Using an Integrated Assessment Model to Understand How U.S. States Can Effectively Reduce Air Pollution Health Costs

Sarah Simm

A thesis submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Masters of Science of Public Health in the Environmental Science and Engineering Department in the Gilling's School of Public Health.

Chapel Hill
2023

Approved By

Dr. Jason West

Dr. Dan Loughlin

Dr. Noah Kittner

ABSTRACT

Sarah Simm : Using an Integrated Assessment Model to Understand How U.S. States Can Effectively Reduce Air Pollution Health Costs

(Under the direction of Jason West)

Measures that reduce air pollutants have the potential to improve air quality and public health. Additionally, decarbonization strategies are expected to yield co-reductions in air pollutants; however, the magnitude of co-reductions depends on the measures implemented. This study uses an integrated assessment model of the U.S. energy system (GLIMPSE/GCAM-USA) to quantify co-reductions and explore how explicitly considering health benefits may change decarbonization pathways. For this study, health impact factors developed by the EPA were added to GLIMPSE/GCAM-USA, which were applied to a Reference Scenario and three policy scenarios. The first policy applies a U.S. economy-wide CO_2 reduction constraint, while the second internalizes the public health costs of $PM_{2.5}$, NO_x, and SO_2 emissions as a tax. The third combines the CO_2 constraint and health cost taxes. Health benefits of a CO_2 reduction policy are shown to mainly come from reductions of electric sector sulfur dioxide (SO_2) and nitrogen oxides (NO_x) emissions. In contrast, the air pollution health taxes mainly cause emission reductions of primary fine particulate matter ($PM_{2.5}$) from buildings and industry, but have minimal impact on CO_2 emissions. Applying the health tax and CO_2 cap together yields greater air pollution benefits due to the pathways implemented by each policy. In the early years the policies act separately, with the HCT electrifying the building and industrial sector and CCap decarbonizing the electric sector. In later years these policies work synergistically both focusing on industrial and building sector transformation.

ACKNOWLEDGEMENTS

Thank you to all three of my advisors. Dr. Jason West, Dr. Dan Loughlin, and Dr. Noah Kittner for taking the time to teach me, answer all my questions, and encourage me. Jason provided me the opportunity to go to the University of North Carolina at Chapel Hill (UNC). Dan taught me GCAM and mentored me while at the U.S. EPA. I will always be grateful for the opportunity you provided me to learn how to use an energy systems model, which forever changed the trajectory of my career. Noah taught and encouraged me through my coursework. My experience at UNC prepared me for my dream career and has enabled me to pursue an industry where I believe I can make a positive impact on the world. I can only give you my highest gratitude for teaching me.

I also want to thank Ou Yang, Steve Smith, and Maridee Weber at the Joint Global Change Research Institute (JGCRI). Ou's research is what inspired me to pursue this research topic. Steve and Maridee both provided expertise and assistance that was invaluable as I conducted my research project. Additionally, thank you to Carol Lenox, Jacky Rosati, and Tom Pierce. Each individual shaped my time at the EPA, which ultimately influenced my decision to attend UNC and pursue this research project. Finally, thank you to all my friends and family who supported me during this time and throughout my life. I could not have achieved this accomplishment without you all.

TABLE OF CONTENTS

1. **Introduction**

The United States (U.S.) has made concentrated efforts to improve air quality over the past few decades; however, there are still more than 100 million people living in communities where air pollution exceeds health-based standards (Nolte et al., 2018). The negative health consequences associated with both short- and long-term exposure continue to make air quality an important public health priority. While multiple air pollutants are dangerous to public health, this study focuses on fine particulate matter with a diameter less than 2.5 microns ($PM_{2.5}$), and two of its precursors, sulfur oxide (SO_2) and nitrogen oxides (NO_x). Exposure to $PM_{2.5}$ is associated with mortality from cardiopulmonary disease and lung cancer (Arden Pope et al., 2020), as well as nonfatal heart attacks, irregular heartbeat, aggravated asthma, decreased lung function, and increased respiratory symptoms (EPA, 2022e). Reductions in air pollution have been shown to reduce negative health consequences (Qiu et al., 2015; Silveira et al., 2016; Schraufnagel et al., 2019). These benefits, however, depend on factors such as geography, population density, emission sources, and intervention type (Fann et al., 2009; Dedoussi, 2020; Henschel et al., 2012).

The process of quantifying the health benefits of air pollution control strategies starts with future emissions projections. The method used to determine emission changes differs by application but typically involves sector-specific models such as the Mobile Vehicle Emission Simulator (MOVES)(EPA, 2023c) for onroad emissions, the Integrated Planning Model (IPM)(EPA, 2023d) for power plant emissions, and the Control Strategy Tool (CoST) (EPA, 2023a) for buildings and industrial emissions. Estimating the impacts of the projected emission changes generally follows one of two approaches. In the first, which is more rigorous, emission changes are processed within an emissions processing system such as the Sparse Matrix Operator Kernel Emissions (SMOKE) modeling system (Baek, 2018), which allocates the emissions to spatial grid cells and time steps. Next, a chemical transport model (CTM) is used to simulate the impact of emission reductions on air quality. The resulting air pollution data is used in a benefit assessment model such as the Environmental Benefits Mapping and Analysis Program (BenMAP) (EPA, 2022f) to quantify exposure and damages. As an alternative to CTMs, reduced-form models are sometimes used to approximate how the changes in emissions translate into changes in air quality or health.

CTMs are mathematical models that use meteorological, emissions, and air chemistry data to provide gridded estimates of air pollution. Qui et al., (2022) and Abel et al., (2019) use the GEOS-Chem and CMAQ CTMs, respectively, to quantify the impacts of increased wind power generation on surface level $PM_{2.5}$ and ozone (O_3). The resolution from these models allows for detailed geographical analysis of air quality and human exposure to changes in pollution. While the detailed data from CTMs is useful, a disadvantage of these models is that they are computationally and time intensive (Fann et al., 2012; Heo et al., 2016; Thakrar et al., 2020). Even when executed on high-performance computers, CTMs can have run times of days or even weeks. Furthermore, to conduct the health benefits analysis from the changes in air pollution requires additional time and the use of other applications, such as BenMAP. The use of multiple models and time and resource requirements of CTMs limits the number of scenarios that can be explored.

An approach to streamline this process is to use reduced-form or reduced-complexity models (RCMs), which make simplifying assumptions about the emissions-to-air quality relationship (Baker et al., 2020). Sergi et al., (2020) and Mayfield et al., (2022) both use three different reduced complexity models - AP3, InMAP, and EASIUR - to estimate county-level emissions concentrations to conduct health impact assessments from power sector transformations. RCMs are often developed by using statistical methods to approximate the emissions-impacts relationships, based upon the results of a large number of simulations that are conducted with the full-scale models. While RCMs thus are computationally intensive to develop, the runtime of the RCM itself can be as quick as seconds to minutes. The faster runtime allows for the analysis of screening a large number of potential control strategies. While RCMs are simpler than CTMs and can streamline the health impact analysis by avoiding the need to run a benefits model such as BenMAP, future emission estimates are still needed, and models such as MOVES, IPM, and CoST, can themselves be resource and computationally intensive to run. An additional challenge to using multiple models for the emission estimates is coordinating assumptions across models. For example, modeling an increase in electric vehicle adoption in MOVES would require properly representing the associated increase in electricity demand in IPM.

To address these challenges, another reduced-form approach is to integrate health impact factors directly into a multi-sector model that projects emissions, allowing health impacts to be an output of the model. One of the first examples of this approach was Ou et al., (2018), which analyzed the public health benefits of alternative decarbonization scenarios using the Global Change Analysis Model with state-level resolution (GCAM-USA) (JGCRI, 2023). Health impact factors provide a simplified method for rapidly analyzing the health impacts of potential control strategies, new and emerging technologies, and environmental, climate, or energy policies (Ou et al., 2020).

An additional benefit of integrating health impact factors into such a model is that it can facilitate the development of control strategies that endogenize benefits to public health. For example, Ou et al., (2020) set national $PM_{2.5}$ mortality cost reduction targets to endogenously determine cost-effective strategies for reducing $PM_{2.5}$ mortality. Using the EPA-MARKet ALlocation Model (ETSAP, 2023), Brown et al., (2013) endogenized the health cost for the six criteria pollutants in the form of a tax while also applying a greenhouse gas (GHG) tax of $30 ton/ CO_2 e to analyze how these costs influenced the electricity generation mix and emissions out to 2055. Roth et al., (2022) used The Integrated MARKAL-EFOM System (US-TIMES) model to apply a national and regional tax that represented the damage costs of $PM_{2.5}$, SO_2, and NO_x in scenarios with differing carbon taxes to analyze potential policy crossovers and their health benefits (ETSAP, 2023).

Since greenhouse gases and air pollutants are emitted from many of the same sources, policies could potentially be developed that take advantage of this synergy. Literature on this topic has mainly focused on calculating the air pollution co-benefits of decarbonization strategies (Ou et al., 2018, Qui et al., 2022, and Sergi et al., 2020). Literature examining how these policies interact simultaneously is limited. Roth et al., (2022) is a good example of identifying the potential “policy spillover”, or how two policies may overlap, when applying the two different taxes. However, their work does not discuss transformations that occur in the industrial sector, which has the potential to play an important role in addressing both climate and air quality goals.

The goal of the research presented in this thesis is to gain insights into how explicitly considering air pollutant health costs would improve the health benefits associated with meeting a decarbonization target. This research is conducted using the GCAM-USA human-Earth systems model to simulate and compare health impacts for a reference scenario, a carbon constrained scenario, a health cost tax scenario, and a scenario that includes both the carbon constraint and the health tax. This study updates the impact factors originally applied by Ou et al. (2018) using factors from Wolf et al., 2019 and EPA, 2021, providing increased sectoral, pollutant, and locational granularity. The results are analyzed to provide insights into how to design decarbonization pathways to yield greater health benefits from air pollutant co-reductions.

2. Methods

3a. GLIMPSE/GCAM-USA

GCAM is a human-earth systems model that is developed and maintained by the Pacific Northwest National Laboratory (PNNL). GCAM represents the interactions among five main systems- energy, water, agriculture and land use, the economy, and climate (JGCRI, 2023). GCAM's core operating principle is to meet market equilibrium, which means it solves for a set of market prices such that supply and demand are equal for all markets (JGCRI, 2022a). GCAM is a dynamic recursive model, indicating that as the model steps through time it solves for the best solution given the current conditions but does not have foresight about future conditions.

GCAM-USA is built upon GCAM, but provides state-level detail for socioeconomics and energy supply and demand, as well as sub-national resolution for land and water systems representations. State-level assumptions about population and economic growth drive demands in the end-use sectors (PNNL, 2023). GCAM-USA includes detailed technology representations for the electricity production, transportation, industrial, and buildings sectors. GLIMPSE is a modified version of GCAM-USA that includes a user-friendly graphical user interface, technology and emission factor updates, and specific public policy representations. GLIMPSE is developed by the U.S. EPA to help support state-level environmental and energy planning (EPA, 2022f). GCAM, GCAM-USA, and GLIMPSE are fully open-source, publicly available models (EPA, 2022g).

3b. Health Costs Calculations

The health benefits associated with the modeled policy are calculated using Equation 1. The difference of the emissions between the applied policy ($P_{s,c}$) and Ref ($R_{s,c}$) are multiplied by the benefit per-ton of reducing the associated pollutant species and source category ($B_{s,c}$). The health benefits are summed based off their pollutant species (s) and source category (c) to then calculate the total health benefits.

$$H = \sum_{S}\sum_{c}[(P_{S,C}-R_{S,C})*B_{S,C}] \qquad \text{(Eq. 1)}$$

where:

H is the monetized health benefit associated with the policy

$P_{s,c}$ are the policy case emissions (tons) of pollutant species s from source category c

$R_{s,c}$ are the reference case emissions (tons) of pollutant species s from source category c

$B_{s,c}$ are the benefit-per-ton ($/ton) of reducing pollutant species s from source category c

There have been three iterations of BPT estimates for the US - Fann et al., (2012), Wolf et al., (2019), and EPA, (2021). For each pollutant and sector combination in GLIMPSE/ GCAM-USA, the most relevant and updated BPT value was utilized to calculate the impact factors. Table 1 shows which BPT estimate is used for each GCAM technological sector emission factor.

Table 1. Source of Benefit Per Ton (BPT) estimates used for each GCAM technology sector.

GCAM Sector	BPT Values	BPT Geographic Granularity
Building Sector	Fann et al., 2012	National
Residential Wood Burning Stoves	EPA, 2021	State
Electric Sector	EPA, 2021	State
Industrial Sector Processes	Fann et al., 2012	State
Industrial Sector Energy Use	EPA, 2021	State
Transportation Sector	Wolf et al., 2019	National

While several health endpoints were analyzed to create the BPT estimates, 98% of the monetized benefits are related to avoided premature deaths. Furthermore, the relative size of the BPT estimates varies depending on emission species, source, and location. An additional note is that the economic value of the impacts of these pollutants increases over the time horizon due to the expected increases in population and GDP (Fann et al., 2012).

Differences among the studies listed in Table 1 include the time horizon, dollar years, and the detail of the regions that were modeled. Fann et al., (2012), estimated benefits for 2016-2030 in 2016 dollars based on national emission reductions, which means the BPT values represent the average benefit-per-ton at the U.S. level (Fann et al., TSD 2012). Wolfe et al., (2019) estimated mobile sector benefits for 2020-2045, in 2017 dollars at the U.S. level. EPA (2021) BPT estimates for a detailed industrial sector were for 2025-2040 in 2015 dollars and included estimates at the state, regional, and U.S. level (EPA, 2021). When utilizing the EPA (2021) BPT estimates the most detailed locational value, which was the state level estimation, was applied. BPT estimates were not available for all the years modeled in this study. For missing years, the BPT values were linearly interpolated or extrapolated before being combined with the emissions factor. This method is appropriate for estimating the missing years since, in general, the change in BPT values depend on changes in exposure related to population, which is anticipated to grow approximately linearly out to 2050. The BPT values were all converted to 2020 dollars using average inflation values from the U.S. Bureau of Labor Statistics (US Department of Labor, 2022). BPT values were not available for Hawaii, Alaska, and US territories, and thus these have been omitted from this study.

3c. Scenario Design

Table 2. Scenario design of the four scenarios modeled in this study.

Scenario	Description

Reference (Ref)	Business as usual scenario with "on-the-books" national and regional level policies.
Carbon Cap (CCap)	Economy wide 50% reduction of CO_2 emissions by 2030 and 80% by 2050 compared to 2005 levels.
Health Cost Tax (HCT)	Policy that endogenizes the health costs in the form of a tax.
Health Cost Tax + Carbon Cap (HCT+CCap)	The tax and carbon constraints applied together.

The Reference scenario (Ref) is an estimate of future economic activity and emissions that includes some "on-the-books" national and regional level policies. These policies are extended out to 2050 instead of ending in the final year the policy specifies. Please refer to the supplemental information to see details of the Ref policies. The Inflation Reduction Act (IRA) is not included in the Ref because it became law while this study was being conducted. The impact factors are applied in Ref to calculate the health cost of emissions, but no additional constraints are included.

The Carbon Cap scenario (CCap) is a hypothetical policy that applies an economy-wide CO_2 constraint that reduces emissions by 50% by 2030 and 80% by 2050 compared to 2005 levels. The air pollution health costs are included as a model output but are not constrained, allowing for analysis of potential co-benefits of a CO_2 reduction policy.

The Health Cost Tax scenario (HCT) seeks to endogenize the public health costs associated with economic activities that have $PM_{2.5}$, NO_x, and SO_2 emissions. This is accomplished by incorporating the pollutant- and sector-specific BPT values as taxes on those activities. Since GCAM-USA's aim is to meet the policy conditions with the least cost solution, GCAM-USA will decide to either pay the tax or switch to a different fuel or technology. The tax is implemented at half the BPT value in 2025, growing to the full BPT in 2030 and beyond. Details related to the calculation and implementation of the BPT-based tax can be found in the Supplement Information.

The HCT+CCap scenario combines the health cost tax with the economy-wide carbon reduction goal of 50% below 2030 and 80% 2050 compared to the 2005 levels.

3. **Results**

Results will first be discussed at a high level, how U.S. health benefits change between scenarios and what sectors have the greatest role on that change. GCAM-USA's state-level resolution allows for a deeper dive into the results where four states, CT, GA, IL, and OR are analyzed to provide insight into how a state's energy system structure influences the pathways taken in response to the policies implemented.

4a. Health Benefits – U.S.

Figure 1a shows the change in health costs compared to 2020 for Ref between 2020-2050. Compared to 2020, Ref has increasing health costs over the time horizon (Figure 1a) despite the decrease in air pollutant emissions (Figure 2). Health impacts increase over time because there are also increases in population, resulting in greater exposure to pollutants, and in GDP, resulting in a higher valuation of damages over time. Compared to 2020, health costs in Ref increase by $89 billion U.S. 2020 dollars in 2030 and $278 billion dollars in 2050 (Figure 1a). CO_2 emissions decrease in Ref by about 20% in 2050 compared to the 2020 emission levels (Figure 3).

For CCap, health benefits total $69 billion in 2030 and $271 billion in 2050, 14% and 32% reductions from Ref health costs, respectively (Figure 1b). By 2050, CO_2 emissions are 192 MTC, an 84% reduction from 2020 (Figure 3). The health benefits in CCap are mainly driven by reductions in SO_2 and NO_x emissions as opposed to directly-emitted $PM_{2.5}$, which changes very little in comparison (Figure 2). In fact, 2050 is the only year in which $PM_{2.5}$ emissions are less in CCap than in Ref; however, for some of the time periods there is a slight increase or no change in $PM_{2.5}$ emissions (Figure 2).

The health benefits in HCT are $110 billion in 2030 and $247 billion dollars in 2050, a 21% and 30% reduction in health costs from the Ref, respectively (Figure 1b). Across all the policy scenarios, directly-emitted $PM_{2.5}$ is reduced the most in HCT, by 27% in 2050, compared to a 3% in CCap, and 15% in HCT+CCap (Figure 2). HCT reduces NO_x emissions more than CCap in the initial years, but by 2045 has fewer reductions. Additionally, of all the scenarios, HCT has the smallest change in SO_2 (Figure 2), and CO_2 (Figure 3) emissions compared to Ref. CO_2 emissions are only reduced by 23% compared to 2020, which is similar to the CO_2 reductions seen in Ref. The limited CO_2 reductions indicate that air pollution policies in isolation may not result in significant climate co-benefits.

The health benefits of HCT+CCap are $179 billion in 2030 and $372 billion dollars in 2050, and reductions in health costs from Ref are 32% and 44%, respectively (Figure 1b). There are greater NO_x and SO_2 reductions when the HCT and CCap policies are combined (Figure 2), but fewer $PM_{2.5}$ reductions. The additional co-benefits from NO_x and SO_2 contribute to the overall greater health benefits of this scenario. The HCT+CCap also reduces CO_2 emissions by 84% compared to Ref 2020 emissions (Figure 3). HCT+CCap meets the CO_2 reduction goal while also reducing air pollution health costs more than when these policies are in isolation. This indicates that there are some different actions taken to reduce emissions. *These pathways are explored below.* Additionally, this result shows that designing carbon reduction policies without explicitly considering air quality can result in fewer air pollutant public health benefits.

4b. System changes – U.S.

The emission policies applied in the study were economy wide, meaning they acted on the building, industrial, electric, and transportation sectors. The contribution of transportation to overall health benefits is small (at most 4%) relative to the other sectors, so analysis of this sector is not presented. The sector- and pollutant–specific impacts on national health benefits are shown in Figures 4a, 4b, and 4c. These sectoral level figures allocate the health benefits relative to Ref to specific pollutants. Figures 5a, 5b, and 6 show how the policies impact fuel use by sector, providing additional information that can be used to understand underlying dynamics.

Figure 4a shows in 2030 in CCap there are some dis-benefits in the building sector related to direct $PM_{2.5}$. These dis-benefits are a result of a slight increase in wood heating, which has a relatively high direct $PM_{2.5}$ emission factor (Figure 5a). However, by 2050 there is greater electrification in the building sector (Figure 5a), decreasing direct $PM_{2.5}$ and leading to health benefits (Figure 4a). Electric sector SO_2 is responsible for the greatest benefits in 2030 in CCap (Figure 4c), which can be attributed to the decrease in coal use in the electric sector (Figure 6). In CCap 2050, the greatest health benefits occur in the industrial sector (Figure 4b), which is a result of reductions in the use of coal, biomass, and refined liquids, which are offset by electrification (Figure 5b). For both 2030 and 2050 the greatest benefits occur in the industrial sector for HCT (Figure 4b). Similar to CCap 2050 results, this is due to decreases in coal, biomass, and refined liquids (Figure 5b). Compared to CCap, electrification of the industrial sector in HCT occurs earlier (Figure 5b), which is one reason there are greater health benefits earlier in HCT's timeline (Figure 1). An additional reason for larger benefits earlier in the timeline is the reduction of building sector biomass use (Figure 5a), which leads to building $PM_{2.5}$ health benefits (Figure 4a).

Compared to HCT and CCap, the HCT+CCap achieves greater health benefits in each sector in both 2030 and 2050 (Figures 4a, 4b, 4c). These greater benefits are because of the different pathways each policy encourages. In 2030, HCT encourages electrification of the industrial and building sectors while CCap encourages electric sector decarbonization (Figures 5a, 5b, & 6). In 2050 both policies work together to promote even greater building and electric sector transformation (Figures 5a & 5b). While both policies encourage transformation of the same sectors in 2050, there are greater overall benefits which indicates that how these policies act on these sectors differs slightly. However, while there are greater benefits in HCT+CCap, the benefits are less than those of the policies applied individually since some of the actions taken are the same between the two policies and are included in HCT+CCap. The partial summation of sectoral changes indicates that there are some synergies, but ultimately the difference in how the policies influence sectoral transformation are what lead to the overall greater health benefits of HCT+CCap (Figure 1b).

4c. Health Benefits & Sectoral Changes - State Level

Next, the level of heterogeneity from state to state is explored. Figures 7a, 7b, 7c rank the 2030 state-level average sectoral and pollutant contribution to health benefits. A ranking of 1 means the most health benefits occurred in that sector and pollutant, while a ranking of 12 means the smallest amount of health benefits occurred in that sector and pollutant. In CCap, health benefits from electric sector SO_2 have the highest average ranking, averaging second (*Figure 7a)*. The building sector contributes the least, more specifically building $PM_{2.5}$ ranks twelfth to average state-level health cost benefits (Figure 7a). In HCT industrial $PM_{2.5}$ ranks as the highest average contributor with building $PM_{2.5}$ following behind it (Figure 7b). In 2030, the electric sector plays a less important role in HCT health benefits. In particular, electric $PM_{2.5}$ on average ranks as the eighth and electric NO_x ranks as the tenth contributor (Figure 7b). The average sectoral and pollutant rankings in HCT+CCap are influenced by each policy. In 2030 the two policies are acting on separate sectors, the CCap mainly acts on the electric sector while HCT influences industrial and building sector transformations. In HCT+CCap industrial and building $PM_{2.5}$ on average rank the highest contributors to health benefits in HCT+CCap. The influence of CCap on the electric sector leads to electric sector SO_2 on average ranking fourth in overall health benefits (Figure 7c).

Four states were chosen for further examination, with the goal of better understanding the differences between state responses to the policy objectives. Connecticut (CT), Georgia (GA), Illinois (IL), and Oregon (OR) were chosen because of their locations across the U.S. and the varying structure of their energy systems. CT has a relatively small industrial and electric sector, but relatively high commercial and residential heating demands. GA and IL have relatively large industrial sectors, but rely on different mixes of fuels. GA's industrial sector is more dependent on biomass, gas, and electricity while IL's industrial sector is reliant on refined liquids, gas, electricity, and coal (Figure 11a). OR's electric sector is heavily dependent on hydropower and gas and the industrial sector is reliant on biomass, electricity, and gas (Figure 9a and 11a).

Total health benefits from one state to another are a function of each state's population size, economic activity, energy consumption, and mix of energy system fuels and technologies. Similar to the national results, all four states have increasing health costs in Ref due to growth in population and GDP

(Figure 7a). In 2050 the costs are $1.97 billion, $8.42 billion, $12.70 billion, and $1.64 billion dollars more than 2020 costs for CT, GA, IL, and OR respectively (Figure 7a). CT and OR have the lowest health benefits in CCap, while the HCT+CCap only has slightly greater health benefits than the HCT alone (Figure 7b). The greatest benefits for GA and IL occur in HCT+CCap; like the national results, these states have greater benefits from HCT early in the timeline but in the long term see more benefits from the CCap (Figure 7b).

Despite CT and OR's differing locations in the U.S., the makeup of their energy systems results in a similar response to the policies. Table 4.1 and 4.4 show CT and OR's sectoral and pollutant rankings for contributing to overall health benefits, with a ranking of 1 indicating that sector and pollutant contributed the most to health benefits. Tables 4.1 and 4.4 show that for CT and OR the industrial sector contributes the most to health benefits in 2030, which can be attributed to the reductions in industrial coal use in CT and refined liquids in OR (Figure 11b). In 2030, CCap increases building biomass consumption (Figure 10b), which is why this sector and pollutant rank lowest in 2030 (Table 4.1 and 4.2). However, by 2050 the increase in building sector electrification and decrease in biomass consumption (Figure 10b), makes this category the number one contributor of overall health benefits in 2050 (Table 8a and 8d). Electric sector health benefits rank low for both CT and OR because these states already have electric grids with relatively low air pollutant emissions. In Ref, CT's electric sector relies on gas and nuclear early in the timeline with nuclear being replaced by wind and solar in later years (Figure 9a). OR is reliant on hydropower and gas, with wind utilization increasing over the time horizon (Figure 9a). As mentioned above, CT and OR see the smallest benefits in CCap, since many of the co-benefits of CCap are due to electric sector SO_2 and NO_x reductions and these states already have relatively low emitting electric sectors means this policy is less impactful for CT and OR.

Table 4.2 and 4.3 show GA and IL's sectoral and pollutant rankings for contributing to overall health benefits. In CCap, the greatest health benefits occur in electric SO_2 in 2030 and industrial SO_2 in 2050, which both result from the reductions in coal consumption (Figure 9b and 11b). In HCT 2030, industrial $PM_{2.5}$ contributes the most to health benefits for both GA and IL; this result is consistent in IL 2050, but in GA 2050 industrial SO_2 contributes the most health benefits (Tables 4.2 and 4.3). These results are due to the decreases in industrial refined liquids and coal and an increase in electricity consumption (Figure 11d). Sectoral and pollutant benefits in HCT+CCap differ between GA and IL. In GA 2030 and 2050 industrial SO_2 contributes the most to the benefits achieved, which is attributed to coal reductions in this sector (Figure 11d). In IL the greatest benefits are from electric SO_2 in 2030, due to the reductions in coal (Figure 9d), and industrial $PM_{2.5}$ in 2050, due to reductions in refined liquids (Figure 11d). The greatest benefits occur in HCT+CCap for GA and IL because CCap encourages reductions of coal consumption in the electric sector, while HCT and CCap encourage even greater electrification and reduction of refined liquids and coal in industry than when the policies are applied separately. These states are examples of how emission sources and fuel types can influence potential health benefits.

4. **<u>Discussion</u>**

5a. Policy Pathways

The differing policy objectives of CCap and HCT result in different sectoral transformations, which leads to the partial realization of the potential health benefits compared to when the policies are applied together in HCT+CCap. The objective of CCap is to cost-effectively reduce economy-wide CO_2 emissions. The mature technology options and its contributions to total CO_2 emissions makes the electric sector a target for this type of policy, especially early in the timeline. The NO_x and SO_2 co-benefits from electric sector decarbonization mainly come from reductions in coal consumption. Other studies have shown the potential health benefits of electric sector NO_x and SO_2 (Mayfield et al., 2020, Abel et al., 2018). While HCT also has some reduction in fossil fuels in the electric sector, this policy focuses on building and industrial sector transformation. The benefit-per-ton of emission reductions from these sectors tend to be greater than those of the electric sector since power plant emissions are typically disbursed and diluted over a greater geographic area. For example, the benefit of reducing a ton of NO_x from an electrical generating unit in 2025 is $6,400 dollars; whereas reducing a ton of NO_x from a residential wood stove is $33,100 dollars (EPA, 2022h). Brown et al., 2013 also found that a GHG fee resulted in greater electric sector transformation compared to an air pollution fee.

Endogenizing the public health costs of $PM_{2.5}$, NO_x, and SO_2 increases the cost of economic activities that have associated emissions; the value of the tax is dependent on the emissions species, source category, and location. The industrial sector and building sector $PM_{2.5}$ have some of the highest public health cost, so GCAM focuses on reducing emissions from these sectors in HCT. Generally the industrial sector has less stringent emission controls in Ref, which means more $PM_{2.5}$ and its precursors are emitted (Ou, 2020), this contributes to the higher public health cost with these emissions compared to other sectors. Building sector biomass also has a high public health cost due to its relatively high $PM_{2.5}$ emissions intensity and its proximity to areas with high populations. The higher cost of emissions in these sectors leads to increased electrification of these sectors earlier than compared to CCap, which is one reason there are greater health benefits earlier on in HCT.

The different sectors and pollutants targeted by each policy result in the greatest co-benefits when the policies are applied together, specifically early in the timeline. This is a result of the policies acting somewhat independently of each other early in the timeline. Early in the timeline CCap focuses on decarbonizing the electric sector because of its CO_2 emissions and mature technology options. HCT focuses on electrifying the industrial and building sectors due to the high tax coming from $PM_{2.5}$ emissions in these sectors. Applying the policies together ensures that there are health benefits across almost all the sectors, instead of one sector being the target of one policy. Around 2045 the policies work synergistically by electrifying the industrial sector to an even greater extent than when the policies are applied separately. Designing a policy that focuses on the public health costs of air pollution with a carbon reduction goal also leads to greater health benefits because it encourages greater reduction of $PM_{2.5}$. CCap in isolation achieves NO_x and SO_2 co-benefits, but minimal $PM_{2.5}$ co-benefits, this emphasizes the importance of designing these policies together.

An additional advantage of combining these policies is that the potential for the policies to work against each other is mitigated. For example, CCap utilizes building sector biomass in 2030 since this fuel is considered carbon-neutral in GCAM. This, however, leads to public health dis-benefits (Figure 4a). When these policies are combined, building sector biomass consumption does not increase in 2030. Instead, the building $PM_{2.5}$ benefits that occur in 2030 HCT are also seen in HCT+CCap (Figure 4a). An additional example is that gas has greater utilization in HCT, due to its relatively low air pollution output. Gas, however, is not utilized in CCap since it can hinder meeting climate goals. There are slight increases in gas in HCT industrial and electric sectors, however, when combined with CCap only reductions of gas occur (Figure 5b, 5c). An example at the technology level is that in the building sector the preference for gas in HCT results in an increase in high efficiency gas furnaces while in CCap the aversion for gas results in increased utilization of electric heat pumps. These examples emphasize how some fuels and technologies are advantageous for certain policies but may conflict with other policy objectives and applying these policies together can safeguard against policy conflict.

The national level results allow for analysis of energy system changes at a high level; however, the state-level results show how different energy systems respond to the policies modeled, and can help inform state policies. For example, while the national narrative shows HCT+CCap having much greater benefits than the policies applied separately, this does not hold true for states with relatively 'clean' electric grids. This is seen in CT and OR where the benefits of HCT and HCT+CCap are almost the same (Figure 7). Additionally, states with high residential heating demands and a historical reliance on biomass can achieve significant public health benefits through electrification of the building sector, as seen in CT and OR. Ou, 2018 and 2020 also found that increases in building biomass consumption leads to higher $PM_{2.5}$ mortality costs. States with high coal consumption, in the industrial or electric sectors, can achieve significant public health benefits through fuel and technology switching, as seen with both GA and IL. Overall, studying the impacts of these policies at the state-level shows that national policies do not have equal benefits for each state. Additionally, it provides a useful first step to identifying cost-effective policy measures to improve state-level public health.

5b. Limitations & Future Research

Limitations of this work include the limits of GCAM's representation of air pollution transport. Air pollution does not adhere to state or national boundaries. This study provides insight into the potential benefits of climate and air quality focused policies but does not provide locational detail to where these benefits are fully experienced. An additional limitation is that not all the health costs calculated have state-level resolution. One of the goals of this study was to increase the granularity of the values calculated in Ou et al., 2018. While this was achieved for a majority of sectors, some still use national averages to calculate the health costs. Additionally, the health benefits achieved through these policies do not have a linear relationship with emission reductions, so interpretation of the health benefits and costs must be done carefully.

Future research opportunities include using GCAM-USA to explore additional policy options, adding the health costs of other pollutants and the social cost of carbon, and modeling with a detailed industrial sector. The policy set here does not include potential electrification and technology development from the recently passed inflation reduction act (IRA). The IRA's potential to influence future technology options could result in changes to energy system evolution. Furthermore, it would be valuable to have estimates of the public health benefits of this new federal policy. Additional policy scenarios that would be of interest in this study include implementing a CO_2 tax instead of a carbon constraint, altering the CO_2 constraint's stringency to provide insight of different CO_2 emission futures, altering the cost of the health tax, and applying state-level health cost reduction constraints. Additional scenarios could include coordination of CO_2 and air pollution mitigation with other countries, which has been shown to result in even greater co-benefits (Zhang 2017). Including the social cost of carbon would also allow for comparison of the climate benefits of these policies, similar to what is done in Brown et al., 2020. Expanding this study to also include the health cost of O_3 and its precursors would better represent the full health costs of air pollution and health benefits of actions. In the EPA's 2021 release of the BPT values includes O_3; unfortunately, the values were only for a detailed industrial sector and for the electric sector, so calculating the impact of technologies in the transportation and building sector would not have been possible. The omission of these technologies is why ozone health impacts were excluded from this study. Another limitation of this study is limited resolution of the industrial sector within GCAM since some aspects of the sector are aggregated. Future work would benefit from increased granularity of this sector, which would also allow for full utilization of the detailed industrial BPT estimates published by the EPA in 2021.

To take full advantage of the detailed industrial sector BPT values, a more detailed industrial sector in GCAM would provide more granularity to this work. Another limitation to this study is that there are aspects of the industrial sector that are aggregated within GCAM. increased resolution of the industrial sector in GCAM would improve our understanding of the industrial sector's true impact on public health in relation to air pollution and the best potential strategies to reducing these impacts.

5. Conclusion

This study uses GLIMPSE/ GCAM-USA to analyze the national- and state-level $PM_{2.5}$, NO_x, and SO_2 emission reductions and associated health benefits for three different public policy scenarios between 2025 and 2050. The CCap policy constrains U.S. economy-wide CO_2 emissions to 50% below 2005 levels by 2030 and 80% below 2005 levels by 2050. The HCT policy endogenizes the air pollution health costs in the form of a tax that is differentiated by source category, emission species, and location. The HCT+CCap policy combines these two policies together. The climate policy in this study had significant air quality co-benefits, but the air quality policy did not have the same potential for climate co-benefits.

The greater public health benefits in HCT+CCap are due to the different emission reduction pathways implemented by each policy. Co-benefits from CCap initially come from transformations in the electric sector. As the CO_2 reduction targets become more stringent over time, decarbonization of end-use sectors grows, and health benefits increase with the electrification of the building and industry In contrast, HCT places an emphasis on reducing emissions from PM-mortality intensive activities such as wood burning stoves in the building sector and fuels such as coal and refined liquids in the industrial sector. Combing HCT with CCap leads to an increase of health benefits of $110 billion dollars in 2030 and $101 billion in 2050 compared to CCap in isolation.

The state-level results of this study show that national policies do not have equal influence on sectoral changes or benefits experienced. The structure of a state's energy system influences how it will respond to each of these policies and where emission reductions can most benefit public health. Understanding the differences between state-level responses to these types of policies provides important insight for how to best approach climate and air quality goals. Overall, at the national and state-level a carbon reduction policy that takes air quality health impacts into consideration ultimately results in greater public health benefits while still being able to achieve CO_2 reduction goals.

6. Figures

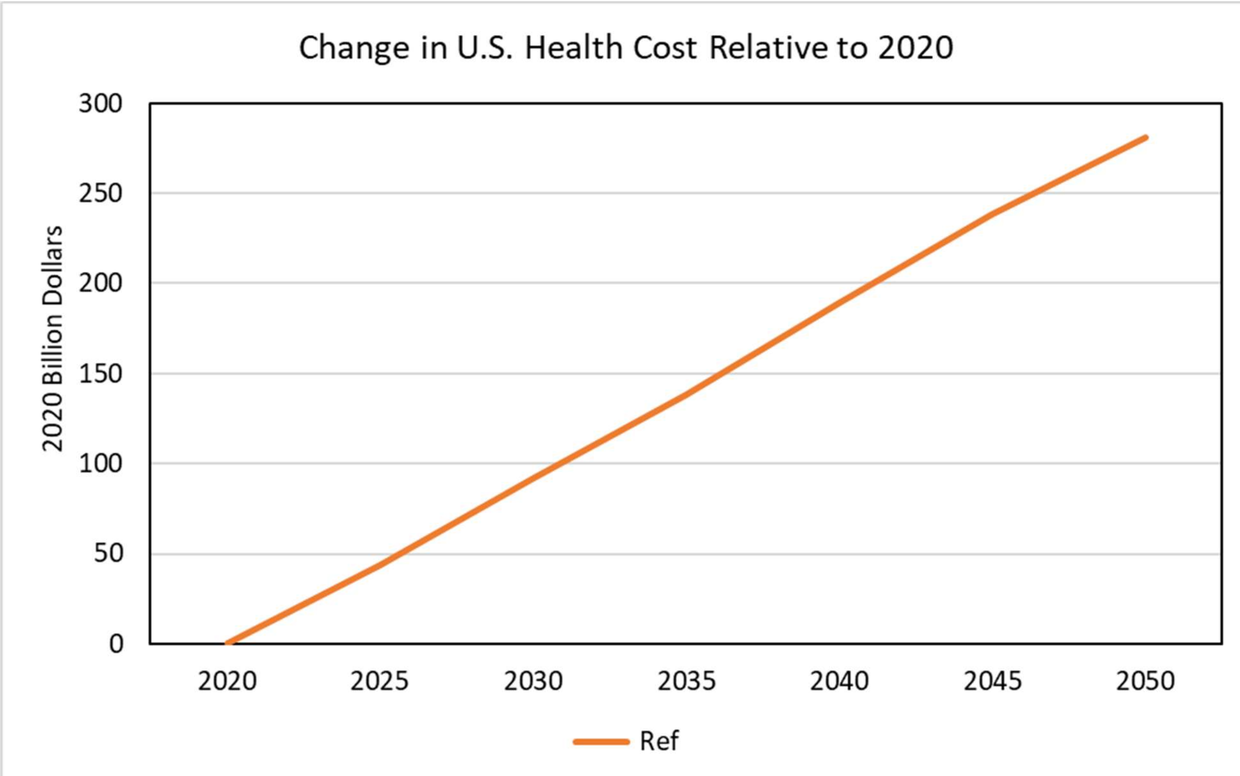

Figure 1a shows the change in health costs in the Ref scenario from the 2020 Ref health costs between 2020-2050. Values are in 2020 billion dollars.

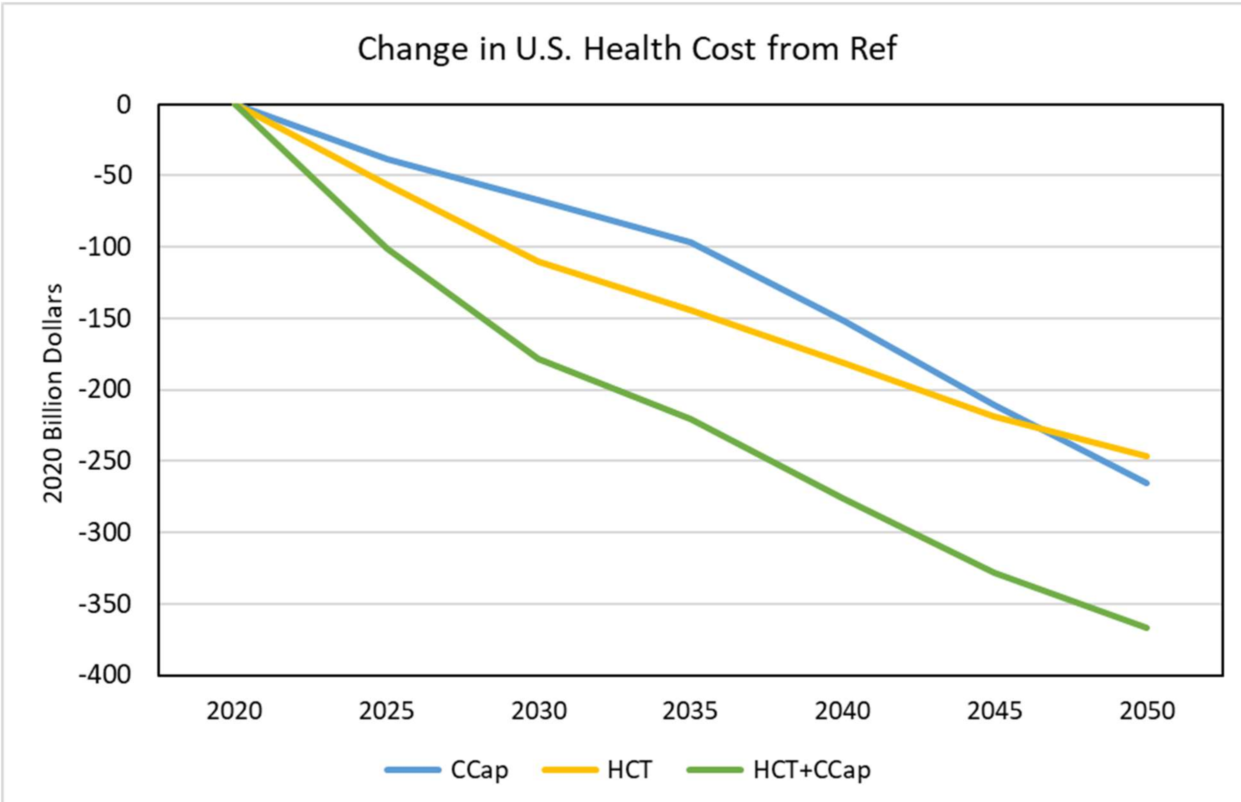

Figure 1b shows the change in U.S. health costs between the policy scenario and Ref between 2020-2050. Values are in 2020 billion dollars.

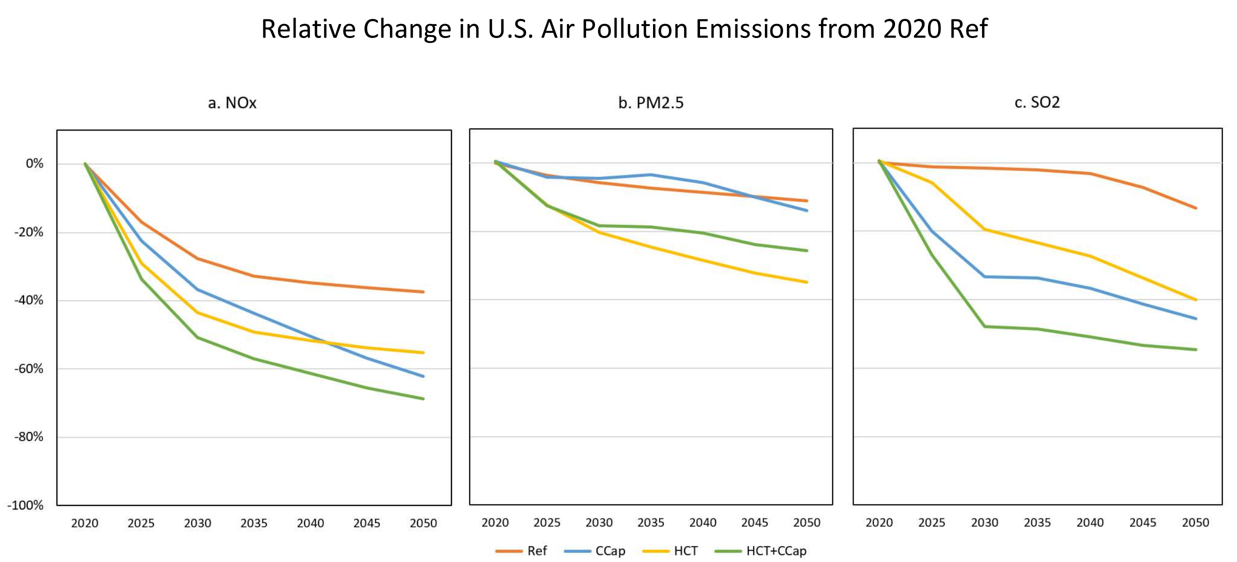

Figure 2 shows the relative difference in U.S. national air pollutant emissions from the 2020 emissions. 2a. shows the relative difference for $PM_{2.5}$, 2b. shows the difference for NO_x, and 2c. shows the difference for SO_2.

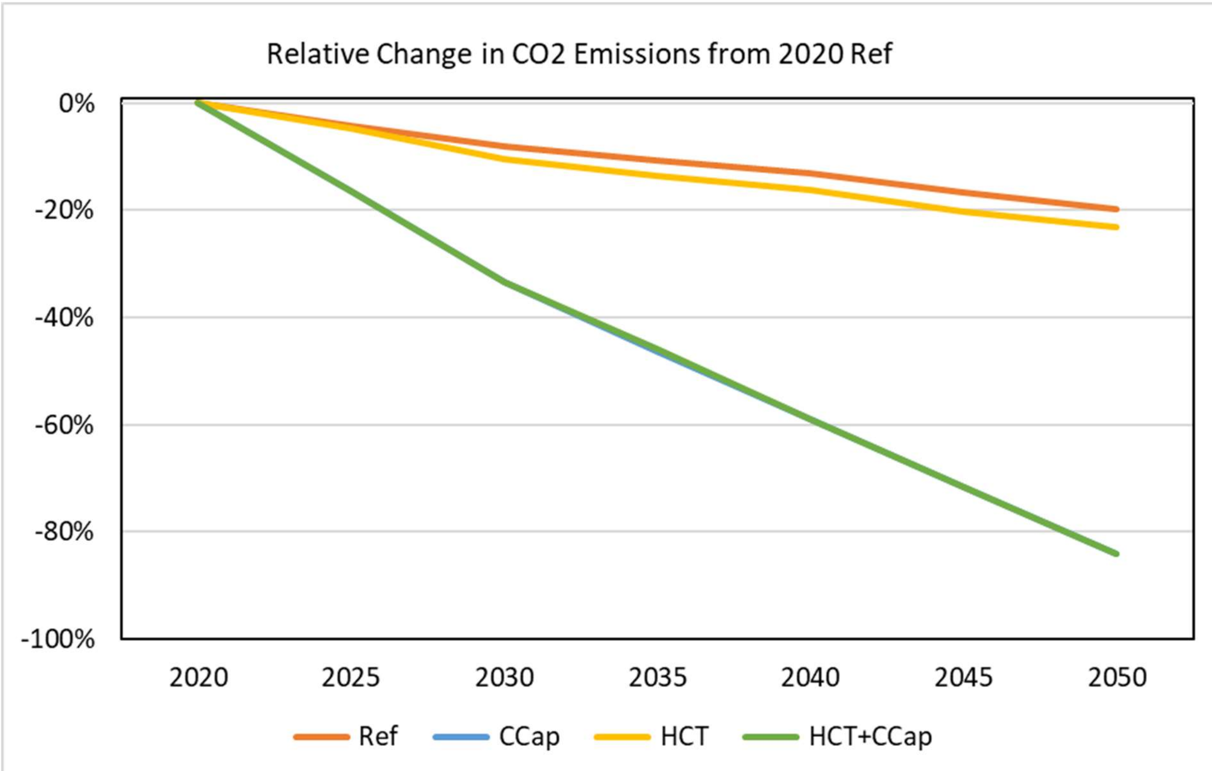

Figure 3 shows the relative difference in CO_2 emissions from the 2020 CO_2 emissions between 2020-2050 for all four scenarios. The CCap and HCT+CCap have the same change in CO_2 emissions, which is why CCap cannot be seen.

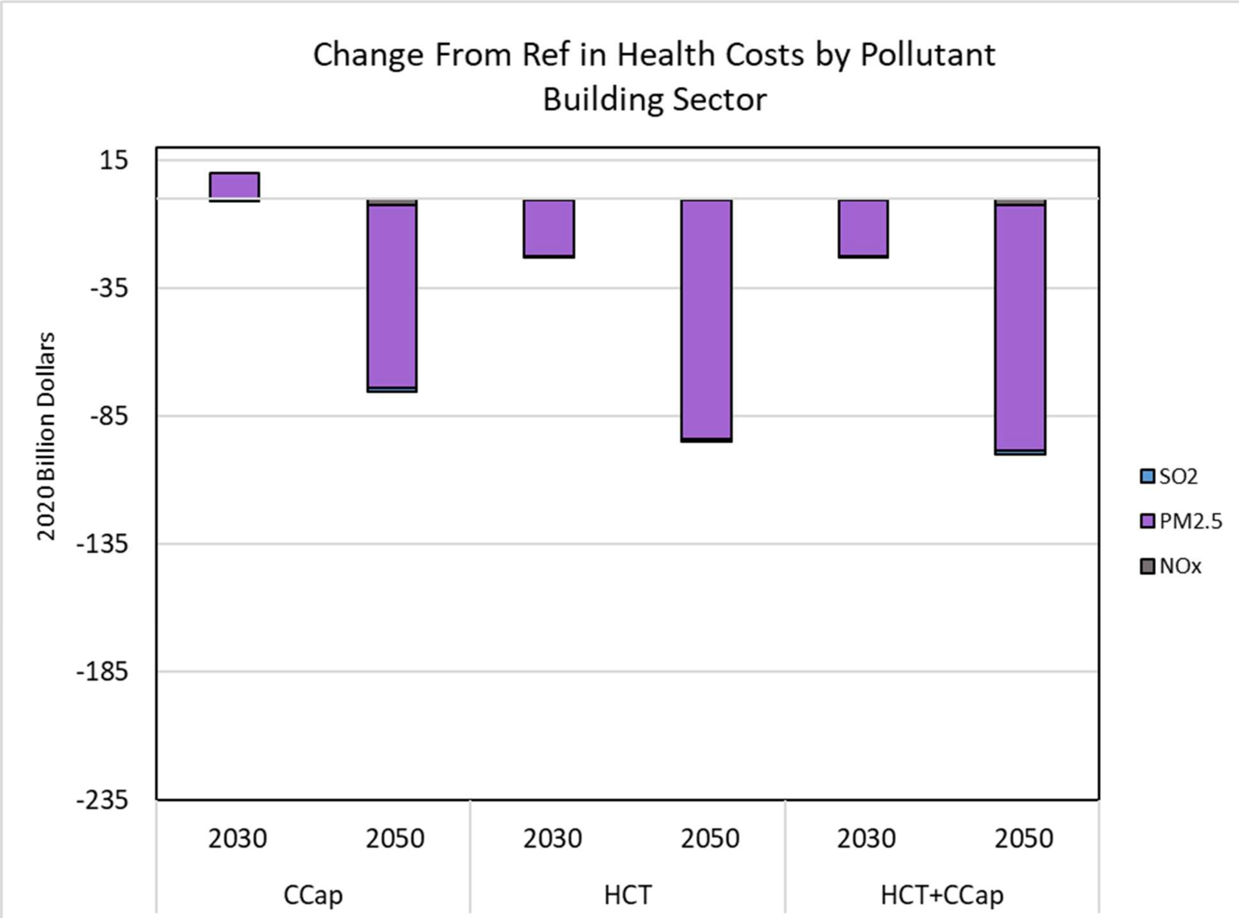

Figure 4a. shows the change in building sector health costs from Ref between the three policy scenarios for 2030 and 2050 at the pollutant level. Values are in 2020 billion dollars.

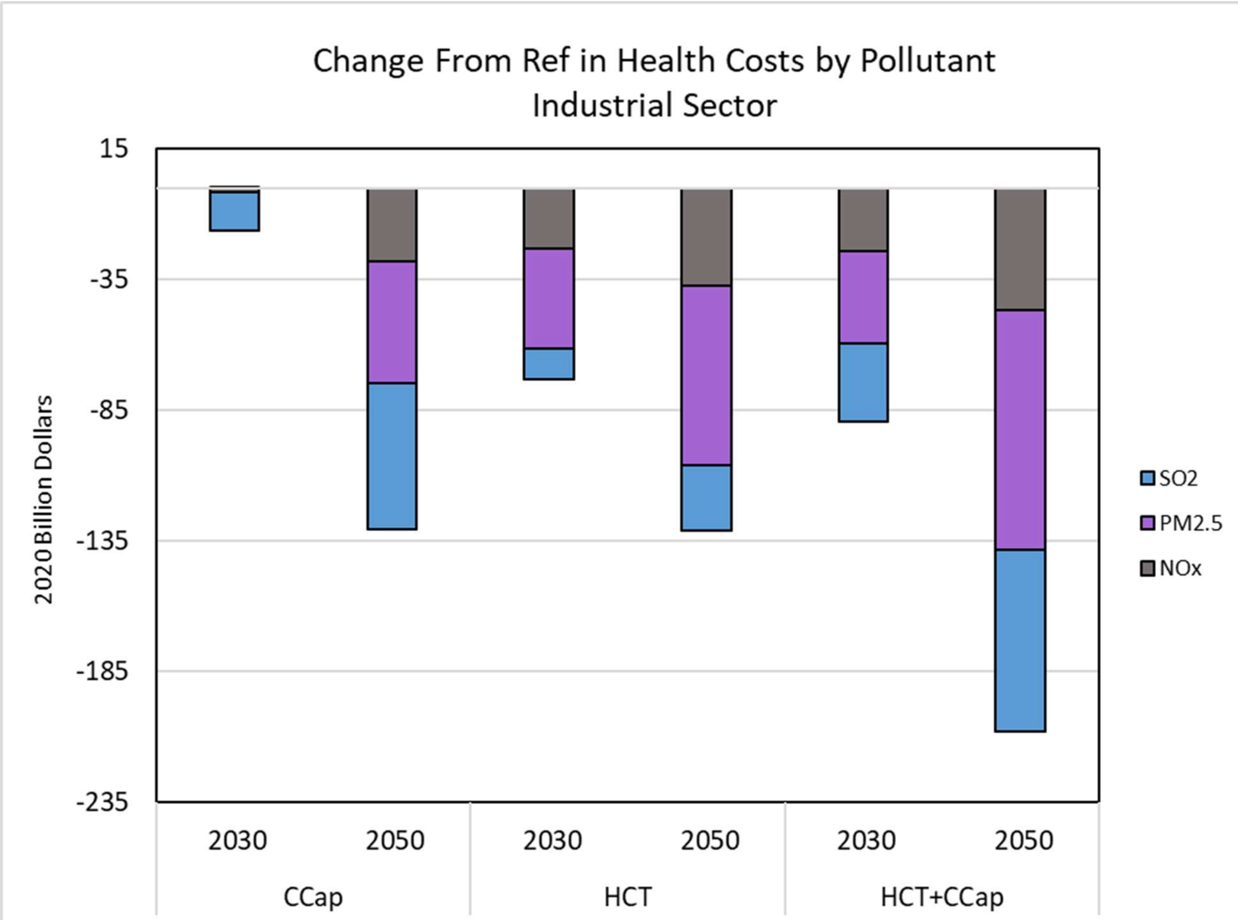

Figure 4b. shows the change in industrial sector health costs from Ref between the three policy scenarios for 2030 and 2050 at the pollutant level. Values are in 2020 billion dollars.

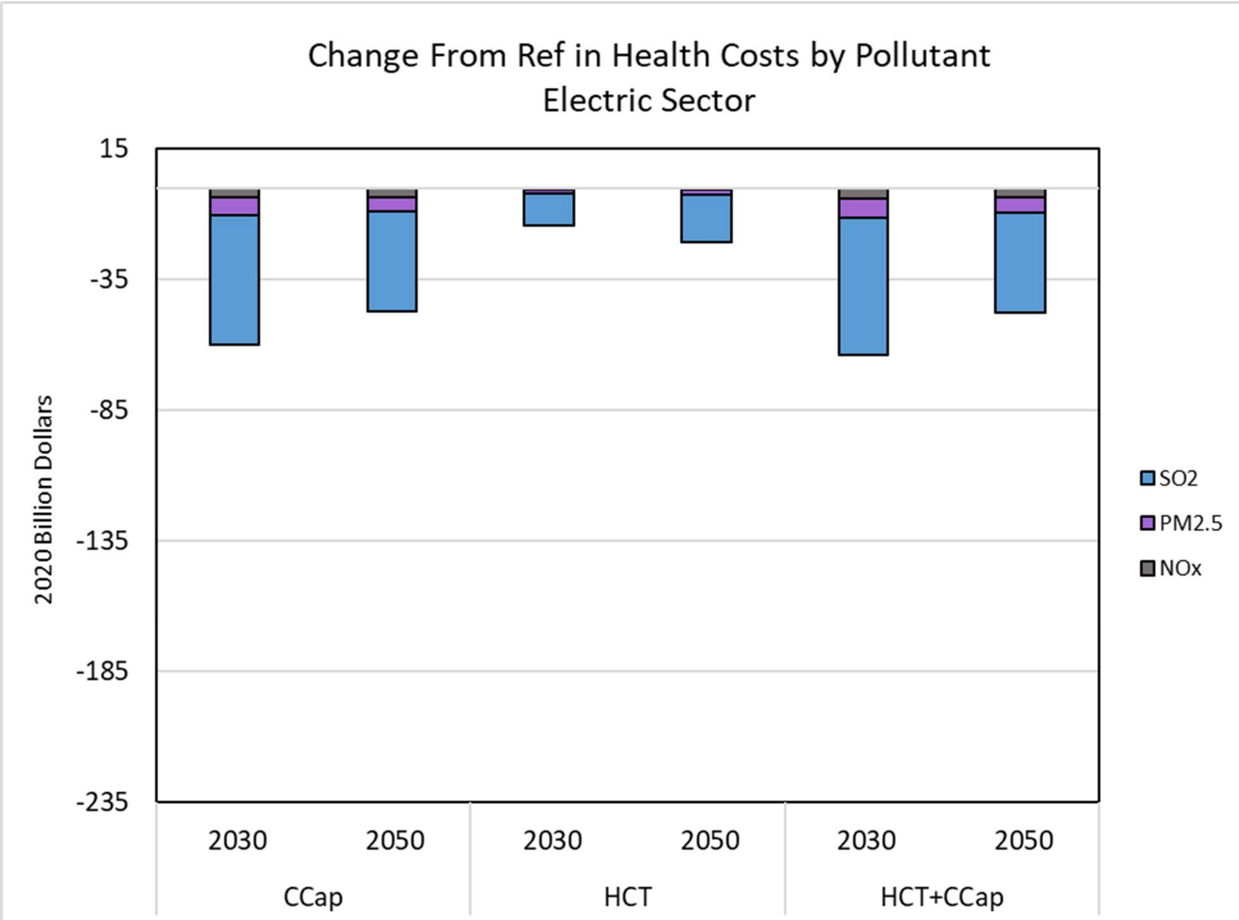

Figure 4c. shows the change in electric sector health costs from Ref between the three policy scenarios for 2030 and 2050 at the pollutant level. Values are in 2020 billion dollars.

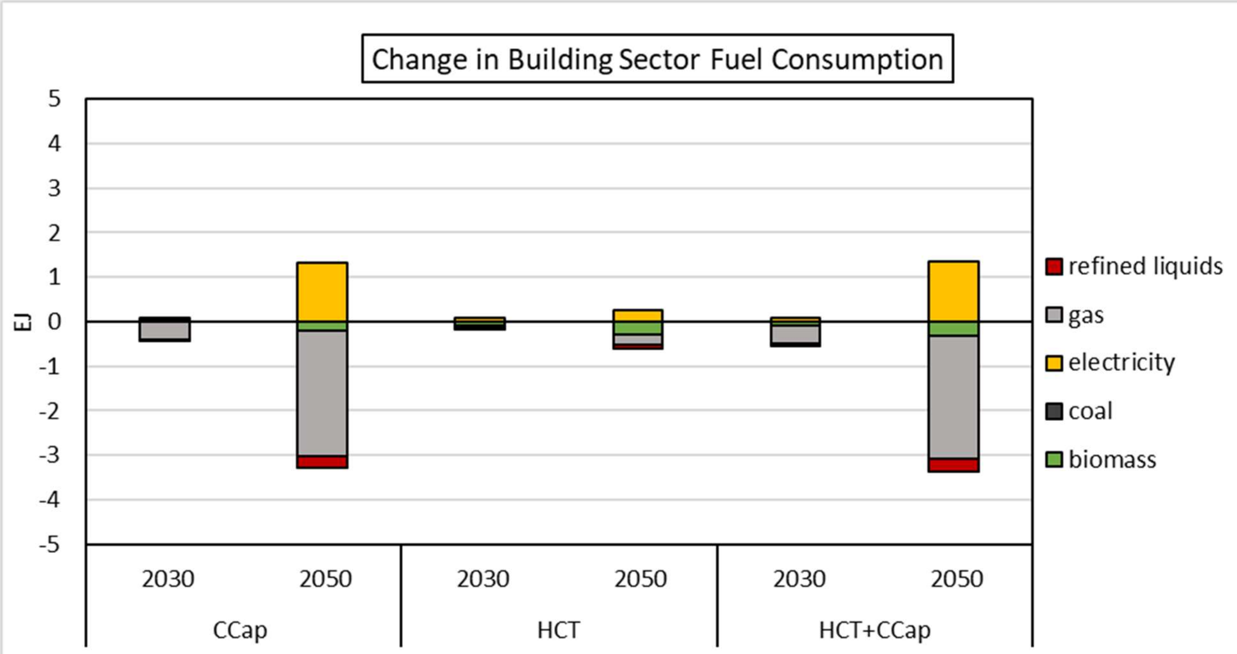

Figure 5a. shows the change in fuel consumption in the building sector between the policy scenarios from Ref for 2030 and 2050. Values are in exajoules (EJ).

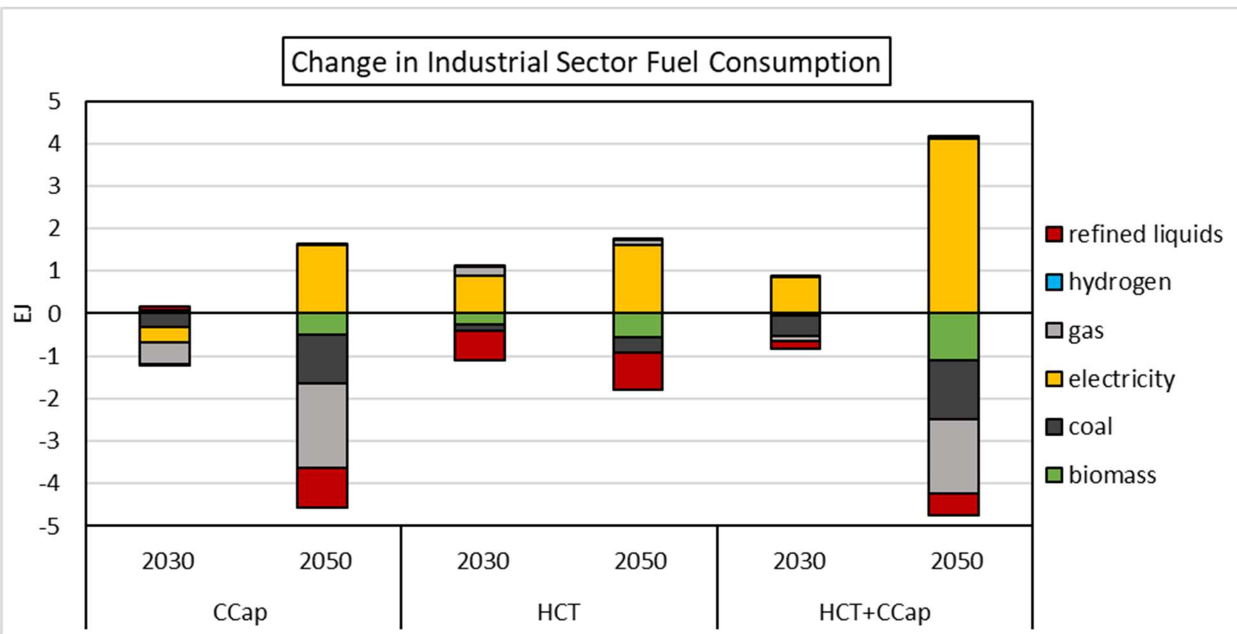

Figure 5b. shows the change in fuel consumption in the industrial sector between the policy scenarios from Ref for 2030 and 2050. Values shown are in exajoules (EJ).

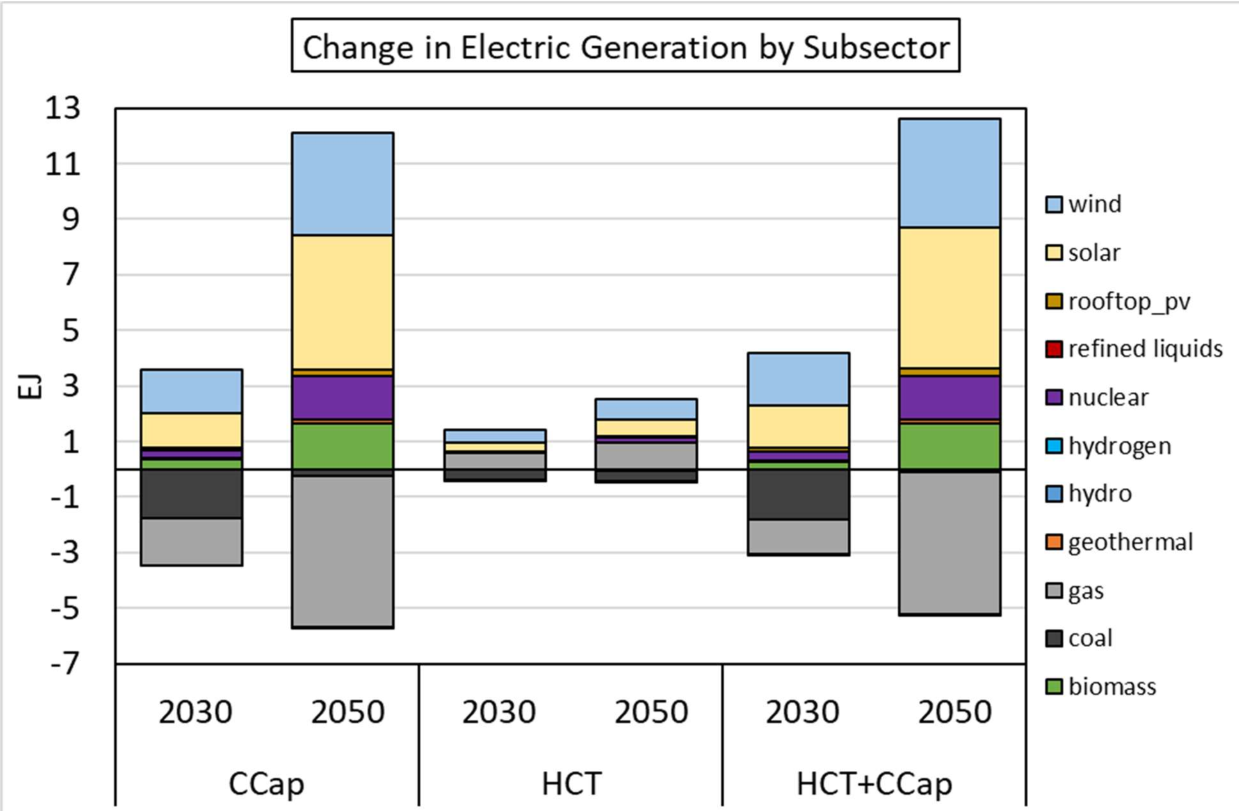

Figure 6 shows the change in electricity generation by subsector between the policy scenarios from Ref for 2030 and 2050. Values are in exajoules (EJ).

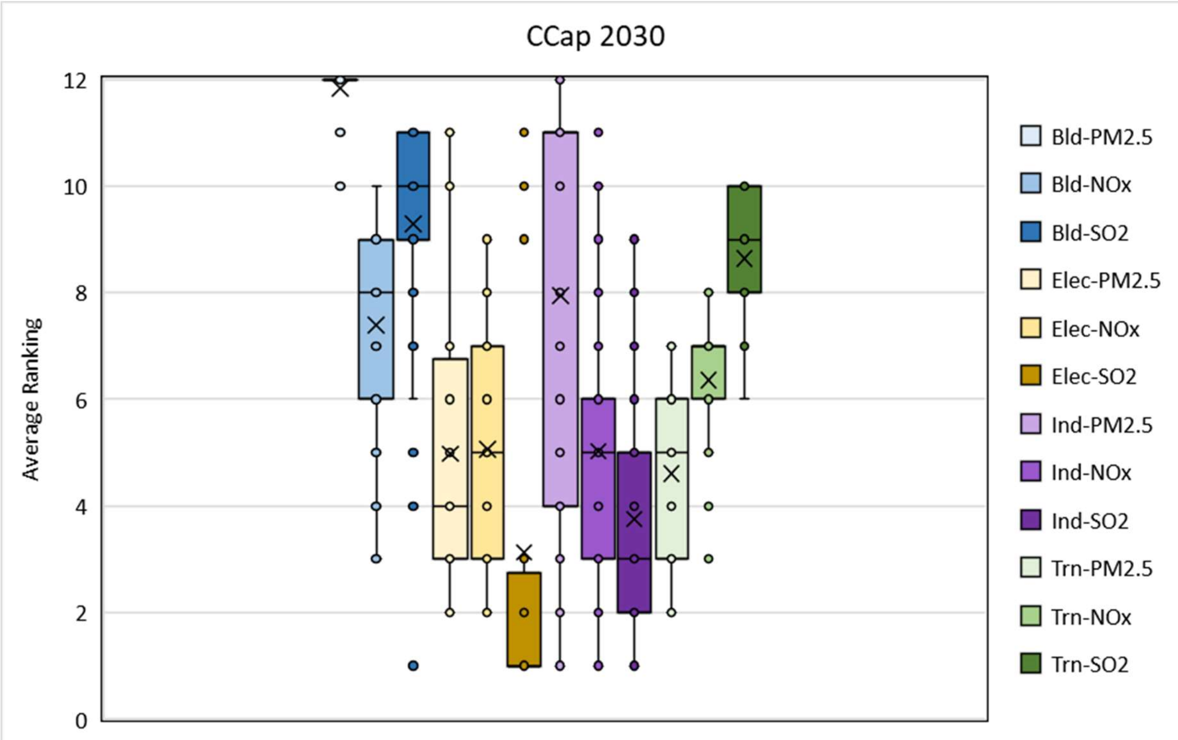

Figure 7a shows the 2030 CCap state-level average sectoral and pollutant contribution to health cost benefits.

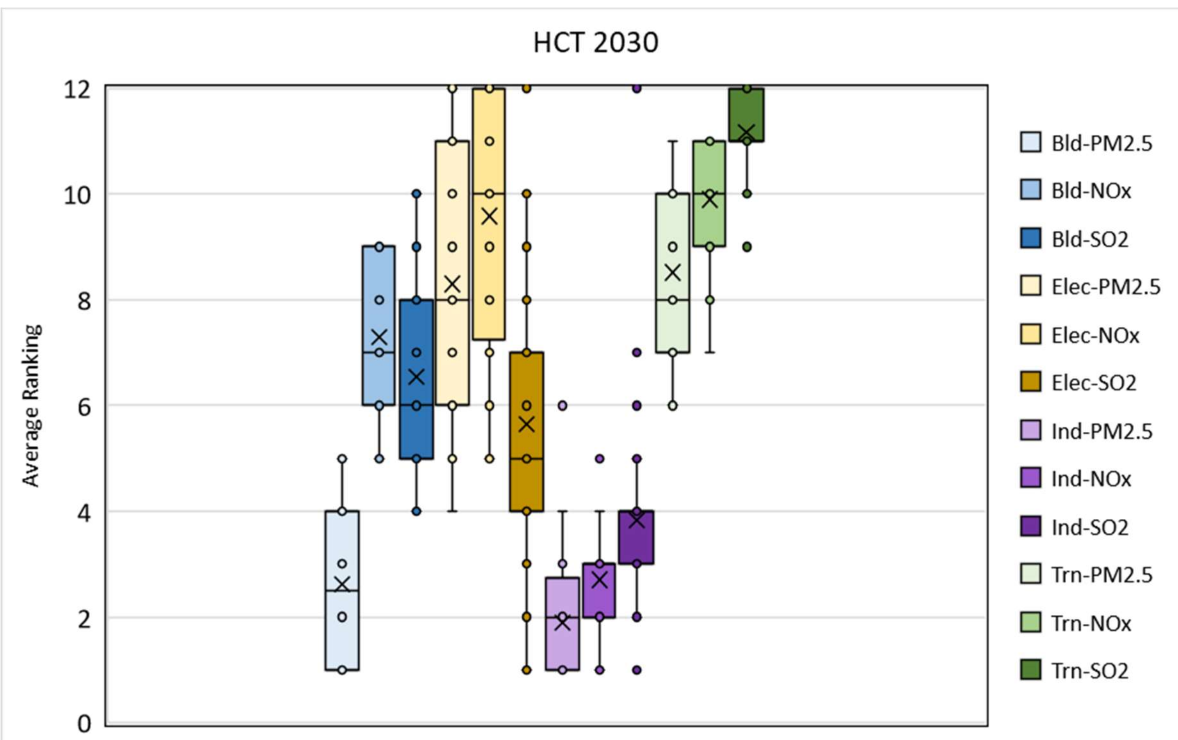

Figure 7b shows the 2030 HCT state-level average sectoral and pollutant contribution to health cost benefits.

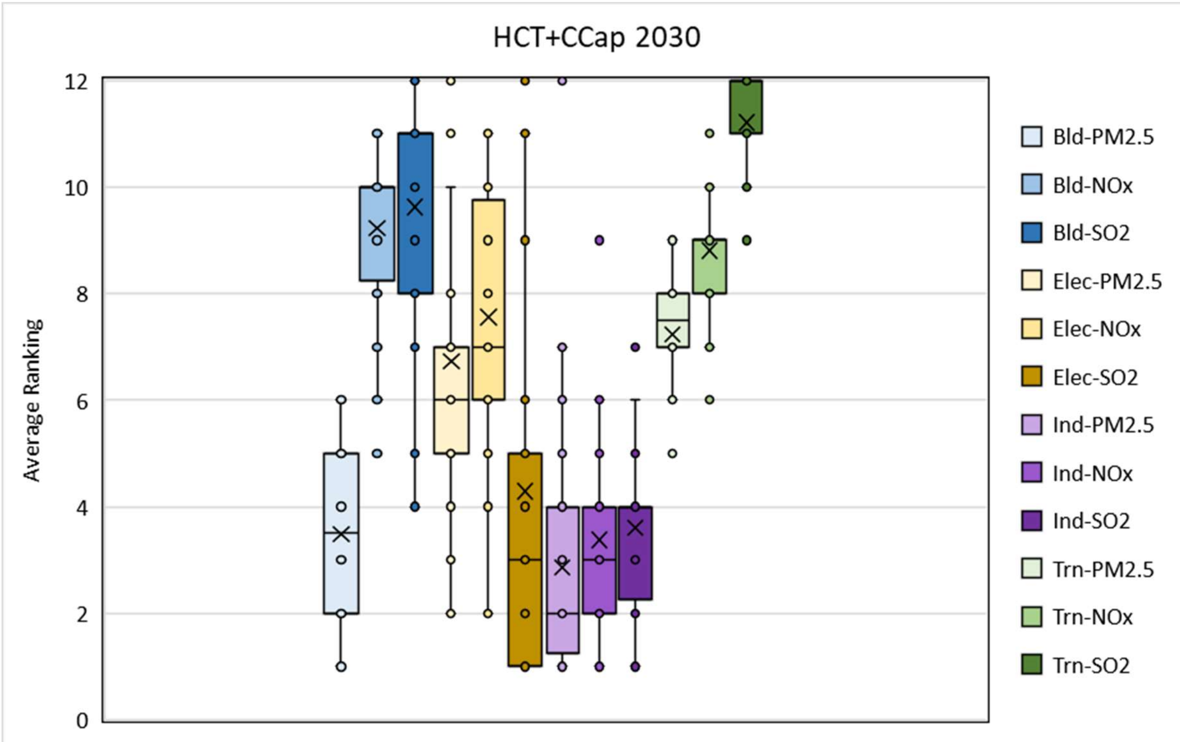

Figure 7c shows the 2030 HCT+CCap state-level average sectoral and pollutant contribution to health cost benefits.

Difference in Health Costs from 2020

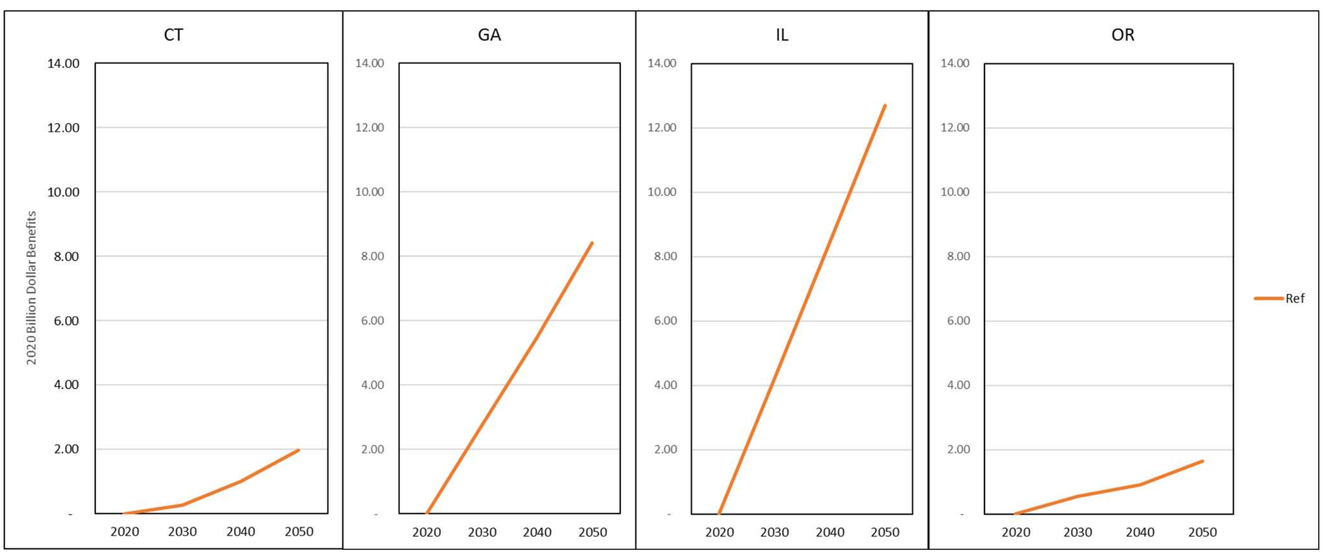

Figure 8a shows the change in health costs for CT, GA, IL, and OR between the policy scenario and Ref. Values are in 2020 billion dollars.

Difference in Health Costs From Ref

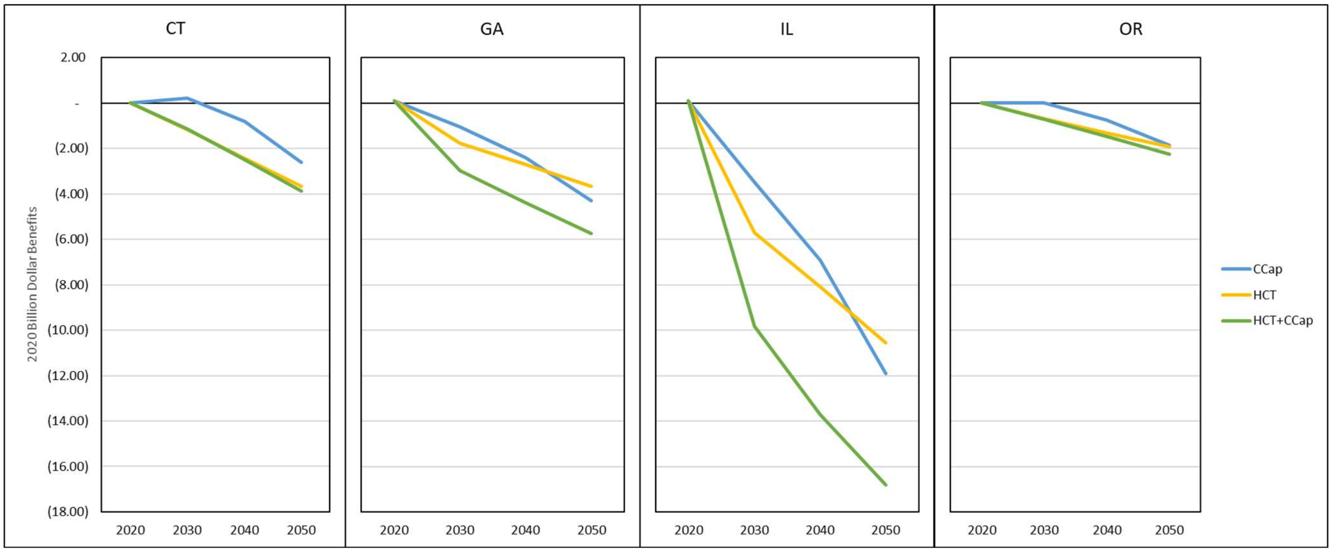

Figure 8b shows the change in health costs for CT, GA, IL, and OR between the policy scenario and Ref. Values are in 2020 billion dollars.

Connecticut	CCap- 2030	CCap-2050	HCT-2030	HCT-2050	HCT+CCap-2030	HCT+CCap-2050
1	Ind-NOx	Bld-PM2.5	Bld-PM2.5	Bld-PM2.5	Bld-PM2.5	Bld-PM2.5
2	Trn-PM2.5	Ind-NOx	Ind-PM2.5	Ind-PM2.5	Ind-NOx	Ind-PM2.5
3	Bld-NOx	Ind-PM2.5	Ind-NOx	Ind-NOx	Ind-PM2.5	Ind-NOx
4	Trn-NOx	Bld-SO2	Bld-SO2	Bld-SO2	Bld-SO2	Bld-SO2
5	Bld-SO2	Trn-PM2.5	Ind-SO2	Bld-NOx	Bld-NOx	Bld-NOx
6	Ind-PM2.5	Bld-NOx	Bld-NOx	Ind-SO2	Trn-PM2.5	Elec-PM2.5
7	Elec-NOx	Elec-PM2.5	Elec-SO2	Elec-SO2	Ind-SO2	Trn-PM2.5
8	Trn-SO2	Trn-NOx	Trn-PM2.5	Trn-PM2.5	Trn-NOx	Trn-NOx
9	Ind-SO2	Elec-SO2	Trn-NOx	Elec-PM2.5	Elec-NOx	Ind-SO2
10	Elec-PM2.5	Ind-SO2	Elec-PM2.5	Trn-NOx	Elec-PM2.5	Elec-SO2
11	Elec-SO2	Trn-SO2	Trn-SO2	Trn-SO2	Trn-SO2	Trn-SO2
12	Bld-PM2.5	Elec-NOx	Elec-NOx	Elec-NOx	Elec-SO2	Elec-NOx

Table 4.1 shows the sectoral and pollutant ranking in relation to public health benefits compared to Ref for each scenario for 2030 and 2050 for Connecticut.

Georgia	CCap- 2030	CCap-2050	HCT-2030	HCT-2050	HCT+CCap-2030	HCT+CCap-2050
1	Elec-SO2	Ind-SO2	Ind-PM2.5	Ind-SO2	Ind-SO2	Ind-SO2
2	Ind-SO2	Elec-SO2	Ind-SO2	Ind-PM2.5	Elec-SO2	Ind-PM2.5
3	Elec-PM2.5	Bld-PM2.5	Ind-NOx	Bld-PM2.5	Ind-PM2.5	Bld-PM2.5
4	Ind-NOx	Ind-PM2.5	Bld-PM2.5	Ind-NOx	Ind-NOx	Ind-NOx
5	Trn-PM2.5	Ind-NOx	Elec-SO2	Elec-SO2	Bld-PM2.5	Elec-SO2
6	Ind-PM2.5	Elec-PM2.5	Bld-SO2	Bld-SO2	Elec-PM2.5	Elec-PM2.5
7	Elec-NOx	Trn-PM2.5	Bld-NOx	Bld-NOx	Trn-PM2.5	Trn-PM2.5
8	Trn-NOx	Trn-NOx	Elec-PM2.5	Elec-PM2.5	Elec-NOx	Trn-NOx
9	Bld-NOx	Bld-NOx	Trn-PM2.5	Trn-PM2.5	Trn-NOx	Bld-NOx
10	Trn-SO2	Elec-NOx	Trn-NOx	Trn-NOx	Bld-NOx	Elec-NOx
11	Bld-SO2	Trn-SO2	Elec-NOx	Elec-NOx	Bld-SO2	Bld-SO2
12	Bld-PM2.5	Bld-SO2	Trn-SO2	Trn-SO2	Trn-SO2	Trn-SO2

Table 4.2 shows the sectoral and pollutant ranking in relation to public health benefits compared to Ref for each scenario for 2030 and 2050 for Georgia.

Illinois	CCap- 2030	CCap-2050	HCT-2030	HCT-2050	HCT+CCap-2030	HCT+CCap-2050
1	Elec-SO2	Ind-SO2	Ind-PM2.5	Ind-PM2.5	Elec-SO2	Ind-PM2.5
2	Ind-SO2	Ind-PM2.5	Ind-NOx	Bld-PM2.5	Ind-PM2.5	Ind-SO2
3	Elec-PM2.5	Bld-PM2.5	Bld-PM2.5	Ind-NOx	Ind-NOx	Bld-PM2.5
4	Elec-NOx	Ind-NOx	Ind-SO2	Ind-SO2	Ind-SO2	Ind-NOx
5	Ind-NOx	Elec-SO2	Elec-SO2	Elec-SO2	Elec-SO2	Elec-SO2
6	Ind-PM2.5	Trn-PM2.5	Bld-SO2	Bld-SO2	Elec-PM2.5	Elec-PM2.5
7	Trn-PM2.5	Elec-PM2.5	Elec-PM2.5	Elec-PM2.5	Elec-NOx	Trn-PM2.5
8	Trn-NOx	Elec-NOx	Elec-NOx	Bld-NOx	Trn-PM2.5	Elec-NOx
9	Bld-NOx	Bld-NOx	Bld-NOx	Trn-PM2.5	Bld-SO2	Bld-SO2
10	Trn-SO2	Bld-SO2	Trn-PM2.5	Elec-NOx	Trn-NOx	Bld-NOx
11	Bld-SO2	Trn-NOx	Trn-NOx	Trn-NOx	Bld-NOx	Trn-NOx
12	Bld-PM2.5	Trn-SO2	Trn-SO2	Trn-SO2	Trn-SO2	Trn-SO2

Table 4.3 shows the sectoral and pollutant ranking in relation to public health benefits compared to Ref for each scenario for 2030 and 2050 for Illinois.

Oregon	CCap- 2030	CCap-2050	HCT-2030	HCT-2050	HCT+CCap-2030	HCT+CCap-2050
1	Ind-PM2.5	Bld-PM2.5	Bld-PM2.5	Bld-PM2.5	Bld-PM2.5	Bld-PM2.5
2	Ind-NOx	Ind-PM2.5	Ind-PM2.5	Ind-PM2.5	Ind-PM2.5	Ind-PM2.5
3	Trn-PM2.5	Ind-SO2	Ind-NOx	Ind-NOx	Ind-NOx	Ind-NOx
4	Trn-NOx	Trn-PM2.5	Ind-SO2	Ind-SO2	Ind-SO2	Ind-SO2
5	Elec-PM2.5	Ind-SO2	Bld-SO2	Bld-SO2	Trn-PM2.5	Trn-PM2.5
6	Ind-SO2	Trn-NOx	Bld-NOx	Bld-NOx	Trn-NOx	Trn-NOx
7	Bld-NOx	Elec-PM2.5	Elec-SO2	Elec-PM2.5	Elec-PM2.5	Elec-PM2.5
8	Trn-SO2	Bld-NOx	Trn-PM2.5	Trn-PM2.5	Bld-NOx	Bld-NOx
9	Elec-NOx	Bld-SO2	Elec-PM2.5	Elec-SO2	Bld-SO2	Bld-SO2
10	Bld-SO2	Trn-SO2	Trn-NOx	Trn-NOx	Trn-SO2	Elec-SO2
11	Elec-SO2	Elec-SO2	Trn-SO2	Trn-SO2	Elec-NOx	Trn-SO2
12	Bld-PM2.5	Elec-NOx	Elec-NOx	Elec-NOx	Elec-SO2	Elec-NOx

Table 4.4 shows the sectoral and pollutant ranking in relation to public health benefits compared to Ref for each scenario for 2030 and 2050 for Oregon.

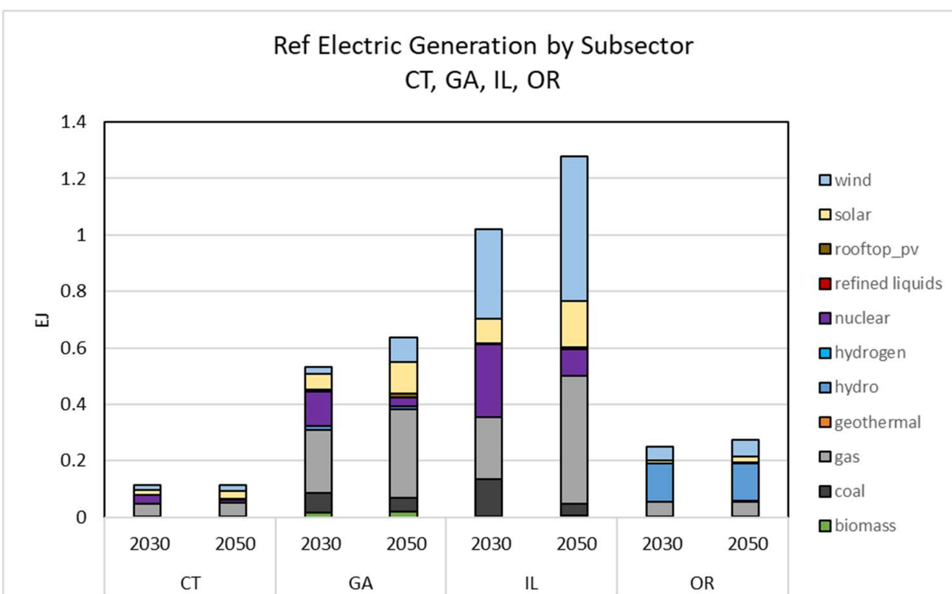

Figure 9a shows the Ref electric generation mix by Subsector for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

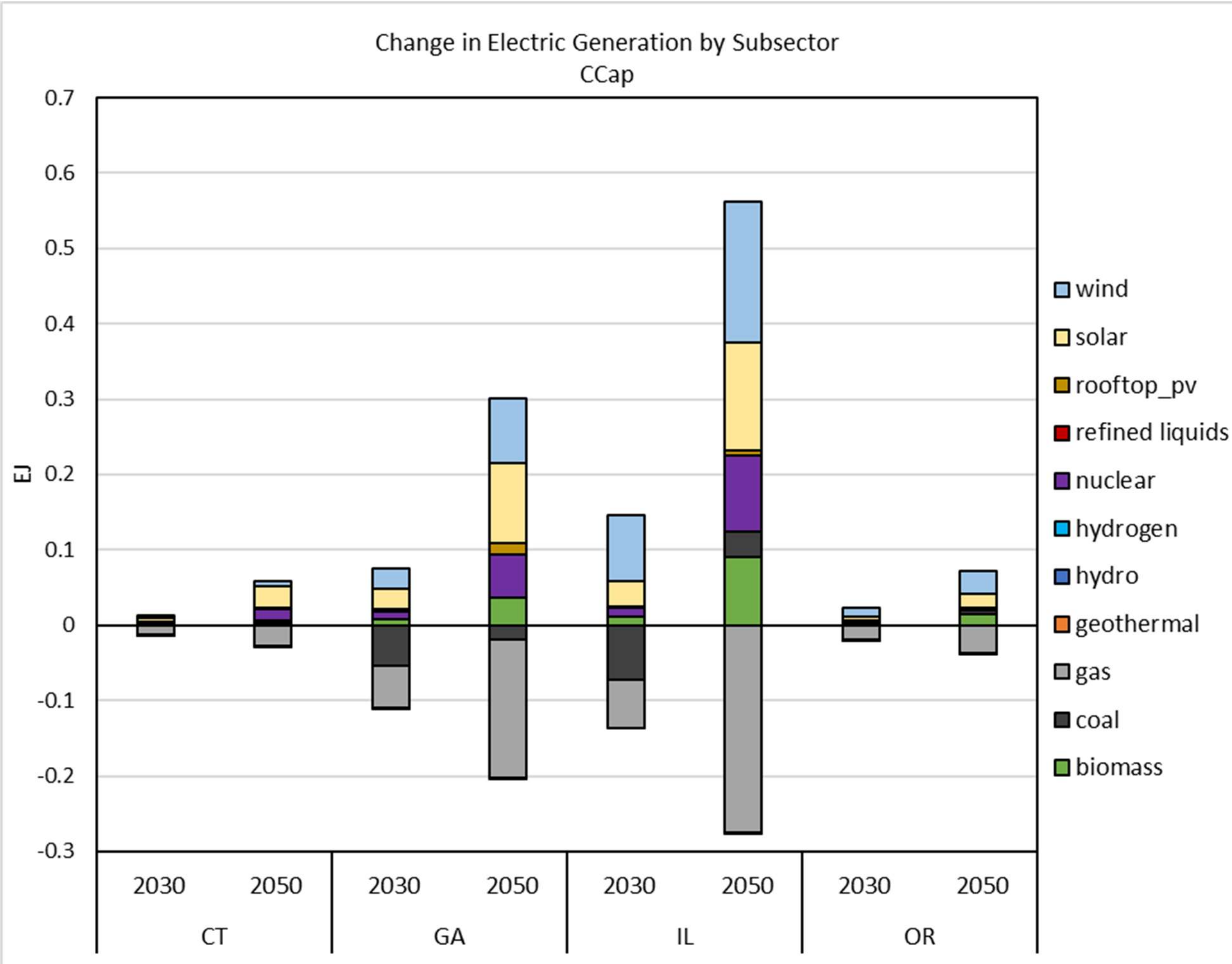

Figure 9b shows the CCap change from Ref in electric sector generation mix by subsector for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

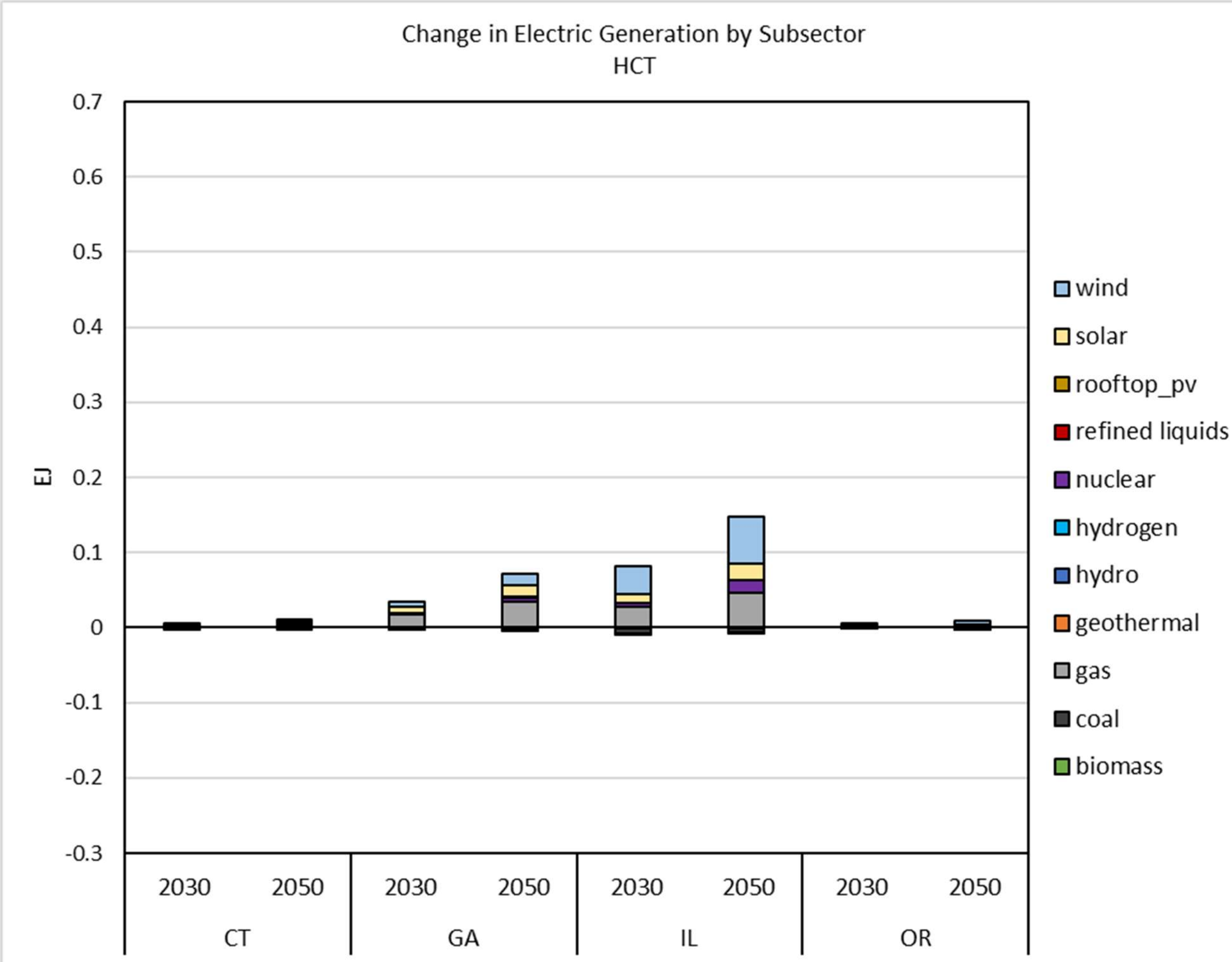

Figure 9c shows the HCT change from Ref in electric sector generation mix by subsector for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

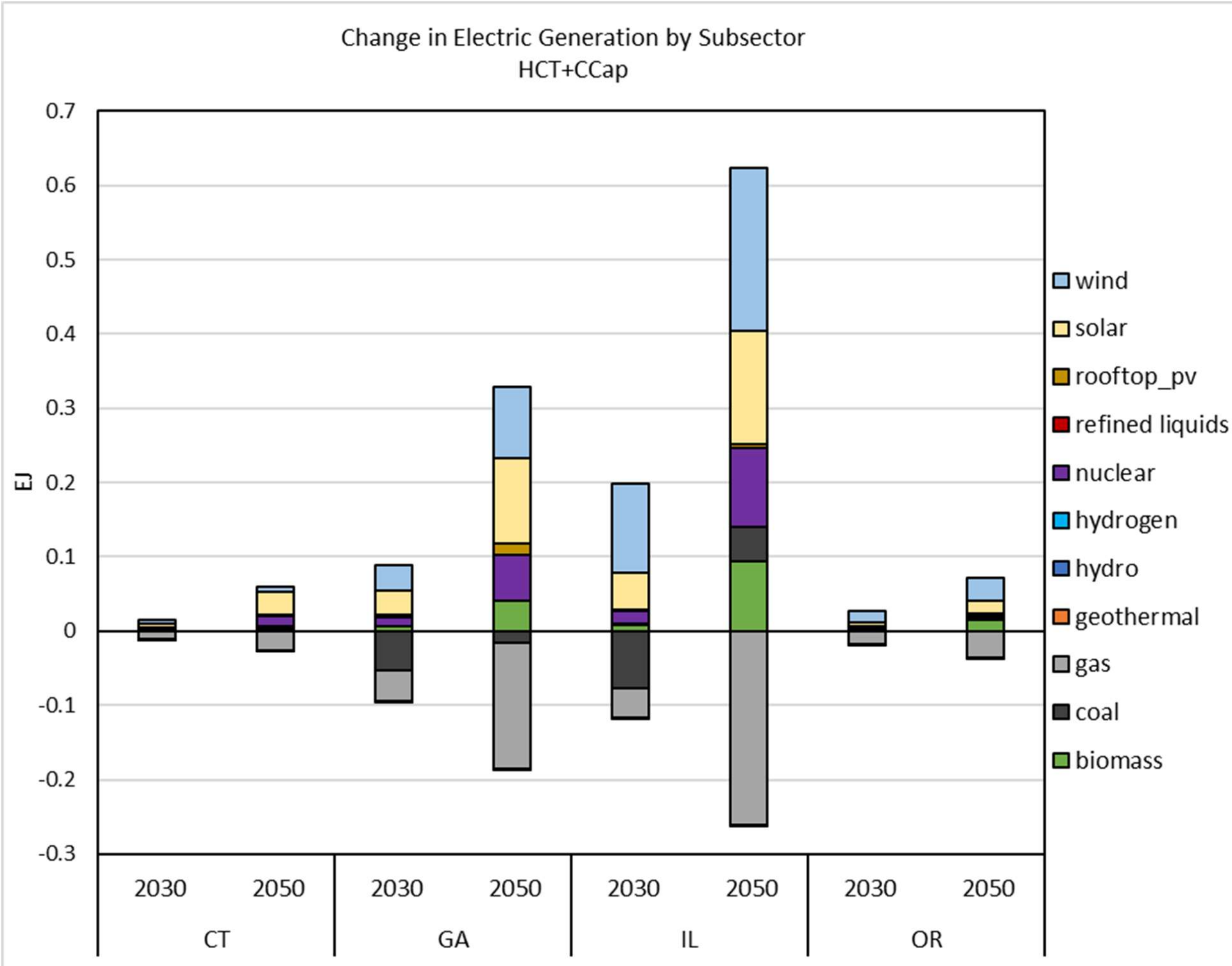

Figure 9d shows the HCT+CCap change from Ref in electric sector generation mix by subsector for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

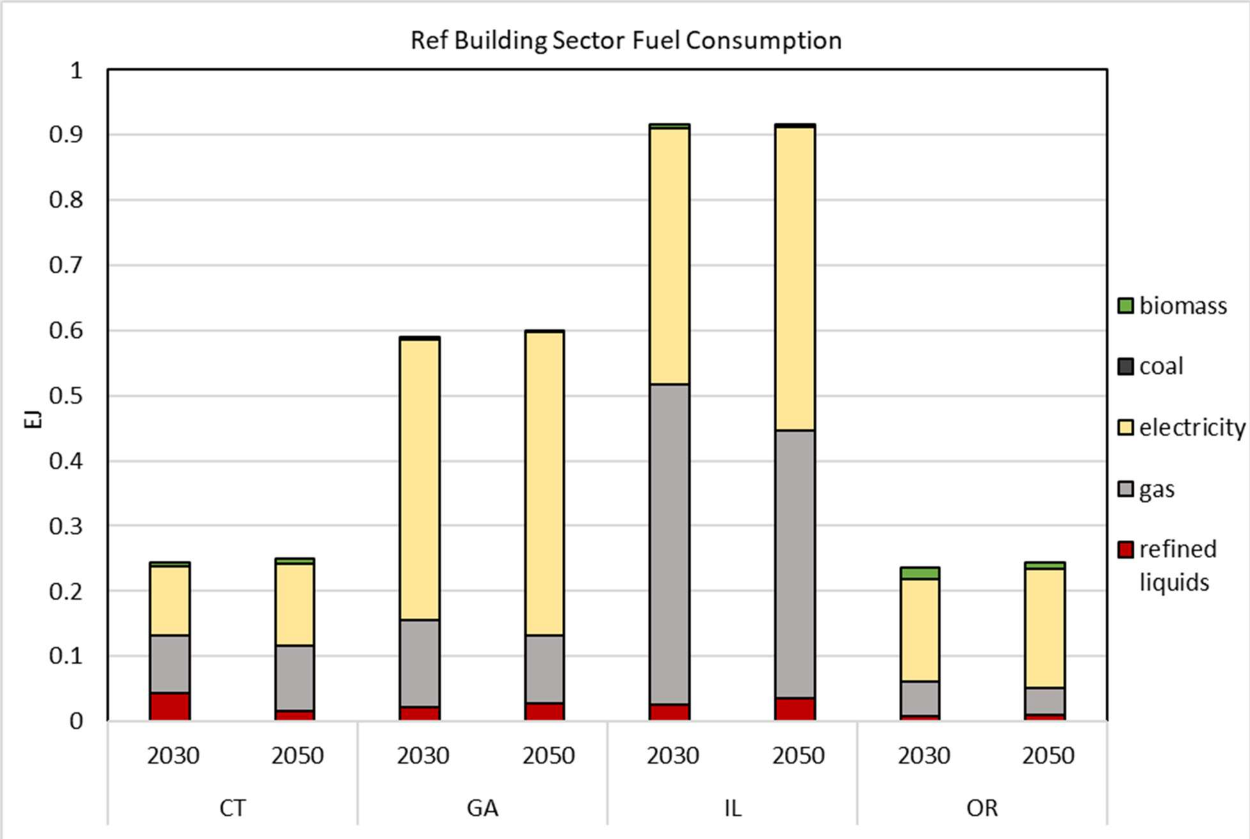

Figure 10a shows the building sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

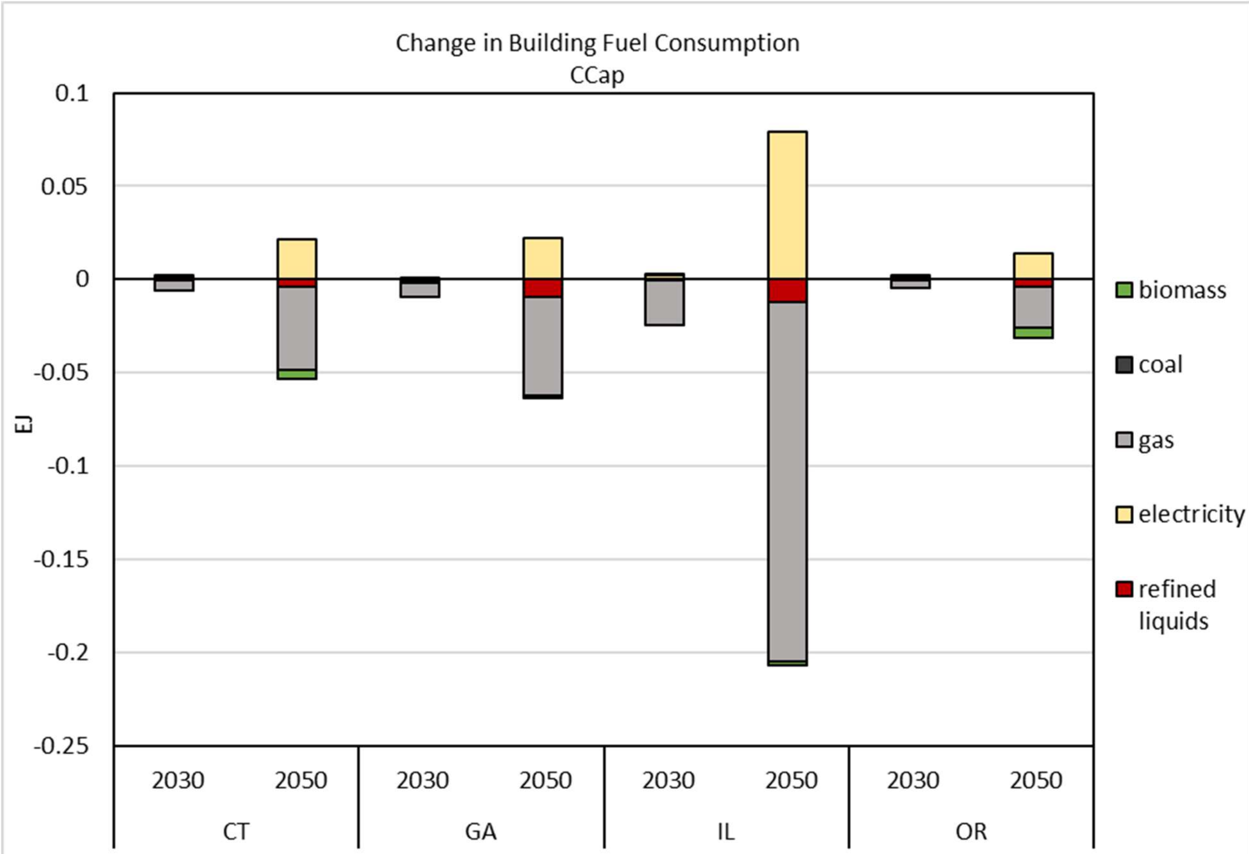

Figure 10b shows the CCap change from Ref in building sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

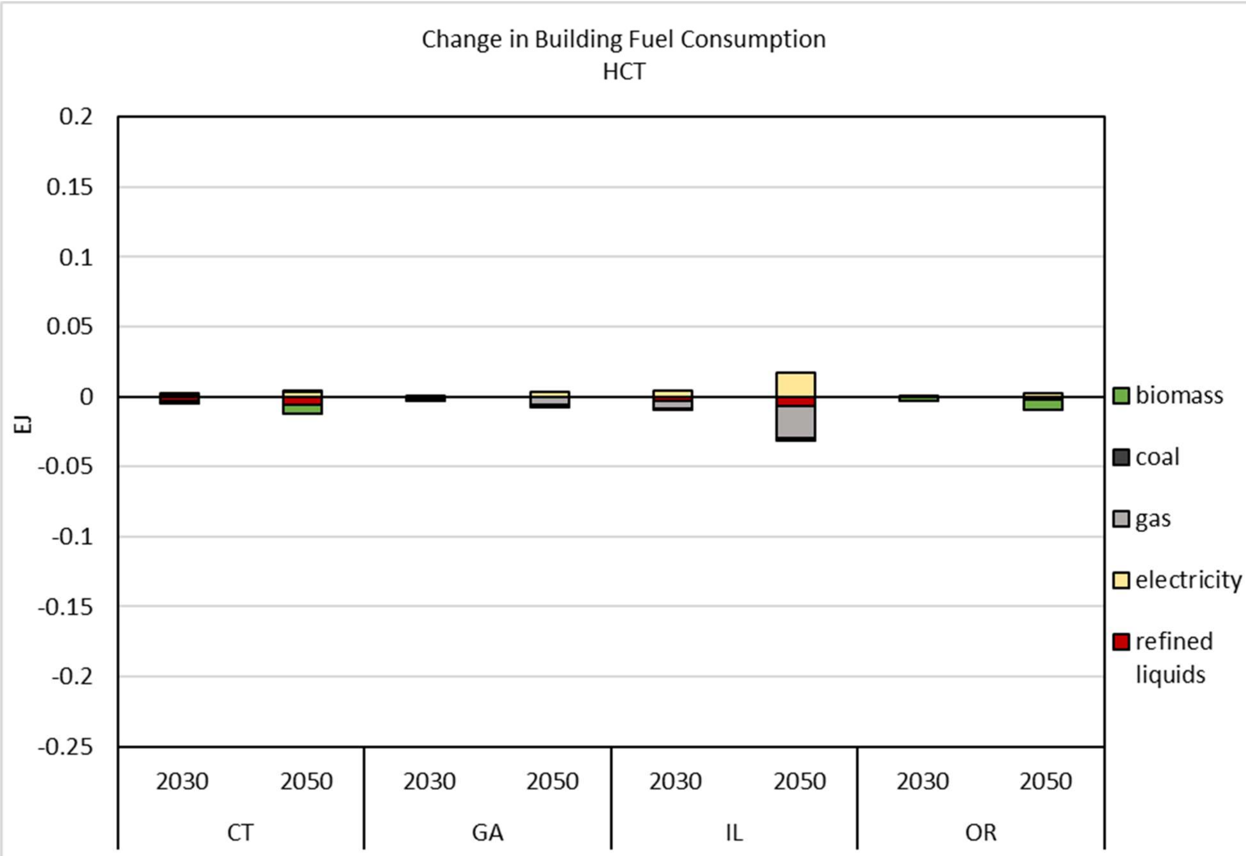

Figure 10c Figure 10b shows the HCT change from Ref in building sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

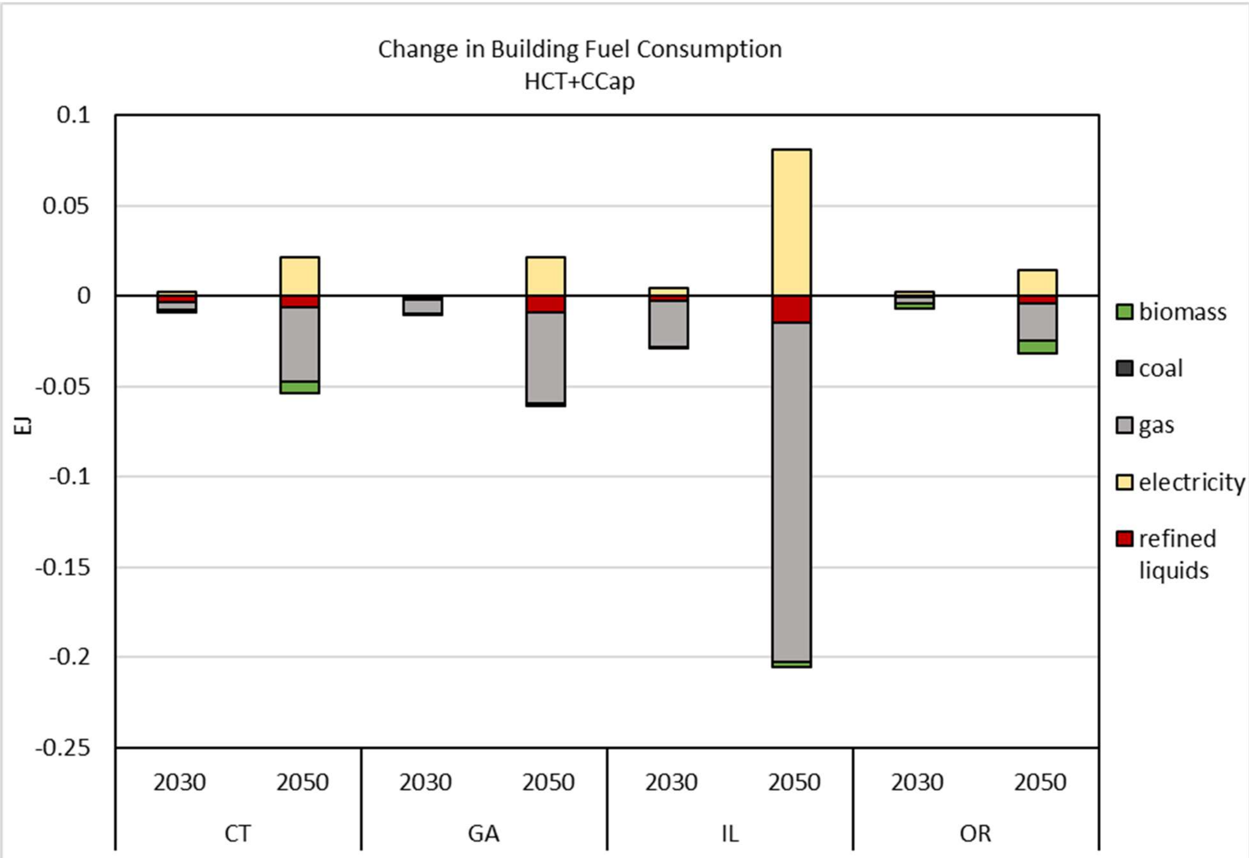

Figure 10d shows the HCT+CCap change from Ref in building sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

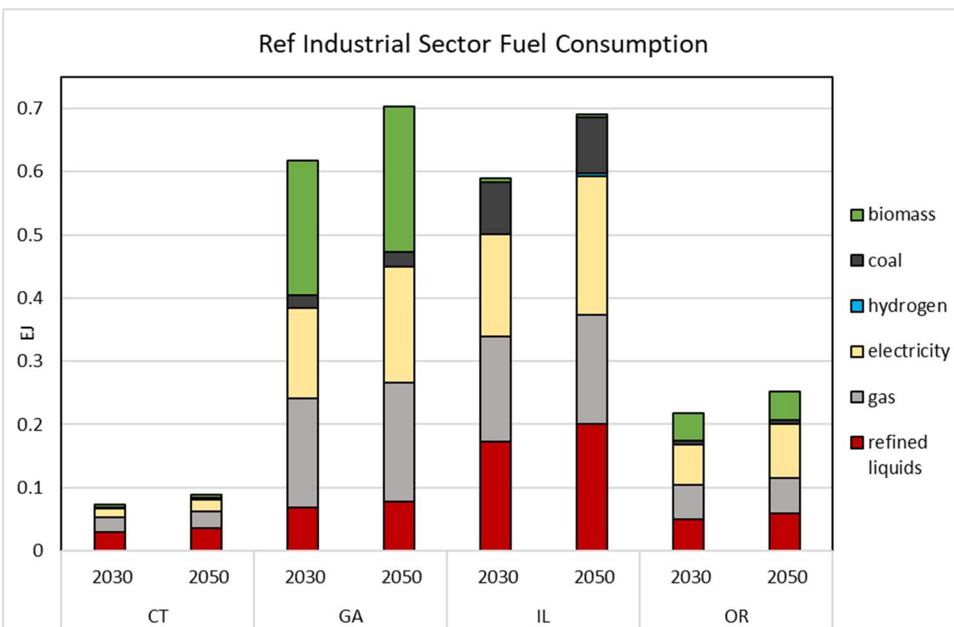

Figure 11a shows Ref industrial fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

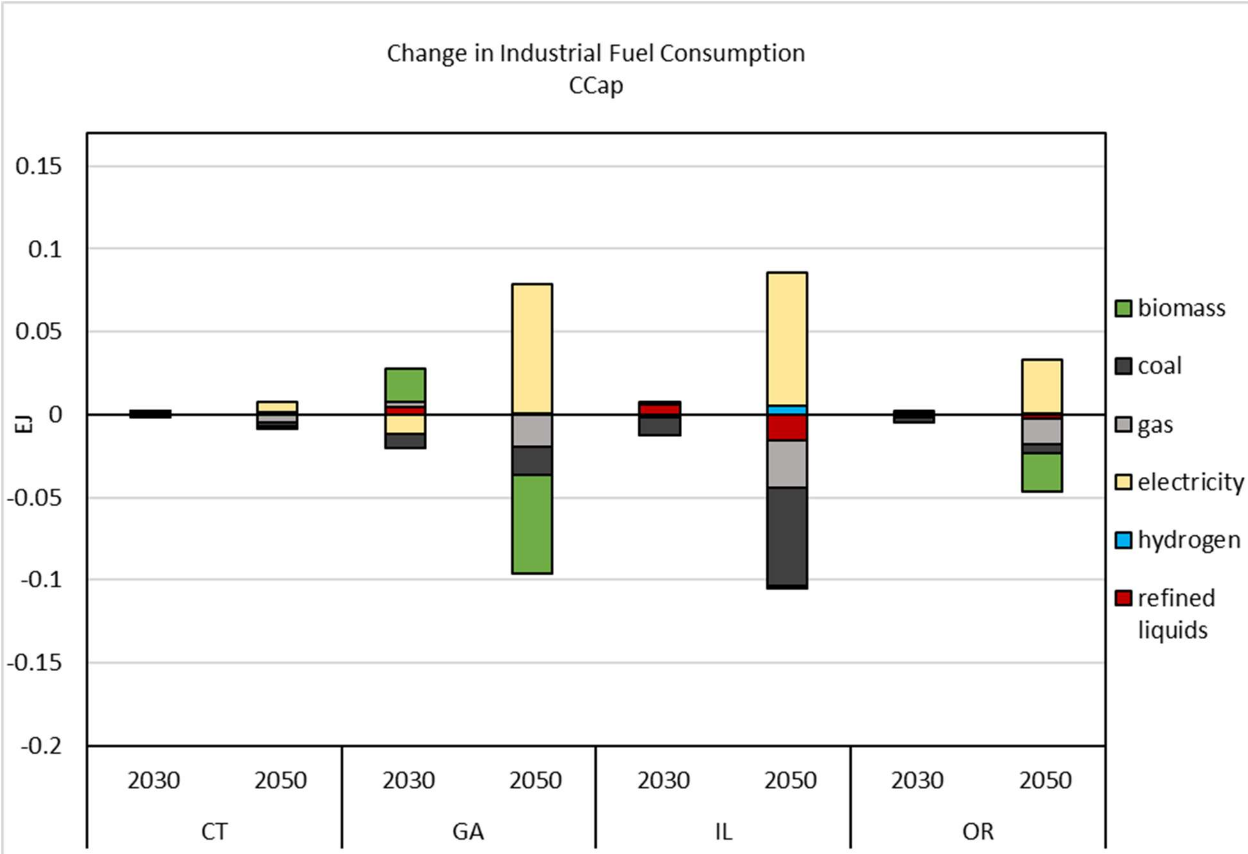

Figure 11b shows the CCap change from Ref in industrial sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

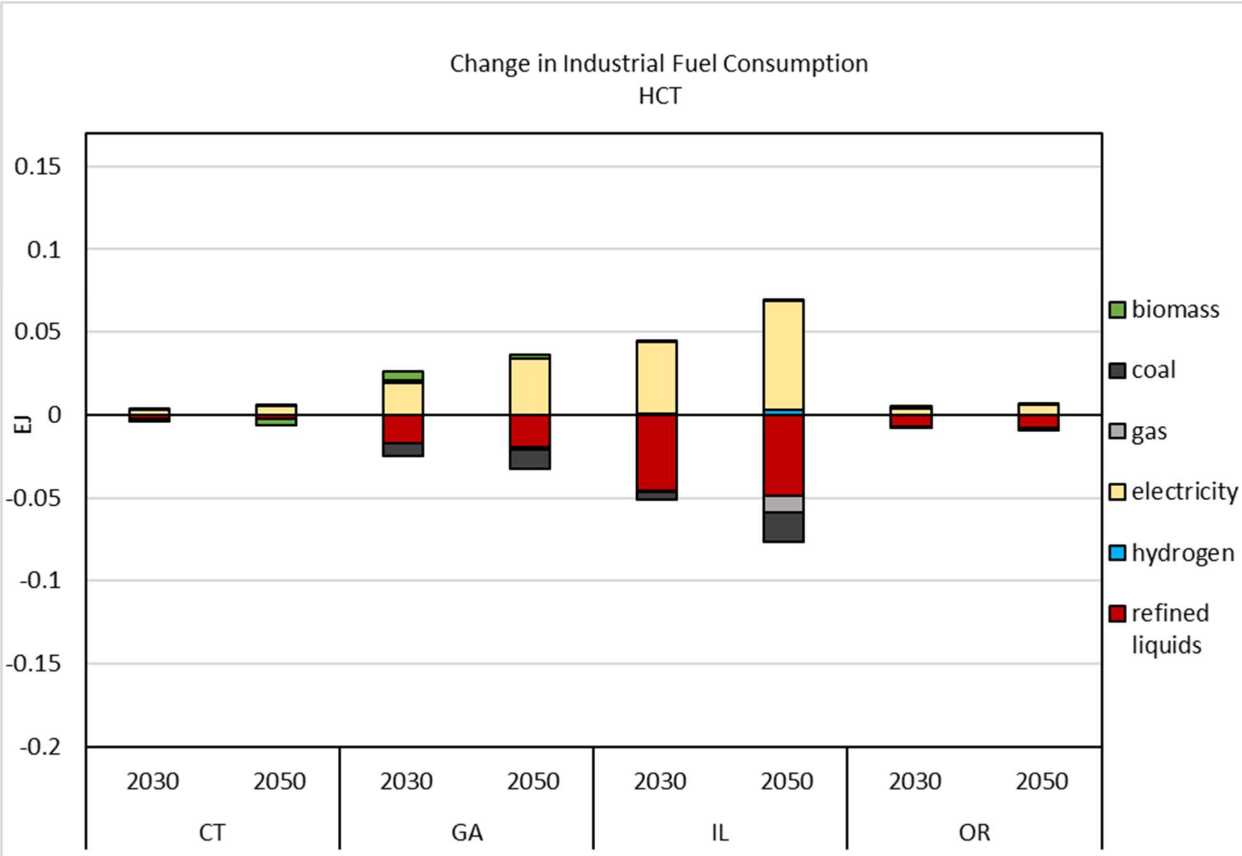

Figure 11c shows the HCT change from Ref in industrial sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

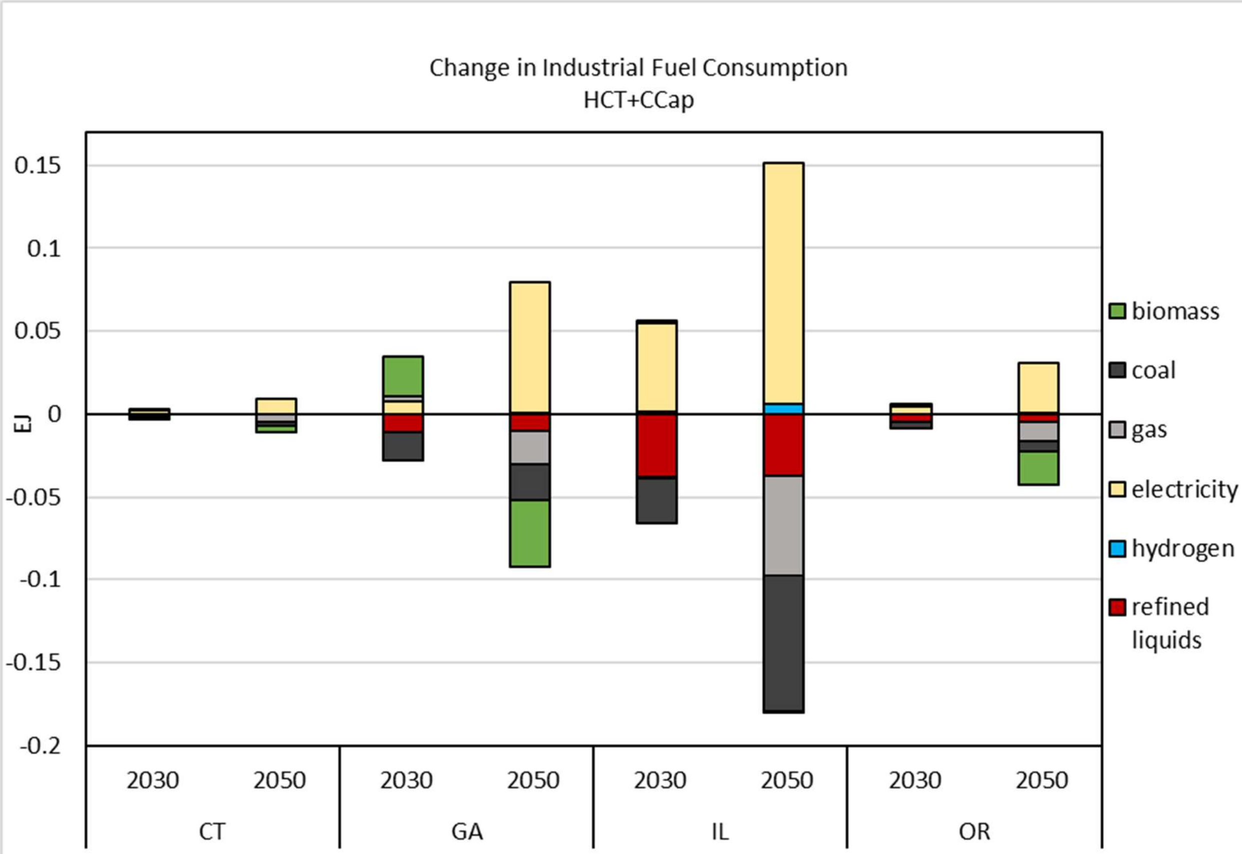

Figure 11d shows the HCT+CCap change from Ref in industrial sector fuel consumption for CT, GA, IL, and OR in 2030 and 2050. Values are in exajoules (EJ).

7. <u>Supplemental Info</u>

8a. Summary of how OAQP Calculated the BPT Values

The BPT values were created following three general steps- first, model air pollutant concentration at the pollutant and sectoral level, use these concentrations to conduct a Health Impact Assessment (HIA), and finally estimate the monetary value of improved health with the reduction of one ton of emission. To model air pollution concentration levels, all three studies use the Comprehensive Air Quality Model (CAMx), which is a photochemical grid model that comprises a 'one-atmosphere' treatment of tropospheric air pollution over various spatial scales (Ramboll US Corporation , 2020). Then the HIA quantifies the changes in adverse health outcomes resulting from changes in air pollution exposure (2021 Support documentation). The HIA is conducted in the Benefits Mapping and Analysis Program (BenMAP), which is an open-source computer program developed the US EPA that uses air quality, demographic, economic, and concentration-response relationship data to streamline the HIA to calculate the number air pollution-related deaths and illnesses (EPA, 2022f). Finally, Once the economic value of these impacts are calculated by dividing the economic metric willing to pay (WTP) by the related observed change in risk, which is calculated using the value of a statistical life, which produces an avoided statistical incident value that can be utilized in a consistent manner across population sizes. Finally, the health and monetized values are then divided by the emissions from the related sector to derive incident-per-ton and dollar-per-ton value for reducing one ton of $PM_{2.5}$ and its precursors (Fann et al., 2009, EPA OAR, 2022).

8b. Scenario Design

Reference Case EPA Policy Parameters

Policy or Parameter	Description
Biomass limitations	Limits the US consumption of bioenergy to the DOE's "2016 Billion Ton Study"
RGGI	CO2 budget trading program between DE, ME, MA, MD, NH, NJ, NY, PA, RH, VT, and VA; NJ is included in this representation
Section 177 Zero-Emission Vehicle Targets	Specifies that a percent of the states share of light-duty vehicle sales must be low-emission or zero-emission vehicles; CA, NY, MA, VT, ME, PA, CT, RH, WA, OR, NJ, MD, DE, CO, MN
Coal Calibration	Reflects witnessed coal plant retirements through 2020 by limiting state-level generation from existing coal plants to 2021 levels
US Northeast Calibration	Requires offshore wind to be equal or greater than the current procurement contracts and planned nuclear plant shutdowns
Transportation Sector Regulations	Includes impacts of new emissions regulations, federal rules and standards from marine and rail sources, and includes lower-bound market share constraints for light-duty vehicles

8c. Summary of HCT Tax Application within GCAM

In the HCT the tax applied is half of the health cost from a particular pollutant, technology, and region; in 2030 and beyond the tax is a dollar-to-dollar match to the health cost. The example below demonstrates how the tax is applied within the model.

Table 5 shows how the HCT is calculated.

State & Technology option	Year	Emission	Emissions (EJ)	Impact Factor (millions of $ per EJ)	Tax amount ($)	Tax Applied to state & technology ($)
Michigan Residential Gas Furnace	2025	PM2.5	.196	120.4678	.5	$11.7 million
Michigan Residential Gas Furnace	2030	PM2.5	.196	130.2355	1	$25 million

California Residential Gas Furnace	2025	PM2.5	.111	1416.63	.5	$78.5 million
California Residential Gas Furnace	2030	PM2.5	.111	1531.492	1	$169.9 million

Even though the tax that is applied is a national level tax, the amount that is calculated is different depending on the state and the technology's impact factors. The difference in damage costs between states, technology, and pollutants is related to differences in emissions activity, populations, and BPT values. Once the tax is calculated GCAM can make the decision to either pay the tax or switch to a different technology type. In this example it might decide to switch to high efficiency gas furnaces or reduce demand. In the example above, since the tax differs between California and Michigan switching technology types might be more cost effective in CA but not in MI, so one might see switching in one state but not in another.

8. Bibliography

Abel, David W. Holloway, Tracey, Harkey, Monica et al., (2018). Potential air quality benefits from increased solar photovoltaic electricity generation in the Eastern United States. *Atmospheric Environment*. 175, 65-74. https://doi.org/10.1016/j.atmosenv.2017.11.049

Abel, David W., Holloway, Tracey, Martinez-Santos, Javier, Harkey, Monica, Tao, Madankui, Kubes, Cassandra, & Hayes, Sara. (2019, March 5). Air quality-related health benefits of energy efficiency in the United States. *Environmental Science & Technology.* 53 (7), 3987-3998. https://doi.org/10.1021/acs.est.8b06417

Arden Pope III, C., Coleman, Nathan, Pond, Zachari A. (2020, April). *Fine particulate air pollution and human mortality: 25+ years of cohort studies.* Environmental Research. 183: 108924. https://doi.org/10.1016/j.envres.2019.108924

Baker, Kirk R., Amend, Meredith, Penn, Stefani, et al., (2020 February). A database for evaluating the InMAP, APEEP, and EASIUR reduced complexity air-quality modeling tools. *Data in Brief.* 28, 104886. https://www.sciencedirect.com/science/article/pii/S2352340919312417

Brown, Kristen, Henze, Daven E., Milford, Jana B. (2013). Accounting for Climate and Air Quality Damages in Future U.S. Electricity Generation Scenarios. *Environmental Science & Technology.* 47, 3065-3072. https://doi.org/10.1021/es304281g

Buchdahl Roth, Michael, Adams, Peter J., Jaramillo, Paulina, et al., (2022). Policy spillovers, technology lock-in, and efficiency gains from regional pollution taxes in the U.S. *Energy and Climate Change.* 3, 100077. https://doi.org/10.1016/j.egycc.2022.100077

Dedoussi, Irene C., Eastham, Sebastian D., Monier, Erwan, Barrett, Steven R.H. (2020, February 12). Preamture mortality related to United States cross-states air pollution. *Nature.* 578, 261-265. https://doi.org/10.1038/s41586-020-1983-8

Dockery, Douglas W., Pope, C. Arden, Xu, Xiping, et al. (1993, December 9). *An Association between Air Pollution and Mortality in Six U.S. Cities.* New England Journal of Medicine. 328: 1753-1759. 10.1056/NEJM199312093292401.

Energy Technology Systems Analysis Program (ESTAP). (2023, June 14). *Overview of TIMES Modelling Tool.* Technology Collaboration Programme. https://iea-etsap.org/index.php/etsap-tools/model-generators/times

Environmental Protection Agency (EPA).(2023a, June 5). *Cost Analysis Models/ Tools for Air Pollution Regulations. https://www.epa.gov/economic-and-cost-analysis-air-pollution-regulations/cost-analysis-modelstools-air-pollution*

Environmental Protection Agency (EPA). (2023b March 1). *Current Nonattainment Counties for All Criteria Pollutants.* Current Nonattainment Counties for All Criteria Pollutants | Green Book | US EPA

Environmental Protection Agency (EPA). (2023c, June 26). *MOVES and Mobile Source Emissions Research. https://www.epa.gov/moves*

Environmental Protection Agency (EPA). (2023d, July 14). *Power Sector Modeling.* Clean Air Markets. https://19january2021snapshot.epa.gov/airmarkets/power-sector-modeling_.html

Environmental Protection Agency (EPA). (2023a, February 16). *Sulfur Dioxide Basics.* Sulfur Dioxide Basics | US EPA

Environmental Protection Agency (EPA). (2022a, March 9). *Progress Cleaning the air and Improving People's Health.* https://www.epa.gov/clean-air-act-overview/progress-cleaning-air-and-improving-peoples-health

Environmental Protection Agency (EPA). (2022b, April 5). *NAAQS Table*. EPA. https://www.epa.gov/criteria-air-pollutants/naaqs-table

Environmental Protection Agency (EPA). (2022c, August 2). *Basic Information about NO2.* Basic Information about NO2 | US EPA

Environmental Protection Agency (EPA). (2022d, August 10). How BenMAP-CE Estimates the Health and Economic Effects of Air Pollution. https://www.epa.gov/benmap/how-benmap-ce-estimates-health-and-economic-effects-air-pollution

Environmental Protection Agency (EPA). (2022e, August 30). *Health and Environmental Effects of Particulate Matter (PM).* Particulate Matter (PM) Pollution. https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm

Environmental Protection Agency (EPA). (2022f, October 4). Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE). https://www.epa.gov/benmap

Environmental Protection Agency (EPA). (2022g, December 21). GLIMPSE- A computational framework for supporting state-level environmental and energy planning. https://www.epa.gov/air-research/glimpse-computational-framework-supporting-state-level-environmental-and-energy

Environmental Protection Agency (EPA). (2022h, December 23). Estimating the Benefit per Ton of Reducing Directly- Emitted PM2.5, PM2.5 Precursors and Ozone Precursors from 21 Sectors. https://www.epa.gov/benmap/estimating-benefit-ton-reducing-directly-emitted-pm25-pm25-precursors-and-ozone-precursors

Environmental Protection Agency (EPA), Office of Air and Radiation (OAR), Office of Air Quality Planning and Standards (OAQPS). (2022, January). *Technical Support Document for Estimating the Benefit per Ton of Reducing Directly-Emitted PM2.5, PM2.5 Precursors and Ozone Precursors from 21 Sectors.*

Fann, Neal, Fulcher Charles M., Hubbell, Bryan J. (2009, June 9). *The influence of location, source, and emission type in estimates of the human health benefits of reducing a ton of air pollution.* Air Quality Atmosphere Health. 2:169-176. 10.1007/s11869-009-0044-0

Fann, Neal, Baker, Kirk R., Fulcher, Charles, M. (2012, November). Characterizing the Pm2.5- related benefits of emission reductions for 17 industrial, area and mobile emission sectors across the U.S. *Environment International.* 49, 141-151. https://doi.org/10.1016/j.envint.2012.08.017

Henschel, Susann, Atkinson, Richard, Zeka, Ariana, Le Tertre, Alain, Analitis, Antonis, Katsouyanni, Klea, Chanel, Olivier, Pascal, Mathilde, Forsberg, Bertil, Medina, Sylvia, & Goodman, Patrick G. (2012, May 17). Air pollution interventions and their impact on public health. *International Journal of Public Health.* 57, 757-768.

Heo, Jinhyok, Adams, Peter J., Gao, Oliver H. (2016, May 6). Public health costs of primary PM2.5 and inorganic PM2.5 precursor emissions in United States. *Environmental Science Technology.* 50 (11), 6061-6070. https://doi.org/10.1021/acs.est.5b06125

Iyer, Gokul, Khan, Zarrar. (n.d.). GCAM-USA: Global Change Analysis Model for the United States. *The Integrated Multisector Multiscale Modeling (IM3) Project, Pacific Northwest National Laboratory.* https://im3.pnnl.gov/model?model=GCAM-USA

Joint Global Change Research Institute (JGCRI). (n.d.a). *GCAM Model Overview.* Documentation for GCAM- The Global Change Analysis Model. http://jgcri.github.io/gcam-doc/overview.html

Joint Global Change Research Institute (JGCRI). (n.d.b). *The Global Change Analysis Model (GCAM) and GCAM-USA.* Documentation for GCAM- The Global Change Analysis Model. http://jgcri.github.io/gcam-doc/v5.4/gcam-usa.html

Kampa, Marilena, Castanas, Elias.(2008, January). Human health effects of air pollution. *Environmental Pollution.* 151 (2), 362-367. https://doi.org/10.1016/j.envpol.2007.06.012

Manisalidis, Ioannis, Stavropoulou, Elisavet, Stavropoulos, Agathangelos, Bezirtzoglou, Eugenia. (2020, February 20). Environmental and Health Impacts of Air Pollution: A Review. *Frontiers in Public Health.*

Mayfield, Erin N. (2022, June). Phasing out coal power plants based on cumulative air pollution impact and equity objectives in net zero energy system transitions. *Environmental Research: Infrastructure and Sustainability.* 2, 021004. Doi: 10.1088/2634-4505/ac70f6

Liao, Kuo-Jen, Hou, Xiangting. (2015, May). Optimization of multipollutant air quality management strategies: A case study for five cities in the United States. *Journal of Air & Waste Management Association.* 65 (6), 732-742. https://doi.org/10.1080/10962247.2015.1014073

Minet, Laura, Chowdhury, Tufayel, Wang, An, Gai, Yijun, Posen, Daniel, Roorda, Matthew, & Hatzopouluo. (2020, April 13). Quantifying the air quality and health benefits of greening freight movements. *Environmental Research.* 183, 109193. https://doi.org/10.1016/j.envres.2020.109193

Nolte, C.G., P.D. Dolwick, N. Fann, L.W. Horowitz, V. Naik, R.W. Pinder, T.L. Spero, D.A. Winner, and L.H. Ziska, 2018: Air Quality. In Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 512–538. doi: 10.7930/NCA4.2018.CH13

Ou, Yang, Shi, Wenjing, Smith, Steve J. et al., (2018, April). Estimating the co-benefits of U.S. low-carbon pathways using an integrated assessment model with state-level resolution. *Applied Energy,* 216, 482-493. https://doi.org/10.1016/j.apenergy.2018.02.122

Ou, Yang. (2019). Application of an integrated assessment model with US state-level resolution to study national and regional air pollution control and human health. (Doctoral Dissertation). University of North Carolina, Chapel Hill.

Impacts of wind power on air quality, premature mortality, and exposure disparities in the United States | Science Advances

Ou, Yang, West, Jason J., Smith, Steve J., et al. (2020). *Air pollution control strategies directly limiting national health damages in the US.* Nature Communications. 11:957. https://doi.org/10.1038/s41467-020-14783-2

Qui, Minghao, Zigler, Corwin M., Selin, Noelle. (2022). *Science Advances.* Impacts of wind power on air quality, premature mortality, and exposure disparities in the United States. 8, 48. DOI: 10.1126/sciadv.abn8762

Qui, Xuezhen, Zhu, Yun, Jang, Cary, Lin, Che-Jen, Wang, Shuxiao, Fu, Joshua, Xie, Junping, Wang, Jiandong, Ding, Dian, & Long, Schicheng. (2015, June 18). Development of an integrated policy making tool for assessing air quality and human health benefits of air pollution control. *Frontiers of Environmental Science & Engineering.* 9, 1056-1065. https://doi.org/10.1007/s11783-015-0796-8

Pacific Northwest National Laboratory. (PNNL) (n.d .). *GCAM v5.4 Documentation*. http://jgcri.github.io/gcam-doc/v5.4/toc.html

Ramboll US Corporation. (2020, December). User's Guide Comprehensive Air Quality Model with Extensions version 7.10. *Ramboll Environment and Health. https://camx-wp.azurewebsites.net/Files/CAMxUsersGuide_v7.10.pdf*

Schraufnagel DE, Balmes JR, De Matteis S, Hoffman B, Kim WJ, Perez-Padilla R, Rice M, Sood A, Vanker A, Wuebbles DJ. (2019, December). Health Benefits of Air Pollution Reduction. *Annals of the American Thoracic Society*. 16 (12), 1478-1487. https://doi.org/10.1513/AnnalsATS.201907-538CME

Silveira, Carlos, Roebeling, Peter, Lopes, Myriam, Ferreira, Joana, Costa, Solange, Teixeira, Joao P., Borrego, Carlos, Miranda, Ana I. (2016, December 1). Assessment of health benefits related to air quality improvement strategies in urban areas: An Impact Pathway Approach. *Journal of Environmental Management.* 183 (3), 694-702. https://doi.org/10.1016/j.jenvman.2016.08.079

Strasert, Brian, Chen The, Su, and Cohan, Daniel S. (2019, January 24). Air quality and health benefits from potential coal power plant closures in Texas. *Journal of the Air & Wastte Management Association.* 69 (3), 333-350. Download citation https://doi.org/10.1080/10962247.2018.1537984

Thakrar, Sumil K., Balasubramanian, Srinidhi, Adams, Peter J., Azevedo, Ines M. L., Muller, Nicholas Z., Pandis, Spyros N., Polasky, Stephen, Arden Pope III, C., Robinson, Allen L., Apte, Joshua S., Tessum, Christopher W., Marshall, Julian D., Hill, Jason D. (2020, July 15). Reducing Mortality from Air Pollution in United States by Targeting Specific Emission Sources*. Environmental Science Technology Letters.* 7 (9), 639-645. https://doi.org/10.1021/acs.estlett.0c00424

U.S. Department of Health and Human Services, Office of Disease Prevention and Health Promotion. (n.d.). *Reduce the number of days people are exposed to unhealthy air- EH-01.* Health People 2030. https://health.gov/healthypeople/objectives-and-data/browse-objectives/environmental-health/reduce-number-days-people-are-exposed-unhealthy-air-eh-01

US Department of Labor. (2022). *CPI for All Urban Consumers*. U.S. Bureau of Labor Statistics. https://data.bls.gov/timeseries/CUUR0000SA0L1E?output_view=pct_12mths

Wolfe, Philip, Davidson, Kenneth, Davidson, Fulcher, Charles, Fann, Neal, Zawacki, Margaret, Zawacki, Baker, Kirk R. (2019, February 10). Monetized health benefits attributable to mobile source emission reductions across the United States in 2015. 640 (2), 2490-2498. https://doi.org/10.1016/j.scitotenv.2018.09.273