissions does not influence their contribution to climate change, the climate benefits of a 30% CO_2 reduction are roughly equivalent across the two optimization scenarios: assuming a SCC of \$40 per ton CO_2, annual climate damages decrease by about \$17 billion, or slightly less than 30%.

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Environ. Sci. Technol. 2020, 54, 7513–7523

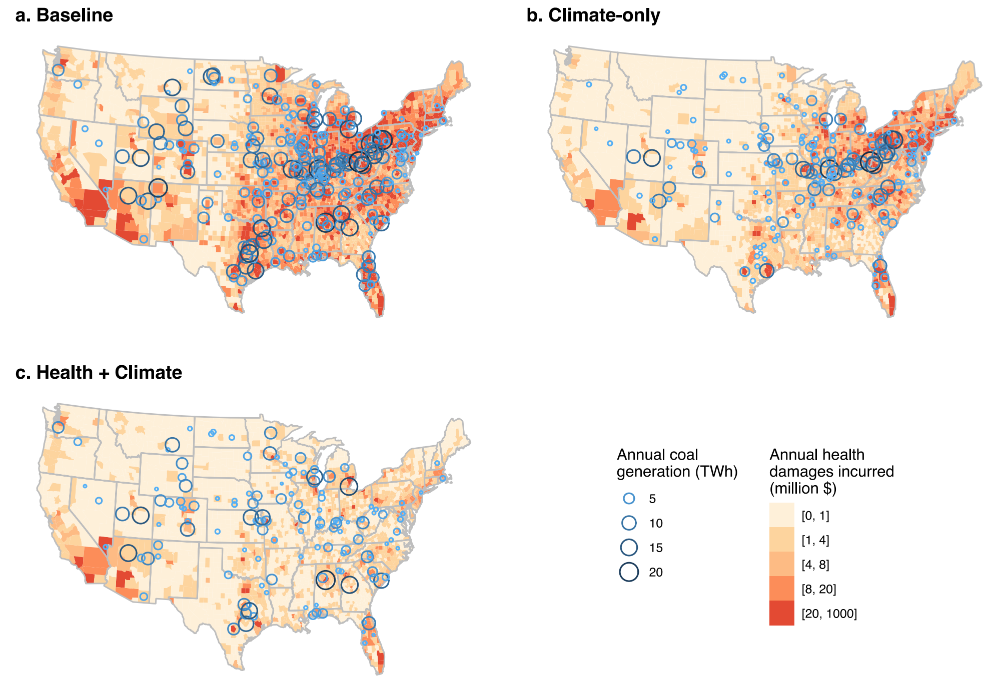

Figure 3. Annual generation from coal power plants (in TWh) and corresponding annualized health damages (in million $) from each scenario, both summarized by county. Baseline shows results based on 2017 CEMS emissions data, while optimization results shown represent the climate-only and health + climate scenarios. Health damages are shown by the county in which those damages occur; legend breaks are based on quintiles of the data. Results are shown for optimization using the AP3 model with the ACS concentration−response function.

Figure 2 compares the costs and benefits of climate mitigation in the two compliance scenarios across a range of air quality models using the ACS concentration−response function (benefits are higher when using the H6C result). Mitigation costs are based on the costs of new natural gas facilities (green bars), and benefits include both climate benefits estimated from the avoided social cost of carbon (orange bars) and health benefits from avoided deaths related to $PM_{2.5}$ exposure (blue bars). Climate-only scenarios incur $14 billion in annual costs against the annual climate benefits of $17 billion; however, when annual health benefits are added, annual net benefits in the climate-only scenario range from $25−35 billion (diamonds in Figure 2).

In the health + climate scenario, power plants with higher health damages are prioritized for replacement, leading to greater health benefits than in the climate-only scenario but also slightly greater mitigation costs ($15−16 billion instead of $14 billion); cost increases slightly since some plants with lower CO_2 emissions but higher health damages are shut down in the health + climate scenario, requiring more capacity to be replaced to meet the CO_2 target. Annual net benefits of the health + climate scenario increase to $32−49 billion.

It is common to evaluate emissions mitigation in terms costs and benefits per ton of pollutant reduced. Co-optimizing for health + climate increases mitigation costs by 14% over the climate-only scenario, moving from $28 to $32 per ton CO_2 avoided. However, it also yields an increase in health benefits of $42−61 to $60−93 per ton of CO_2 avoided; if climate benefits are also included, total benefits per ton of CO_2 avoided rise from $49−69 to $64−96 per ton of CO_2 avoided. Although climate benefits alone do not exceed costs of mitigation, they do when health benefits are included.

Mitigation cost estimates are sensitive to natural gas prices; if gas prices triple from ~$3.2 per mmBtu (baseline) to $10 per mmBtu, annual mitigation costs would increase from $14−16 billion to nearly $23−27 billion (around $45 per ton of CO_2) and substantially more wind is deployed in lieu of expensive natural gas. However, benefits per ton are similar whereas the incremental cost of enacting the health + climate strategy remains small relative to total costs.

Under baseline assumptions, the model primarily builds new natural gas capacity, with a modest amount of wind concentrated primarily in locations with favorable resource; see SI Section F for total generation by generation and a map of new generation by county. In high gas price scenarios, the reverse is true: the model primarily builds new wind capacity, with gas located in a few locations of poor wind resource. When accounting for constraints in the gas network using the LCOE approach, wind is favored over gas in the Midwest while utility-scale solar dominates the Southwest (see SI Section G)

Spatial Heterogeneity in Benefits and Emissions Reductions. A 30% reduction in CO_2 emissions is accompanied by 56% and 66% reductions in annual NO_x and SO_2 emissions in the climate-only scenario and 65% and nearly 90% reductions in the health + climate scenario. Depending on the scenario, between 47 and 60% of coal units are retired and replaced, with another 15−25% of coal units operating at reduced utilization rates.

Figure 3 depicts the spatial variation in county-level health damages in the different scenarios (red shading, with damages shown for the county where they occur), along with the total annual coal generation in each county (blue circles). Under the current baseline (Figure 3a), both coal generation and the highest annual health damages are concentrated in the densely populated Midwest and Mid-Atlantic regions. The health + climate scenario (Figure 3c) prioritizes retirements of coal generation in these two regions, whereas the climate-only scenario (Figure 3b) yields greater reductions in coal capacity

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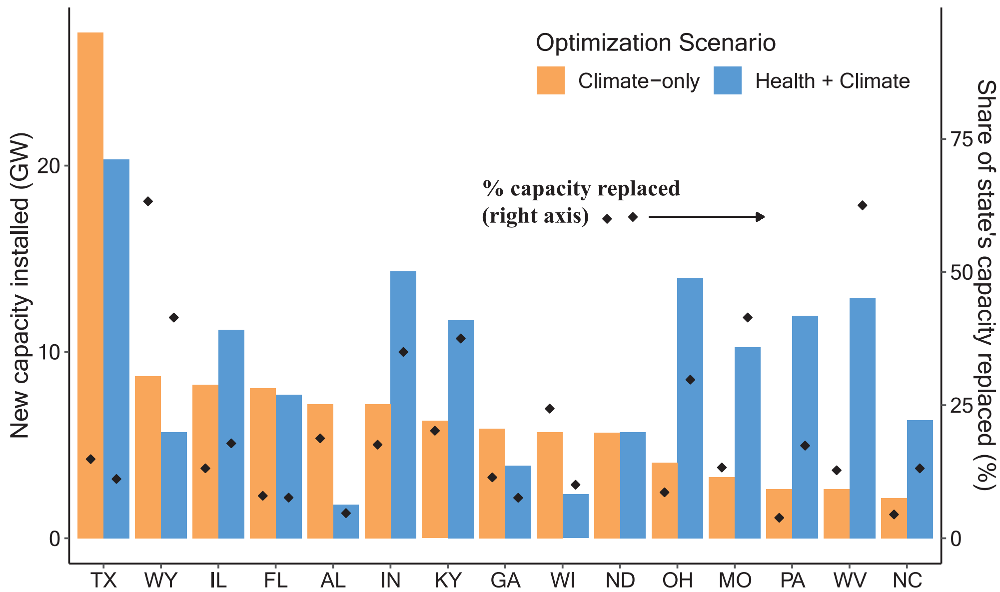

Figure 4. New generation capacity (in GW) installed in both optimization scenarios. Results are shown for the 15 states that fall in the top 10 for most new capacity in each scenario (climate-only and health + climate). Diamonds indicate the share (in percent) of each state's generating capacity that would be replaced with this amount of new capacity; percentages are calculated relative to total installed capacity of each state from all sources—including utility-scale non-fossil generation—taken from 2016 EPA eGrid data set, the most comparable version to the CEMS 2017 data used. The results indicate that the amount of generation replaced by state can vary substantially depending on the optimization criteria used.

in the West and Southwest. States that receive the greatest additional health benefits from moving from a climate-only to a health + climate scenario include Pennsylvania (an additional \$2.2 billion in avoided damages), Ohio (\$2 billion), and New York (\$1.2 billion). Overall, 14 states each gain an additional \$500 million in avoided damages annually, including Kentucky, Texas, North Carolina, Maryland, Illinois, Virginia, Indiana, New Jersey, Michigan, and Missouri.

Although a few Western states with less stringent emissions requirements under a health + climate approach experience increased damages relative to a climate-only strategy, these lost opportunities for damage reduction are comparatively small (< \$60 million) relative to the gains in other states and still represent improvements over the baseline. Similarly, the vast majority of counties receive additional benefits from moving to a health + climate approach, with only a few faring better in a climate-only scenario (SI Section F).

The spatial distribution of benefits of the health + climate scenario can be contrasted with the corresponding variations in the stringency of emissions reductions by location. Figure 4 shows the total new capacity installed by state for the top 15 states installing new capacity in the two optimization scenarios, along with the percentage the new gas represents as share of that state's current existing capacity based on all fossil and nonfossil resources (results for all states and maps of statewide CO_2 reductions are shown in SI Section F). The amount of new capacity installed varies dramatically between the two scenarios in some states. For example, Indiana, Kentucky, Ohio, Pennsylvania, Missouri, and West Virginia all replace coal with gas at much higher rates under the health + climate scenario.

Moreover, although some of the greatest changes in capacity are in the states where health benefits are also large (e.g., Ohio, Pennsylvania), in other cases substantial coal capacity is replaced by states where the in-state health benefits are more modest. Although West Virginia replaces 60% of its installed capacity in the health + climate optimization, roughly 40% of the related health benefits accrue to three downwind states (Pennsylvania, New York, and New Jersey), with only 11% of the health benefits gained by West Virginia itself (see SI Section F for plots of all states).

Equity and environmental justice are critical to consider when determining the location of optimal emissions reductions. A policy that optimizes for total welfare at the expense of specific groups is not likely to be desirable, particularly if those groups are low-income, racial minorities, elderly, or other at-risk populations, which already tend to experience poorer air quality and higher health damages from air pollution.[63−68] Although our analyses compute county-level health damages and are thus somewhat coarse for a rigorous environmental justice analysis, we can evaluate how the benefits from the different optimization scenarios are distributed across different subgroups using county-level statistics. As an example, we compare median, household income, and share of nonwhite populations by county against the median health damages incurred per household for each optimization scenario using the AP3 air quality model and ACS concentration−response function (figures shown in SI Section F).

We find that the climate-only scenario has median positive benefits across all income quintiles but that the lowest 60% of households by income have higher benefits (\$490−550 in annual health benefits per household) relative to the 20% highest-income counties (\$310 in health benefits). Furthermore, moving from a climate-only to a health + climate scenario provides additional median benefits of \$220−300 annually per household for bottom 60% of counties by income and \$190 per household for the top 20%.

In contrast to income, we find that counties with lower shares of minority populations accrue the most health benefits per person regardless of the optimization strategy employed. Counties with the lowest share of minority population experience a median of \$210/\$330 per person in health benefits for the climate-only and health + climate scenarios,

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Environ. Sci. Technol. 2020, 54, 7513−7523

respectively, while counties with the highest shares accrue a median of only \$160/\$240 in benefits per person.

Sensitivity to Modeling Assumptions. In addition to the sensitivity analysis on air quality model, concentration–response function, and natural gas prices discussed above, we also explore how spatial variability in the cost of new capacity, choice of VSL and SCC, CO_2 target level, and the inclusion of renewables. The sensitivity analysis suggests that assumptions of VSL and concentration–response function tend to be the strongest drivers of the results, with the H6C concentration–response and larger VSL values leading to substantial additional benefits from a health + climate optimization.

Net annual benefits are positive and large for all but the lowest combinations of VSL and SCC values and range from -\$0.6–85 billion for the climate-only scenario and \$3–123 billion for the health + climate scenario when using the AP3 model with the ACS concentration–response function (SI Figure S20). The only scenario with negative annual net benefits is a climate-only optimization with \$6 per ton SCC and \$3 million VSL. However, the additional benefits of the health + climate scenario tend to peak for CO_2 reduction targets of 10–20%, implying diminishing marginal returns at higher decarbonization levels (SI Figure S22).

Finally, although modeling assumptions related to cost and the use of renewables tends affect the total cost of mitigation, the choice of mitigation technology, and where new capacity is installed, our findings on the additional benefits of a health + climate optimization are robust across most plausible input assumptions.

A summary of these findings and the other sensitivity analyses can be found in SI Section G.

DISCUSSION

Even without including health in policy design, the reduction of emissions to meet climate goals brings substantial health benefits, making such policies strongly net beneficial from a societal standpoint. The range of health benefits estimated here for a climate-only scenario (~ \$20–70 billion annually) is similar in magnitude to the cobenefits estimated for the Clean Power Plan (\$13–34 billion)[8] and other proposed carbon reduction strategies for the power sector (\$2–68 billion).[69] However, by not including health benefits or only assessing them as "co-benefits" of climate action, policy makers risk drastically underestimating the societal benefits of reducing CO_2 emissions or pursuing policies that are suboptimal from the perspective of climate and human health.

We show that optimizing to include health as an objective creates differentiated responsibility across U.S. states for emissions reductions, with certain states or regions increasing their share of mitigation. The variation in responsibility and benefits by jurisdiction illustrates the importance of interstate cooperation and potential value of a continued federal role in designing and implementing emissions controls. Increased cooperation may amplify total benefits for the U.S. but decrease benefits for specific regions; accordingly, metrics for assessing disparity in impacts should be incorporating in the evaluation of proposed co-optimized policies. Policy makers might use these results to determine the disparities between benefits and costs across health-informed climate strategies and use those estimates to tailor air quality regulations, clean energy incentives, or subsidies to offset transition costs. The approach from this study may also help states—which are often the lead actors in U.S. emissions control—determine which locations within their jurisdictions are optimal for reducing emissions when considering health, as well when interstate cooperation might be needed to attain additional improvements. Although our analysis suggests that considering health could benefit lower-income groups, previous work has shown that county-level statistics tend to underestimate disparities, particularly in race.[70] Future work and policy analysis on the benefits of co-optimized strategies such consider finer spatial resolutions and pursue more rigorous evaluations of equity and distributional impacts.

Our model focuses on the role of location in determining the additional health benefits achievable by a health + climate approach; we do not evaluate the merits or feasibility of different technologies or decarbonization pathways, which other research has explored.[29,33] Achieving the deep decarbonization necessary to address climate change is also likely to require a range of technologies not considered here. Future work should focus on how incorporating health into production cost or capacity-expansion models would affect decisions across a range of low-carbon options with more detailed temporal, spatial, and operational modeling.

Nemet et al. discuss a number of potential implications of including health in climate policy discussions, including effects on the "robustness to discount rates, incentives for international cooperation, and the value of adaptation, forests, and climate engineering relative to mitigation".[24] Furthermore, the health benefits of climate mitigation should be considered relative to traditional air pollution interventions, such as low-NO_x burners or scrubbers. Regardless, understanding the health implications of different emissions reduction strategies can help refine and enhance policy design across a range of potential objectives.

Ultimately, emissions reductions will provide meaningful benefits to society from the perspective of both climate mitigation and improved human health from better air quality. While moving away from fossil fuels to reduce CO_2 emissions will bring wider societal and environmental benefits in the long term, the design of the pathway to those reductions can greatly impact the immediate benefits to human health in the short- and medium-term, potentially at only comparatively modest cost. Integrating climate and health factors when designing and evaluating emissions reduction policies thus offers an opportunity to provide additional benefits to society.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.9b06936.

Details on data and modeling assumptions, air quality model performance, optimization model formulation, additional results, and sensitivity analyses (PDF)

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B.S. and I.A. proposed the study idea and development the methods for analysis, consulting with N.M., P.A., S.D., and A.R. to refine the approach. B.S. developed the model and performed the analysis. B.S. wrote the paper, with edits and input from all collaborators. All authors have given approval to the final version of the manuscript.

Notes

The authors declare no competing financial interest.

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