Applied Energy 367 (2024) 123376

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Exploring equality and sustainability trade-offs of energy transition outcomes in the United States in 2050

Teagan Goforth [a,*], Destenie Nock [a,b,*], Maxwell Brown [c,d], Tapajyoti Ghosh [d], Patrick Lamers [d]

[a] Department of Engineering & Public Policy, Carnegie Mellon University, Pittsburgh, PA, United States of America
[b] Department of Civil & Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA, United States of America
[c] Department of Economics & Business, Colorado School of Mines, Golden, CO, United States of America
[d] National Renewable Energy Laboratory, Golden, CO, United States of America

HIGHLIGHTS

- Trade-off analysis across sustainability criteria for decarbonization outcomes.
- Include distributional equality as social sustainability criteria.
- Multi-criteria decision analysis across eleven stakeholder preference scenarios.
- Indefinite tax credit extensions score highest in sustainability.

ARTICLE INFO

Keywords:
Multi-criteria decision analysis
Distributional impacts
Sustainability
Energy transition

ABSTRACT

With increasing focus on equitable and just energy transition, it is critical to understand the trade-offs of different decarbonization outcomes across economic, environmental, and social sustainability criteria. In this analysis, we use a multi-criteria decision analysis to quantify sustainability outcomes across 32 decarbonization outcomes in 2050 in the U.S. The economic sustainability criteria we use are system cost, national average retail rate, and electricity system employment. The environmental sustainability criteria we use are life cycle greenhouse gas emissions, life cycle water depletion, life cycle land transformation, and air pollution fatalities. The social sustainability (distributional impacts) criteria we use are retail rate equality across states, electricity employment equality across low-income households, and air pollution disparities across census tracts. We evaluate performance across these criteria under eleven different stakeholder preference scenarios. We find that decarbonization policies with indefinitely extended tax credits have the highest sustainability score under equal criteria weighting, with greater investments in renewable energy technologies, and result in better environmental, system cost, job, and air pollution disparities compared to mid-case scenarios, that only include current policies and CO_2 reduction targets. We also see that our multi-criteria decision analysis identifies decarbonization outcomes that would not have been identified as optimal under a single objective, which highlights the importance of trade-off analyses to understand decarbonization outcomes more holistically.

1. Introduction

As countries commit to decarbonization targets, goals to achieve environmental and energy justice are also increasingly common. In November 2021 and August 2022 respectively, the U.S. Congress passed the Bipartisan Infrastructure Law and the Inflation Reduction Act (IRA), both of which provide tax credits and incentives for the energy transition [1–3]. Further, the Biden Administration introduced the Justice40 initiative in 2021, which states that 40% of the benefits of federal investments are allocated to result in an equitable distribution of benefits across communities [4]. Along with these policies, investments in clean electricity generation are critical precursors to an economy-wide decarbonization [5,6]. Given these new policies and focus on equitable distribution of benefits, understanding who bears the costs and benefits across different electricity system investments and policies is crucial as well as capturing overall sustainability performance of

* Corresponding authors at: Department of Engineering & Public Policy, Carnegie Mellon University, Pittsburgh, PA, United States of America.
E-mail addresses: tgoforth@andrew.cmu.edu (T. Goforth), dnock@andrew.cmu.edu (D. Nock).

https://doi.org/10.1016/j.apenergy.2024.123376
Received 7 March 2024; Accepted 1 May 2024
Available online 10 May 2024

decarbonization pathways [7].

The three key tenets of sustainability are economic, environmental, and social [8]. Within energy system modeling, an economic and technical focus is the prevailing paradigm, with least cost optimization models dominating energy system analysis [9]. Most electricity capacity expansion models minimize the combined cost of power system investment and operations [9], while environmental and social sustainability metrics are often a secondary, post-processed measurement or constraints in these models [10,11]. One reason for the focus on least cost minimization is that it is difficult to endogenously capture multiple non-linear metrics within an optimization framework. However, an energy transition has many different trade-offs in decision-making, planning, and operation that may conflict with each other. For example, and all else equal, imposing an additional emissions constraint of co-pollutants (e.g., sulfur dioxide (SO_2) or nitrous oxides (NO_x)) could decrease the amount of pollution in the system, while increasing electricity system costs in some parts of the country due to building new, lower emission capacity to meet emissions policies or renewable portfolio standards. As represented in this example, traditional energy system modeling with an economic perspective may not represent socially or environmentally preferred outcomes [12], so post-processing methods can help capture these aspects. Therefore, knowing how these models perform across multiple other sustainability tenets (social and environmental) is valuable to holistically inform energy system planning.

Trade-off analyses in the literature commonly include environmental (e.g., greenhouse gases or land use) and economic (system cost or levelized cost of energy) considerations [13–17]. The social sustainability, like power plant fatalities, employment, or social acceptance, of energy transitions are sometimes included through multi-criteria decision analyses (MCDA) [18–20] and investigation of stakeholder preferences [16,21–23]. Within energy system analyses, MCDA techniques are useful to quantify the trade-offs of different energy transition outcomes and technology choices. Klein and Whalley [18] use an MCDA to quantify the sustainability of energy technologies and include technical, economic, environmental, and social sustainability criteria within the U.S. Their analysis looks at individual technologies and does not include different potential energy transition pathways. Nock and Baker [19] look at specific grid mixes in the Northeast U.S. by using an MCDA to investigate the sustainability, but only at the system level (no regional impacts). Outside of the U.S., Choi et al. [21] quantify the sustainability of policy outcomes in Korea and Volkart et al. [16] use MCDA to evaluate energy transition pathways across environmental, economic, social, and security criteria in Switzerland. While these papers have begun to address the multi-faceted sustainability outcomes of energy systems through MCDA techniques, these papers do not include the distributional impacts (e.g., distribution of air pollution or employment opportunities across regions or demographics) in their MCDA of the energy system.

During the energy transition, there is a risk of exacerbating inequalities, like unequal burden of air pollution or loss of electricity system jobs [24]. It is important to investigate the distributional impacts of energy transitions across air pollution, employment, and costs to understand how people, the economy, and the environment may be impacted by the energy system. Here we highlight seven key studies that have investigated the distributional impacts of energy transitions. Sasse and Trutnevyte [25] assess a suite of near-least-cost optimal decarbonization outcomes and their associated trade-offs across costs, distributional impacts, and regional inequalities across Central Europe through a Modeling to Generate Alternatives approach. They find that there is a trade-off between system cost and evenly distributed impacts of these costs, but do not capture demographic or community level impacts of their outcomes. Goforth and Nock [26] show that decarbonization outcomes under least-cost objective, inequalities in air pollution across race and income groups may continue over the energy transition, but reach equality in scenarios with renewable energy mandates and aggressive carbon caps. They do not quantify distributional impacts beyond air pollution and include a small subset (eight scenarios) of potential decarbonization outcomes. Sasse and Trutnevyte [27] quantify the distribution of risks and benefits from potential decarbonization outcomes across regions in Europe. They find that the benefits of decarbonization revolve around employment and emissions decreases, but these benefits may not be distributed equally across Europe, with benefits concentrated in wealthy regions. However, this analysis did not investigate different policy implementation that may impact distributional benefits or risks from the energy transition.

Other studies investigate the distributional impacts on the energy expenditures and household level income impacts from U.S. energy policies. Bistline et al. [28] investigate the distributional impacts of net-zero carbon policies on household energy expenditures. Their study estimates that the costs of net-zero policies in the US results in higher energy expenditures for low-income households compared to other income groups. They do not evaluate regional impacts or distributional impacts beyond energy expenditures. Brown et al. [29] look beyond just energy expenditures and examine the Inflation Reduction Act‘s bulk power clean electricity generation incentives compared to cap-and-trade policies with equivalent emission reductions across a range of policy options, including the health costs of air pollution and household income across demographic groups [29]. While this paper addresses income distributional impacts across different policy outcomes in the energy system, it is limited to only six different scenarios. García-Muros et al. [30] investigate the distributional impacts of carbon pricing schemes in the U.S. using household microdata as well as the trade-offs between equity and efficiency of revenue schemes. They do not evaluate impacts beyond revenue recycling schemes. While these studies begin to address the distributional impacts of energy transitions, there is a gap in assessing how distributional impacts trade-off with other sustainability criteria across decarbonization pathways.

Here, we build on this literature by evaluating the distributional equality of decarbonization efforts along with other important sustainability metrics, i.e., costs and environmental impacts. We quantify how different decarbonization pathways may trade-off across different energy transition goals. To assess this, we tie a U.S.-wide capacity expansion planning model to an MCDA. Using MCDA, we assess the cost, environmental, and social sustainability trade-offs across 32 possible electricity pathways. When evaluating social sustainability, we focus on the distributional equality of health and economic impacts across different regions and demographic groups (e.g., distribution of air pollution or retail electricity rates). The economic sustainability focuses are system costs, retail rates, and jobs, and the environmental sustainability focuses are life cycle greenhouse gases, life cycle water depletion, life cycle land change, and premature deaths from air pollution.

2. Methods

The overview of this analysis is presented in Fig. 1. Initially, 32 decarbonization pathways are evaluated across technology costs and availability, decarbonization goals, and policies. The outputs (e.g., generation, capacity, system costs, emissions) are used to evaluate economic, environmental, and social sustainability criteria, as shown in Table 1. The values for each criterion are obtained either from direct outputs of a capacity expansion model or connecting ReEDS outputs to post-processing models. These metrics are then input into an MCDA to evaluate the overall sustainability score of a pathway. We focus on the long-term outcomes of decarbonization by focusing on impacts in 2050.

2.1. Electricity planning model and decarbonization scenarios

The electricity capacity expansion model used in this analysis is the Regional Energy Deployment System (ReEDS) model from the National Renewable Energy Laboratory (NREL) [31]. ReEDS is a least-cost optimization capacity expansion model that simulates the bulk power

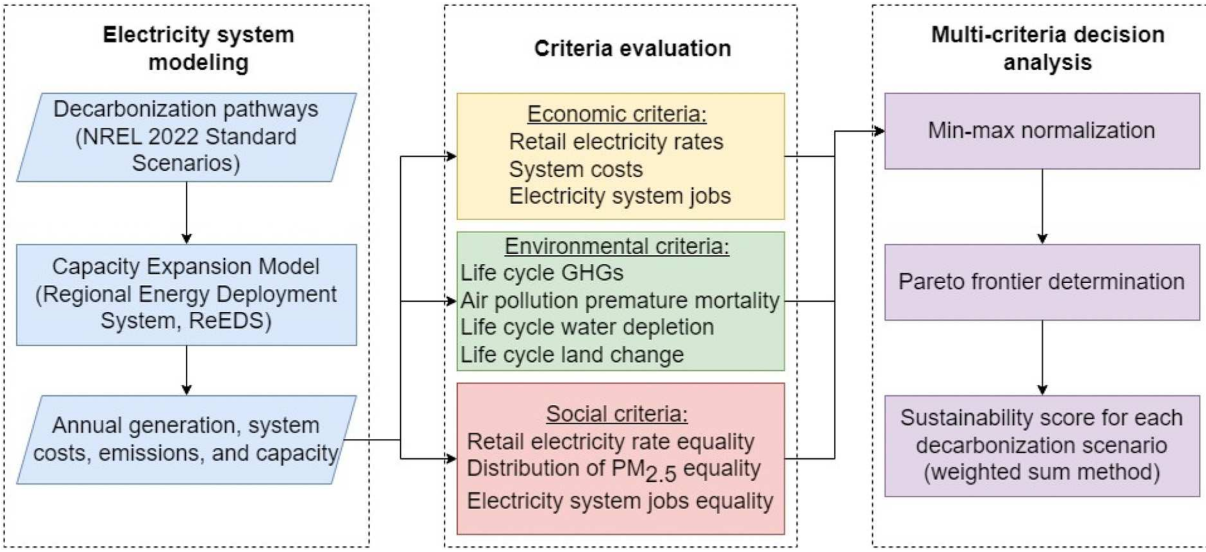


Fig. 1. Overview of trade-off analysis methods.

Table 1
List of criteria used across three different tenets of sustainability.

Tenet	Criteria	Units
Economic	System cost	Billion 2020$
	Retail electricity rates	Cents (₵)/kWh
	Electricity system jobs	Full-Time Equivalent
Environmental	Life cycle greenhouse gas emissions (carbon dioxide equivalent – CO_2e)	Kilogram of CO_2-equivalent (kg CO_2e)/kWh
	Premature fatalities from co-pollutants	Fatalities
	Life cycle land change	Square meters (m^2)/kWh
	Life cycle water depletion	Cubic meters (m^3)/kWh
Social (distributional equality)	Air pollution disparity	Difference in μg/m^3 $PM_{2.5}$ concentration
	Regional equality of retail rate	Unitless
	Regional equality of electricity job access across low-income households	Unitless

system from 2010 to 2050. The version of ReEDS (v2022) used in this analysis is publicly available and the model is open-sourced [10]. We use capacity, generation, system costs, and emission output from ReEDS to estimate the different sustainability impacts.

This analysis uses results from 32 decarbonization scenarios defined and published by NREL as the '2022 Standard Scenarios' [32] to quantify the trade-offs across potential electricity system outcomes. We include seven different input sensitivities that capture different technology and policy impacts across five carbon cap and technology set scenarios, displayed in Fig. 2. We assume moderate projections of technology costs from the 2022 Annual Technology Baseline, reference fuel prices from the Annual Energy Outlook 2022 [33], either ReEDS default resource availability or limited siting supply curves for wind and solar photovoltaics (*Reduced RE Resource* scenarios), moderate Electrification Demand Growth load growth from the Electrification Futures Study [34], and inclusion of the Inflation Reduction Act (IRA) and all other existing policies as of September 2022 [32]. While most of the scenarios include IRA policies (30), we include two 'No IRA' scenarios for comparison to pathways with the IRA.

The carbon cap scenarios we include are: no carbon cap (no additional policies), 95% CO2 reduction by 2050, or 100% CO2 reduction by 2035. The carbon cap scenarios either include an expansive set of technologies (nascent technologies included) or a conservative technology set (no nascent technologies). Nascent technologies are defined as emerging technologies such as enhanced geothermal systems, floating offshore wind, coal with carbon capture and sequestration (CCS), natural gas combined cycle with CCS, biopower with CCS, nuclear small modular reactors, and renewable energy combustion generators [32]. Note that the term 'nascent' does not imply anything to a technology's cost-competitiveness or performance, only that they have not been demonstrated in equivalent deployment levels relative to other technologies. These carbon cap scenarios and technology sets are defined by

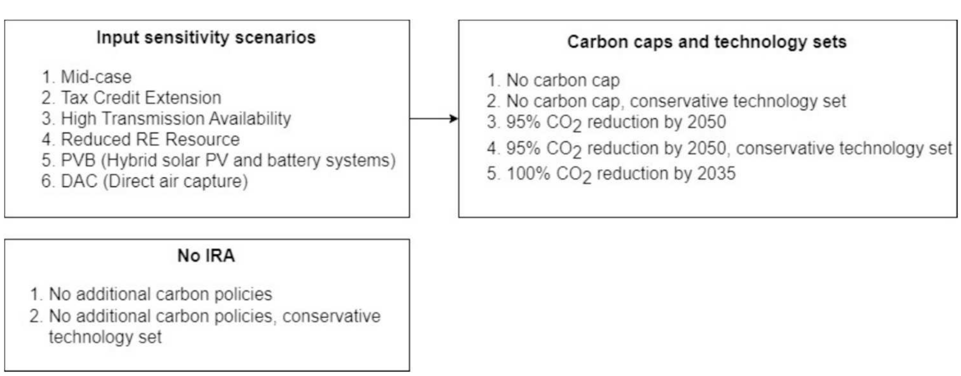


Fig. 2. There are six input sensitivities across technology availability and policies. Each input sensitivity is iterated over five different carbon cap and available technology set options. We also include two No IRA scenarios with no additional carbon policies and a conservative or expansive technology set.

NREL's 2022 Standard Scenarios report.

2.2. Sustainability model

We use a weighted sum MCDA to quantify a decarbonization pathway's sustainability score. MCDA is a decision analysis tool that we use to calculate 1) the trade-offs between different decarbonization pathways and 2) how the distribution of benefits changes for at-risk groups under different decarbonization pathways. The impact of each pathway is driven by stakeholder preferences that inform the weights used in the weighted sum method. To illustrate this, we use eleven representative preference scenarios.

Eq. 1 outlines the weighting for the sustainability score, where S is the total 'score' of a given pathway by summing the normalized criteria value multiplied by the criteria weight for a given preference scenario (see Eq. 1). A higher score means that a scenario performs better based on our applied criteria and weights. The weights (w_n) represent different preferences across criteria values ($c_{n,t}$) within a given year (t). The weights range from zero to one, and always sum to one across all criteria. For this investigation, we vary weights across different criteria to perform a sensitivity analysis to illustrate the different preferences that may result from a stakeholder engagement activity. The weights vary under our 11 illustrative preference scenarios (i.e., if a stakeholder has a particular interest in economic or climate change outcomes, they will place different weights on greenhouse gas emissions).

$$S = \sum_n w_n c_{n,t}$$

Equation 1. Sustainability score calculation. The weights (w_n) of each criterion (c_n) are multiplied by their associated normalized metric value and then summed to produce a total score for each scenario within a given year (t).

To sum across different units of measure, we normalize the criteria between zero and one, using a min-max normalization to calculate the total, unitless sustainability score. The performance of each criterion is ranked across pathways from the 'best' to 'worst' relative outcome. Then, the outcomes from each criterion are normalized between zero and one, with zero being the worst ranked pathway, and one being the best ranked pathway within a given metric. The normalization (N) is outlined in Eq. 2, where P_s is the current pathway's metric outcome and P_w (P_b) is the worst (best) pathway within a given criterion. Across all criteria, except for jobs, the minimum value is the best relative outcome (i.e., lower system costs or lower greenhouse gases are positive outcomes). For the job criteria, a maximum value is the best relative outcome (i.e., higher number of jobs is a positive outcome). We use this normalization to unitless scores (from 0 to 1) for each criterion since some criteria are unable to be converted into dollar values.

$$N = \left|\frac{P_s - P_w}{P_b - P_w}\right|$$

Equation 2. Min-max normalization calculation that returns a value between 0 and 1 for a given sub-criteria and scenario (P_s) based on its proximity to the best performing scenario within the given metric (P_b, 1) and worst performing scenario within the given metric (P_w, 0).

Once the metrics are normalized, the Pareto frontier, which is the set of outcomes with equal or better outcomes, is determined (the non-dominated set). The non-dominated decarbonization scenarios are then scored by applying the weighted sum method.

To capture a suite of potential decision maker preferences, we created 11 different weighting makeups, described in Table 2. The prioritized criteria of each preference scenario are bolded. We use methods similar to [18,19] to determine the weights of preferred and other criteria weights, which assigns a weight of 0.90 distributed equally across the prioritized criteria and a weight of 0.10 distributed equally across the unprioritized criteria. For example, in the economic preference scenario, the three economic criteria (prioritized) are assigned a weight of 0.3 each, and the remaining seven criteria (unprioritized) are assigned a weight of 0.014.

2.3. Sustainability criteria

2.3.1. Economic criteria

The economic criteria included in this analysis are system costs, national retail electricity rates, and electricity system employment. Annualized system costs are output from ReEDS. ReEDS solves for total system costs using a 20-year present value factor of operations, the costs are then annualized by determining the payments made for investments and operating costs for facilities (e.g. variable operating and maintenance, fixed operating and maintenance, and fuel costs).

Retail electricity rates are determined through a post-processing module that estimates retail electricity rates given outputs from ReEDS across regions [35]. The retail electricity rates consider system cost outputs from ReEDS, historical data, and retail rate structure under an investor-owned utility (IOU) [35]. The retail rate ($C_{R,state}$) [in ₵/kWh] is determined by the annual revenue target for a state IOU (R_{state}) divided by the annual retail electricity demand at the state level (D_{state}), as shown in Eq. 3. The IOU revenue target is determined by the return to capital from the rate base (value of property used to provide services), operating expenses, and income taxes [35]. This model and its associated limitations are outlined more in detail in Brown et al. [35].

$$C_{R,state} = R_{state}/D_{state}$$

Equation 3. Retail rate estimations at the state level ($C_{R,state}$) are determined by dividing the revenue at the state IOU level (R_{state}) by the annual retail demand (D_{state}). The national level rates are determined by summing

Table 2
Different stakeholder preference weightings across criteria. The preferred criteria for each stakeholder preference scenario are bolded in each row.

	Economic			Environmental				Social (distributional equality)		
Weighting preference scenario	System cost	Retail rate	Jobs	Greenhouse gases	Fatalities from co-pollutants	Life cycle water use	Life cycle land use	Air pollution equality	Retail rate equality	Jobs equality
Equal	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100
Economic	**0.300**	**0.300**	**0.300**	0.014	0.014	0.014	0.014	0.014	0.014	0.014
Environmental	0.017	0.017	0.017	**0.225**	**0.225**	**0.225**	**0.225**	0.017	0.017	0.017
Social	0.014	0.014	0.014	0.014	0.014	0.014	0.014	**0.300**	**0.300**	**0.300**
Climate change	0.010	0.010	0.010	**0.900**	0.010	0.010	0.010	0.010	0.010	0.010
Jobs and jobs equality	0.010	0.010	**0.450**	0.010	0.010	0.010	0.010	0.010	0.010	**0.450**
Air pollution	0.013	0.013	0.013	0.013	**0.450**	0.013	0.013	**0.450**	0.013	0.013
Jobs-system cost	**0.450**	0.013	**0.450**	0.013	0.013	0.013	0.013	0.013	0.013	0.013
Climate-system cost	**0.450**	0.013	0.013	**0.450**	0.013	0.013	0.013	0.013	0.013	0.013
Social-economic	**0.150**	**0.150**	**0.150**	0.025	0.025	0.025	0.025	**0.150**	**0.150**	**0.150**
Environment-social	0.033	0.033	0.033	**0.129**	**0.129**	**0.129**	**0.129**	**0.129**	**0.129**	**0.129**

both the revenue and demand to the national level before calculating the quotient (based on Brown et al. [35]).

Jobs (in full-time equivalent (FTE)) from the electricity sector are estimated using employment factors from Mayfield et al. [36] by using technology generation and capacity (new, retired, and total) values across technologies. Mayfield et al. [36] developed a regression analysis to estimate employment factors using historical employment and energy activity data. The electricity jobs included span across production of fuels (coal and natural gas), manufacturing for renewable energy (solar and wind), construction, and operation of power plants.

Eq. 4 displays a generalized equation for estimating FTE for each technology and activity ($E_{i,a}$) by multiplying technology attributes (e.g., capacity, new capacity, generation, and retirements) ($A_{i,a}$) by associated employment factor for each technology and activity type ($EF_{i,a}$).

$$E_{i,a} = EF_{i,a} {}^{*} A_{i,a}$$

Equation 4. Generalized equation for estimating employment in full-time equivalent in 2050 (E). For each technology and activity, the product of technology attributes ($A_{i,a}$) and an associated employment factor ($EF_{i,a}$) are summed. Technology attributes used in these estimates are technology generation, capacity, new capacity, and retirements.

2.3.2. Environmental criteria

The environmental sustainability criteria included in this analysis are premature fatalities from co-pollutants, life cycle greenhouse gas emissions (represented as carbon dioxide equivalent, CO_2e), and life cycle water and land impacts.

Premature mortalities from co-pollutants are determined using a reduced-complexity model (the Intervention Model for Air Pollution – InMAP) with [26,37]. InMAP estimates the annual average $PM_{2.5}$ concentrations given regional co-pollutant emissions from ReEDS (NO_x, SO_2, and $PM_{2.5}$) across 25,000 grid regions. Premature deaths are determined using a concentration response function from [38]. Fig. 3 summarizes the workflow for estimating the premature deaths within a given year.

To assess the life cycle impacts (greenhouse gases, land transformation, and water depletion) of various technologies over time, we use a code-based life cycle analysis tool, LiAISON (Life-cycle Assessment Integration into Scalable Open-source Numerical models) [39]. LiAISON integrates the outcomes of larger system models, like ReEDS in this case, with the ecoinvent life cycle database, which is a repository that contains data on environmental impacts of different activities and processes [40], to create prospective modified life cycle inventories based on the given system model context and grid mix in this case. LiAISON-ReEDS computes life cycle impacts along the temporal and geographical resolution of ReEDS. LiAISON-ReEDS uses ReEDS electricity generation outputs with the base version of ecoinvent 3.8 [40] to generate time-step life-cycle inventory datasets for each decarbonization pathway and model year. LiAISON-ReEDS then computes environmental life cycle impacts like the life cycle emissions, water, and material consumption per kilowatt-hour (kWh) of electricity produced using these modified life-cycle inventory datasets. The system boundary of the life cycle impact assessment performed here encompasses power plant construction and operational activities including upstream fuel and material supply, construction, and transportation activities. Some decommissioning activities are also included. The impacts are presented as normalized values over the total lifetime electricity production of the power plants as a functional unit per one kilowatt hour of electricity produced.

2.3.3. Social sustainability (distributional equality) criteria

Social sustainability criteria included are air pollution disparities, equality of retail electricity rates, and equality of electricity jobs across low-income households. The equality of these values is determined using either the Gini coefficient or a disparity metric.

To evaluate the distributional equality of air pollution across scenarios, we use a disparity metric that evaluates the difference across air pollution concentrations across census tracts. The air pollution disparity metric is quantified using InMAP to quantify the annual average $PM_{2.5}$ concentration at the census tract level [37]. To include $PM_{2.5}$ and its impact on communities and associated equality into the MCDA framework, we calculate the difference in $PM_{2.5}$ concentrations across the census tracts with the highest and lowest $PM_{2.5}$ concentrations. We calculate the average $PM_{2.5}$ concentration across the upper ($x_{highest20}$) and lower ($x_{lowest20}$) quintile of $PM_{2.5}$ concentration, and then calculate the difference between the two averages to get a disparity value (D), as displayed in Eq. 5.

$$D = \overline{x_{highest20}} - \overline{x_{lowest20}}$$

Equation 5. Disparity calculation across the census tracts with the highest ($x_{highest20}$) and lowest ($x_{lowest20}$) $PM_{2.5}$ population weighted concentrations.

To capture the distributional equality of retail electricity rates across states, we use the Gini coefficient (Eq. 6). The Gini coefficient is a measure of regional equality, valued between zero (perfect equality of retail rates across states) and 1 (perfect inequality of retail rates across states). This metric measures whether people across states are paying similar rates of electricity.

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| x_i - x_j \right|}{2n^2 \overline{x}}$$

Equation 6. Gini coefficient (G) where x is the observed value (like air pollution concentration) for a metric and region and n is the number of regions (sourced from Stats Direct) [41].

To quantify the distributional equity impacts of direct electricity employment, we focus on the distribution of jobs across states and the associated percentage of low-income households within each state. We use this metric to evaluate the access to opportunities that low-income households may have because this has been identified as a potential risk of an unequitable energy transition [24,42]. To estimate the number of low-income households within a state, we count the number of households in low-income census tracts. We identify low-income census tracts as those where the median income is <80% of the area median income of the state. AMI data is sourced from the U.S. Department of Housing and Urban Development The income data used is for 2021 from the U.S. Census Bureau [43]. We then calculate the Gini coefficient across states to measure the equality of access to electricity jobs across low-income households.

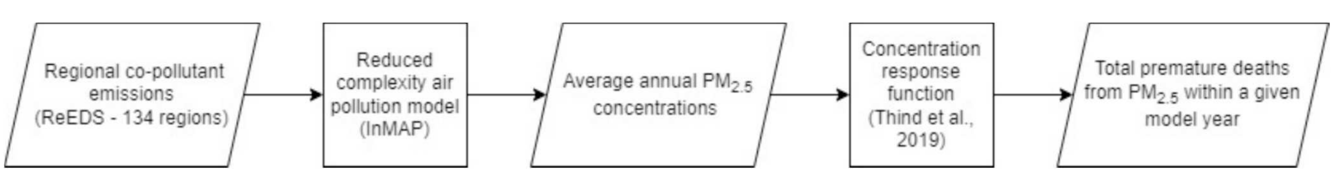


Fig. 3. Summary of calculating pre-mature deaths from $PM_{2.5}$ by connecting ReEDS emissions outputs to a reduced complexity air pollution model. The total premature deaths were calculated using a concentration-response function.

2.4. Limitations and caveats

2.4.1. Model limitations

The employment factors used are based on historical estimates of employment at different stages of the electricity system. A caveat here is that the job estimates from Mayfield et al. [36] do not consider broader economic employment impacts. For the work presented here, we limit the estimates from Mayfield et al. [36] in this analysis only capture employment from the electricity sector and thus do not consider transportation and petroleum-based fuel employment implications across the entire energy system (e.g., natural gas pipelines for heating). Further, we do not account for wage impacts or differentiate between short-term construction jobs or long-term operational jobs. For coal production, we assume 63% is from underground mines, and the remainder is from surface level [44]. We do not model changes to petroleum/ethanol production and jobs related to the potential electrification of transportation. Upstream natural gas jobs were distributed to the nearest associated reservoir (e.g., Bakken, Niobrara, etc.). We assume all biomass demand in the power sector is woody biomass, which is also the default assumption within ReEDS. Costs and jobs for electricity and CO_2 network transmission buildouts are split between sending and receiving regions. For solar and wind manufacturing, we assume that equipment manufacturing occurs in the same state as the capacity is installed in.

For modeling air pollution impacts, we downscale emissions from the ReEDS region (134 regions) to the InMAP grid (25,000 regions) through area weighting of emissions across ReEDS regions. Because we do not model point sources of power plant emissions, we may be missing higher magnitude air pollution concentration impacts on people who live in the communities directly surrounding the power plants.

Our life cycle impact model (LiAISON-ReEDS) does not capture the impacts of electricity transmission beyond transmission losses (fixed value of 2.5%) and most technologies do not include decommissioning impacts (end-of-life stage). We also do not include life cycle impacts from utility battery systems due to limited historical data. Further, the life cycle impacts are normalized over the lifetime of the power plants, which does not capture when specific processes and impacts occur. For example, emissions from construction are distributed over the facility's lifetime.

Another limitation of this analysis is the additional costs of tax credits outside of the electricity sector are not included. This misses some costs of tax credit policies, like increasing capital taxes. Future work could include these as additional costs within the system cost criteria. The expected result if these costs were included is that scenarios with tax credits would be more expensive.

2.4.2. Representation of the Inflation Reduction Act

We generally apply the incentives from IRA for bulk power clean electricity generation, distributed generation incentives (via link with the Distributed Generation Market Demand Model from NREL (dGen)), and the carbon captured and storage tax credit. However, in this work, we do not represent the clean hydrogen production tax credit, commonly known as 45V. The IRA is represented in ReEDS as tax credits for renewable energy technologies, nuclear, and CCS [32]. For detailed information on the representation of the IRA in ReEDS, see [45,46]. We do not capture the additional tax credits that apply to designated ‘energy communities’ under the Qualifying Advanced Energy Project Credit (48C) Program [47], the impact of Climate and Environmental Justice Block Grants, and other funding in the IRA that may help improve air pollution in historically disadvantaged and marginalized communities [48].

3. Results

Here we discuss the outcomes of the sustainability model across the 32 decarbonization pathways. We focus on the ten pathways with the highest sustainability score to highlight the strengths and weaknesses of the best performing scenarios from the perspective of three different sustainability tenets. Beyond the overall sustainability score performance, we evaluate the pairwise relationships between criteria to highlight trade-offs and synergies between criteria. Different decision-maker preferences may also change the sustainability score of different pathways. We quantify these differences in a ranking table. Finally, we compare different policy outcomes to the current policy landscape in the US (*Mid-case* vs. *Tax Credit Extension* vs. *No IRA*).

3.1. Trade-offs and synergies across decarbonization scenarios

The trade-offs between each criterion for the top nine scoring scenarios in 2050 under equal weighting are shown in Fig. 4. The spider plots in Fig. 4 show the total sustainability score in parentheses and the normalized score (0 to 1) for each criterion on the axes, with the blue text indicating the best performing criteria value across the top nine pathways, and the red text indicating the worst performing criteria value across the top nine pathways. Scoring closer to one indicates better performance within the criteria (e.g., lower CO_2 emissions or higher number of jobs). The five *Tax Credit Extension* scenarios are all included in the top nine scenarios, with the *Tax Credit Extension with a 95% CO_2 reduction by 2050* scenario with the highest score (sustainability score = 7.992). This result indicates that *Tax Credit Extension* policy results in positive overall sustainability impacts compared to other policy or technology sensitivities, whether a carbon cap is imposed or not. The top scoring scenario (i.e., *Tax Credit Extension with 95% CO_2 reduction by 2050*) does not perform the absolute best or worst across any of the criteria, indicating that it is well rounded, but would not be found as the optimal pathway under equal weighting if only one objective was used.

The top nine scenarios perform better across environmental and air pollution disparity criteria overall compared to other criteria, meaning that they have lower greenhouse gas emissions, water depletion, land change, and air pollution disparities compared to other scenarios. This is seen visually in Fig. 4 with the spider plot shape being “fuller” toward the environmental criteria, as well as in their normalized scores: life cycle greenhouse gas scores range from 0.76 to 1.00 (raw values range between 0.05 to 0.1 grams CO_2eq./kWh), life cycle land transformation scores range from 0.74 to 1.00 (raw values range between 1.04E-05 to 1.20E-05 m^2/kWh), air pollution fatalities scores range from 0.78 to 1.00 (raw values range between 295 to 1,290 premature deaths), and air pollution 0.80 to 1.00 (raw values range between 0.04 to 0.15 $\mu g/m^3$). This indicates that environmental sustainability may be driving the determination of the most sustainable pathways under equal weighting, which may also be in part be because there are more environmental criteria than social or economic criteria. However, life cycle water depletion is impacted negatively when more solar capacity is in the system: the third ranked scenario, *Reduced RE Resource, 95% CO_2 reduction, conservative*, has the lowest (worst) water depletion normalized score across the top nine scenarios due to higher solar capacity investments in 2050 compared to other pathways (about 200 GW more solar capacity, likely in lieu of wind capacity).

Mid-case, *PVB (solar photovoltaic + battery systems)*, and *No IRA* sensitivities do not have any decarbonization pathways in the top nine sustainability scores under equal weighting. Specifically, the *No IRA* scenarios are ranked 29th and 30th in total sustainability score (worst and second to worst).

Fig. 5 shows the pairwise comparisons of criterion in and 2050, with the top ten scenarios highlighted in orange. The diagonal of the plot shows the distribution of the normalized score within each criterion. There are 30 non-dominated scenarios included in the plot. The *Reduced RE Resource 95% CO_2 reduction by 2050* scenario is dominated scenario by the *High Transmission, 95% CO_2 reduction by 2050* and *PVB, 100% CO_2 reduction by 2035* is dominated by *Tax Credit Expiration, 100% CO_2 reduction by 2035*. We call out some interesting relationships below.

The retail rate versus life cycle GHGs relationship is “V” shaped, with a large range of retail rate scores (0.2–1) while life cycle greenhouse gas

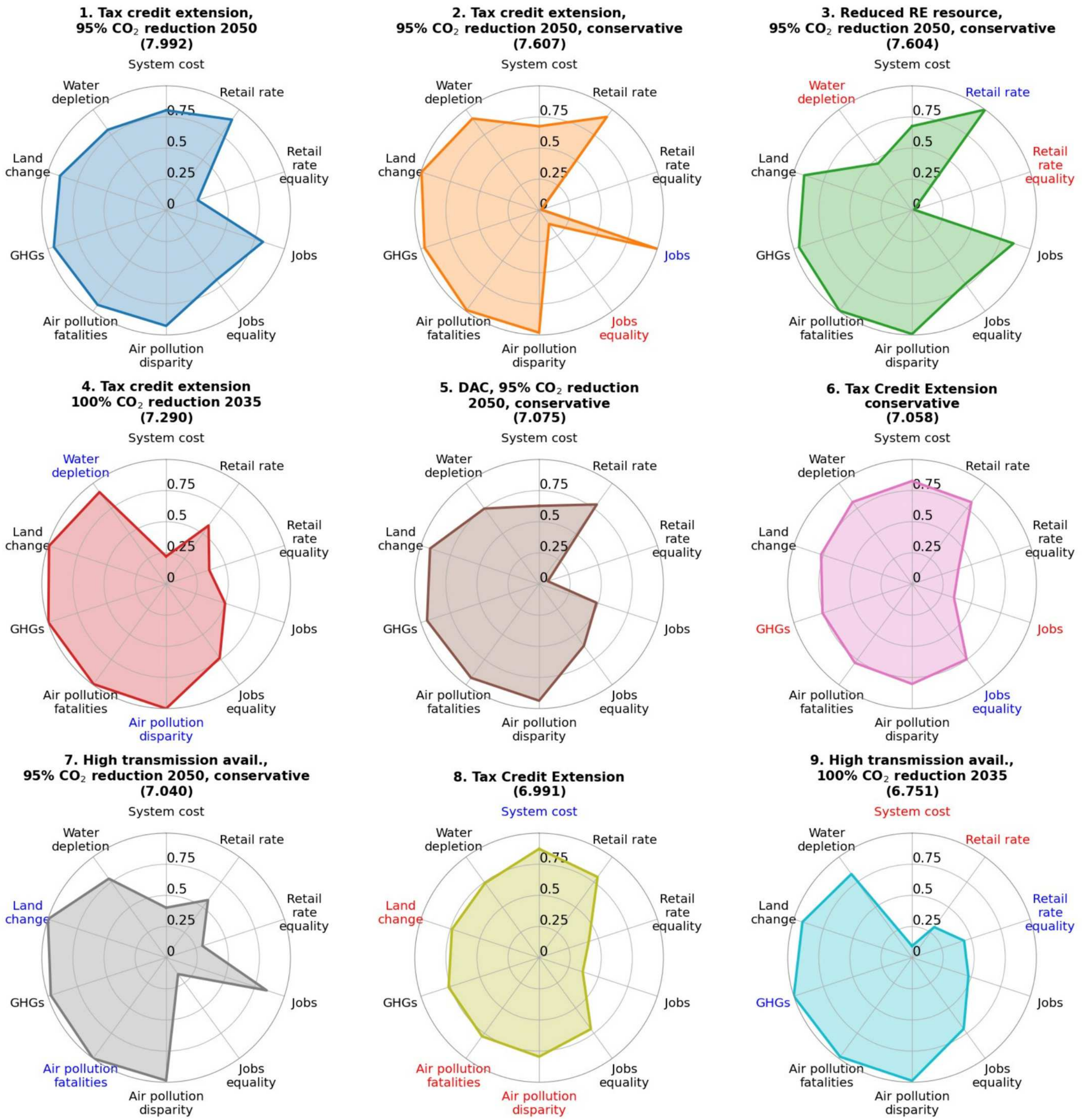


Fig. 4. Normalized score across criteria for top nine performing scenarios under equal weighting in 2050. Blue text for a criterion symbolizes that it is the best performing scenario within that criterion among the top nine. Red text for a criterion symbolizes that it is the worst performing scenario within that criterion among the top nine. The total scores under equal weighting are shown in parentheses underneath the scenario names. The minimum and maximum values associated with each criterion among the top nine are as follows: **System cost**: \$47.9–\$64.8 billion, **Retail rate**: 9.10–10.33 ₵/kWh, **Retail rate equality:** 0.31–0.36, **Jobs:** 2.5–3.7 million, **Jobs equality:** 0.43–0.55, **Air pollution fatalities:** 295–1290 premature deaths, **Air pollution disparity:** 0.04–0.15 μg/m^3, **life cycle GHGs (greenhouse gas emissions):** 0.05–0.10 kg/kWh, **life cycle land change:** 1.04E-05-1.20E-05 m^2/kWh, **life cycle water depletion:** 0.0018–0.0019 m^3/kWh. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emissions scores are >0.9. The pathways that have low retail rate scores and high life cycle greenhouse gas emissions scores have higher amounts of Gas-CCS capacity and generation, which may be contributing to higher retail rates, while keeping greenhouse gas emissions low. This relationship with retail rates is also seen in air pollution fatalities and air pollution disparity scores, due to the same reason.

Air pollution fatalities and disparity are positively related to life cycle greenhouse gas emissions, indicating co-benefits from decarbonization. The Kendall coefficient (τ_B), which evaluates the ordinal relationship between two variables and indicates if two variables are positively or negatively monotonically related, between air pollution fatalities and life cycle greenhouse gas emissions is 0.876 (p-value <0.001) and a τ_B of 0.867 (p-value <0.001) between air pollution disparity and life cycle greenhouse gas emissions, indicating a

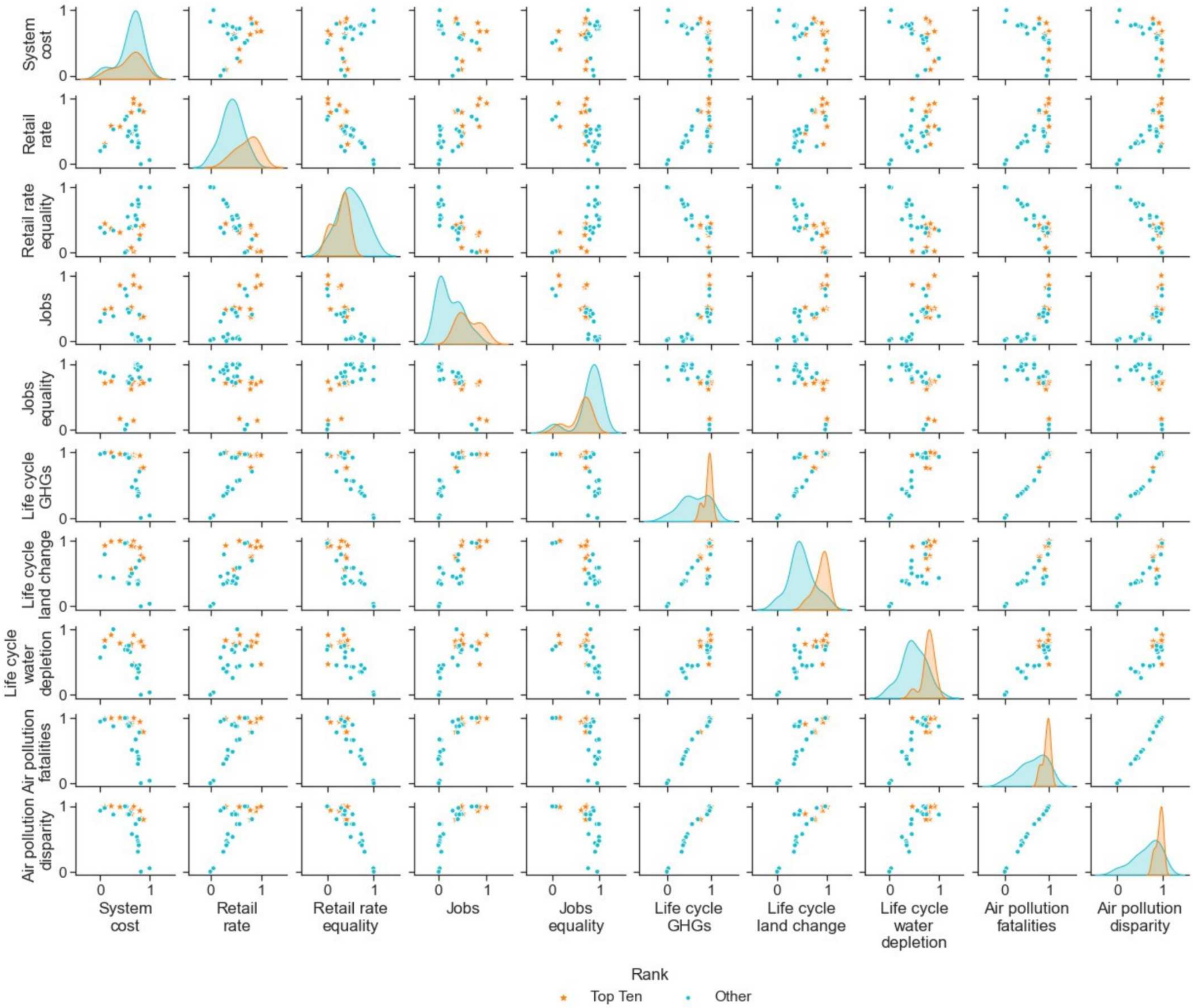


Fig. 5. Pairwise comparisons of each criterion to each other in 2050 across the non-dominated set. The plot differentiates between the top ten performing scenarios under equal weighting (orange stars) and all other scenarios (blue circles). The diagonal shows the distribution of the normalized criterion score across the two groups (orange stars – top ten scoring, blue circles – all others). The scatter plots across the diagonal are mirrors of each other. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

statistically significant strong positive monotonic relationship between these criteria (see SI Table S-3 for all Kendall coefficients and *p*-values). Beyond life cycle greenhouse gas emissions, there is also a positive relationship between jobs and the two air pollution criteria: air pollution fatalities versus jobs relationship has a τ_B of 0.738 (p-value <0.001) and air pollution disparity versus jobs has a τ_B of 0.720 (p-value <0.001). This relationship may be due to new capacity additions of renewable energy technologies and the influx of construction and manufacturing jobs necessary.

System costs have a statistically significant negative relationship to life cycle greenhouse gases, air pollution fatalities, and air pollution disparity criteria. However, while the overall relationship is negative, there are some pathways that maintain lower system costs and lower greenhouse gas emissions, air pollution disparity, and air pollution fatalities comparatively: *Tax Credit Extension* (normalized scores - system cost = 0.87, air pollution fatalities = 0.78, air pollution disparity = 0.79, life cycle greenhouse gases = 0.77) and *Tax Credit Extension, conservative* (normalized scores - system cost = 0.81, air pollution fatalities = 0.78, air pollution disparity = 0.80, life cycle greenhouse gases = 0.76).

This negative relationship between system costs and environmental and air pollution disparity criteria indicates there are trade-offs between system costs and these criteria. The scenario with the best (lowest) system cost is the *No IRA* scenario with a system cost of $45.1 billion and life cycle greenhouse gas emissions of 0.25 grams CO_2eq. per kilowatt-hour. By increasing annualized system costs by $2.7 billion, which is the second-best system cost value (under the *Tax Credit Extension* scenario), life cycle greenhouse gas emission decrease by 0.15 grams CO_2eq. per kilowatt-hour. To go from worst (highest emissions) to best (lowest emissions) in terms of life cycle greenhouse gas emissions, system costs increase by $19.7 billion to reduce life cycle greenhouse gas emissions by 0.20 grams CO_2eq. per kilowatt-hour. However, the reductions in life cycle greenhouse gas emissions are marginal beyond an increase in system cost of 4 billion 2020$ and reduction of life cycle greenhouse gases by 0.19 grams CO_2eq. per kilowatt-hour, where the *Tax Credit Extension, 95% CO_2 reduction by 2050* scenario has life cycle greenhouse gas emissions of 0.06 grams CO_2eq. per kilowatt-hour.

For air pollution disparity criteria, similar to the system cost-greenhouse gas emissions trade-offs, increasing system costs by 2.7 billion 2020$ would decrease the air pollution disparity from 0.52 to 0.15 μg/m^3. The *Tax Credit Extension, 95% CO_2 reduction by 2050* scenario again has the most efficient (best) trade-off, with an increase of $4 billion compared to the cheapest scenario to decrease the air pollution disparity by 0.46 μg/m^3 (air pollution disparity value of 0.08 μg/m^3).

The relationship between retail rate equality and air pollution disparity ($\tau_B = -0.692$, p-value <0.001) may be a result of high CO_2 credit prices and the design of the policy as a carbon cap. Regions with higher fossil fuel generation would have higher retail rates under a carbon cap due to the CO_2 credit prices, resulting in regional inequality of retail rates. Thus, states that can transition to high renewable energy systems are better off in terms of retail rates (lower rates), which is beneficial for the people within the state.

While air pollution fatalities versus air pollution disparity criteria are complementary to each other (positively related), total jobs versus job equality and national retail rate versus retail rate equality are both negatively related to each other. This indicates there is a trade-off between preference of outcome (regional equality versus national outcomes) within jobs and retail rates.

3.2. Impact of preferences on outcomes

We also investigate how the rankings of scenarios will change under different stakeholder preference scenarios (see Table 3). The rankings across all 30 non-dominated scenarios are displayed in SI Table S-4. The top performing scenario in 2050, *Tax Credit Extension with a 95% CO_2 reduction by 2050*, ranks within the top five under all stakeholder preferences except for social (rank = 16), climate (rank = 9), and air pollution (rank = 9) preference scenarios. This scenario also has the highest number of number 1 rankings, at 30% (equal, climate-system costs, and socio-economic preference scenarios). This highlights the multi-faceted benefits of energy systems that invest in majority renewable energy technologies and retire fossil fuels or install CCS.

Top ten under equal weighting have the lowest ranks under social weighting preference, except for *High Transmission Availability, 100% CO_2 reduction by 2050*, which is ranked third. This is mainly due to low scores across retail rate equality. This highlights that the preference for equality versus equity may impact desired outcomes: while some scenarios are low scoring in retail rate equality, they score high in national retail rate. An example of this is the *Reduced RE Resource, 95% CO_2 reduction by 2050, conservative pathway* has the best average retail rate (score = 1, retail rate = 9.10 cents/kWh), but low retail rate equality, comparatively to other pathways (score = 0.02, retail rate equality = 0.36). With the preference of equality, pathways with higher retail rates, but better equality may be preferred. If equity was preferred, the equality of retail rates reaching a given threshold (deemed “equitable”) could be defined.

Looking across carbon cap and technology set scenarios, we find that most scenarios with a carbon cap of *100% CO_2 reduction by 2035* rank in the top half of scenarios (higher than 16th) across climate, jobs-jobs equality, air pollution, and environment-social preference scenarios mostly driven by the net-zero CO_2 emissions, low air pollution, and high employment creation. In contrast, these scenarios score in the bottom half (rank less than 15th) across jobs-system cost, climate-system cost, and economic preference scenarios, mostly driven by the high system costs. The five non-dominated *100% CO_2 reduction by 2035* scenarios score the lowest within system costs (normalized score ranging from 0 to 0.26).

The *95% CO_2 reduction, conservative* carbon cap scenarios rank lower than 22nd under the social preference scenario. This is driven by low scoring in jobs equality and retail rate equality criteria.

While the scenarios with no carbon cap rank worse than scenarios with a carbon cap generally, the *Tax Credit Extension* and *Tax Credit Extension, conservative* are exceptions and rank in the top ten across equal, economic, jobs-system cost, climate-system cost, and social-economic preference scenarios. This shows that even without a carbon cap policy, indefinitely extending tax credits make renewable technologies and nuclear economically preferred under a least-cost optimization.

Table 3
Ranking of top 10 scenarios under 11 stakeholder preference scenarios in 2050. The blue shading indicates ranks closer to 1st (best) and the red shading indicates ranks closer to 30th (worst).

Scenario	Equal	Economic	Environmental	Social	Climate	Jobs-jobs equality	Air pollution	Jobs-system cost	Climate-system cost	Social-economic	Environmental-social
Tax Credit Extension, 95% CO_2 reduction 2050	1	2	5	16	9	2	9	2	1	1	2
Tax Credit Extension, 95% CO_2 reduction 2050, conservative	2	1	2	28	4	11	3	1	2	5	7
Reduced RE Resource, 95% CO_2 reduction by 2050, conservative	3	3	10	22	8	1	1	3	3	2	5
Tax Credit Extension, 100% CO_2 reduction by 2035	4	15	1	6	1	5	2	19	18	11	1
DAC, 95% CO_2 reduction by 2050, conservative	5	9	8	25	11	15	10	11	6	8	8
Tax Credit Extension, conservative	6	5	13	14	18	14	17	8	5	4	9
High Transmission Avail., 95% CO_2 reduction by 2050, conservative	7	10	3	27	5	18	4	5	14	14	6
Tax Credit Extension	8	4	14	19	17	16	18	6	4	3	12
High Transmission Avail., 100% CO_2 reduction by 2035	9	27	4	3	2	9	7	28	22	19	3
High Transmission Avail., 95% CO_2 reduction by 2050	10	11	12	15	12	6	13	10	7	9	11

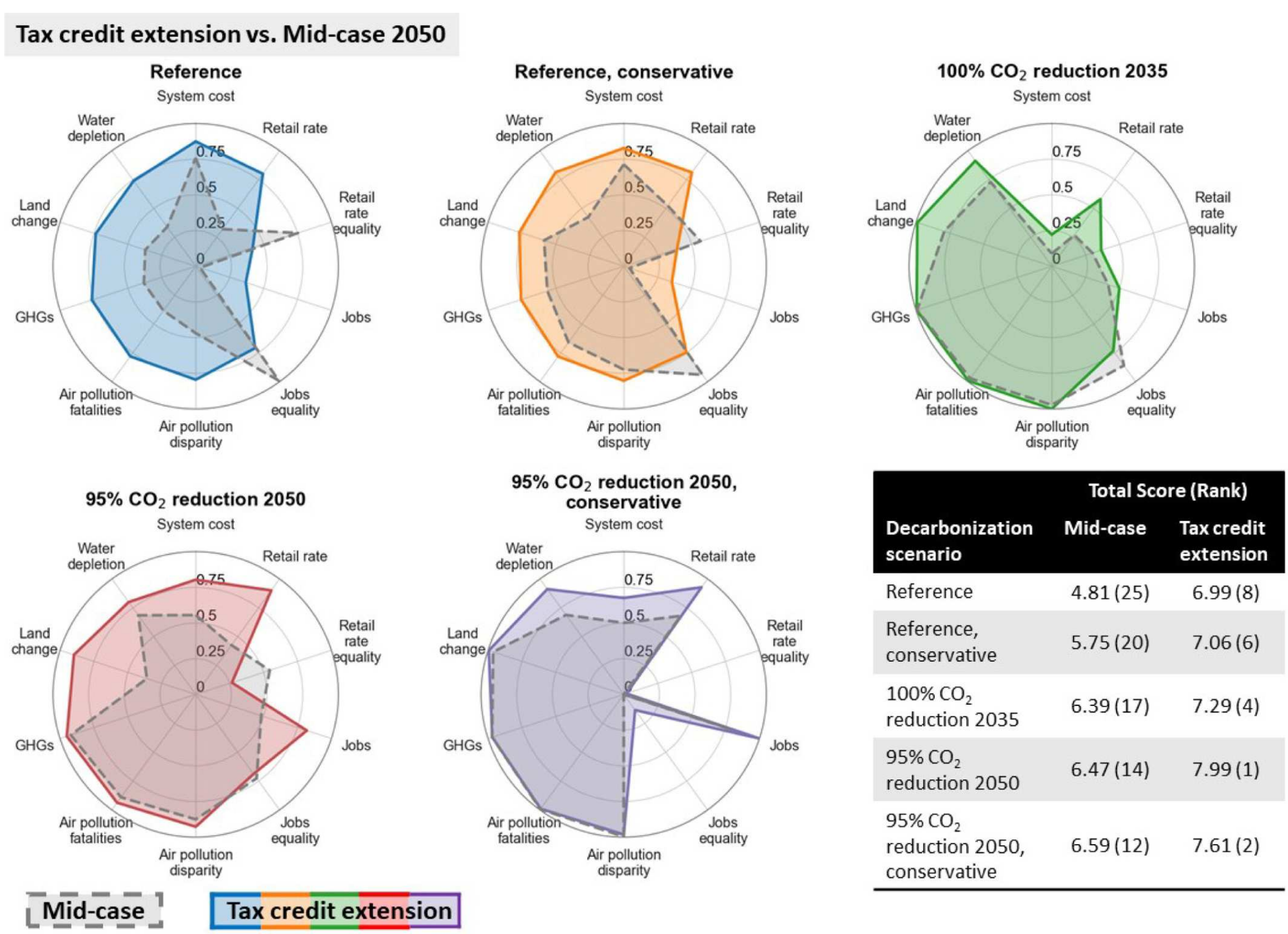
3.3. Policy impacts

The *Tax Credit Extension* and *No IRA* policies modeled in our analysis present interesting divergences from the *Mid-case* decarbonization scenarios across certain criteria. In Fig. 6, we highlight how the *Tax Credit Extension* and *No IRA* policy inputs compare to the *Mid-case* decarbonization scenarios across carbon cap pathways (that include the Inflation Reduction Act). We see that the *Tax Credit Extension* scenarios perform better across all environmental criteria, air pollution fatalities, system costs, jobs, and retail rates compared to the *Mid-case*. The *Mid-case* scenarios perform better in the jobs equality criteria across four carbon cap pathways (all except the *95% CO_2 reduction by 2050 with conservative technologies* carbon cap). These differences are caused by continued investment in renewable energy technologies under the *Tax Credit Extension* scenarios. This indicates that while current tax credits under the IRA result in better environmental outcomes compared to *No IRA*, extending the tax credits indefinitely is even more beneficial. However, a caveat of this is we only account for cost reductions from tax credits within the electricity system through system costs, which may miss broader economy or distributional impacts [29].

The *No IRA* scenarios perform better than the *Mid-case* in system costs and retail rate equality criteria. However, while the retail rate equality performs well in the *No IRA* scenarios (*No IRA Reference*: Gini = 0.25 and *No IRA Reference conservative*: Gini = 0.24) the national average retail rates are two of the highest (*No IRA Reference* = 10.75 ₵/kWh, *No IRA Reference, conservative* = 10.86 ₵/kWh). Therefore, while retail rates are more equal across states, higher overall rates may not be desirable for customers, and may have negative impacts on energy burden, for example. While the system costs of the *No IRA* scenarios are slightly better than the *Mid-case* scenarios (*No IRA Reference* = \$45.1B, *Mid-case Reference* = \$50.3B, *No IRA Reference, conservative* = \$50.0B, *Mid-case Reference, conservative* = \$51.3B), there are many benefits not captured in system costs, like avoided deaths from air pollution reductions and a more environmentally sustainable system, which we see presented across our other criteria.

4. Conclusions

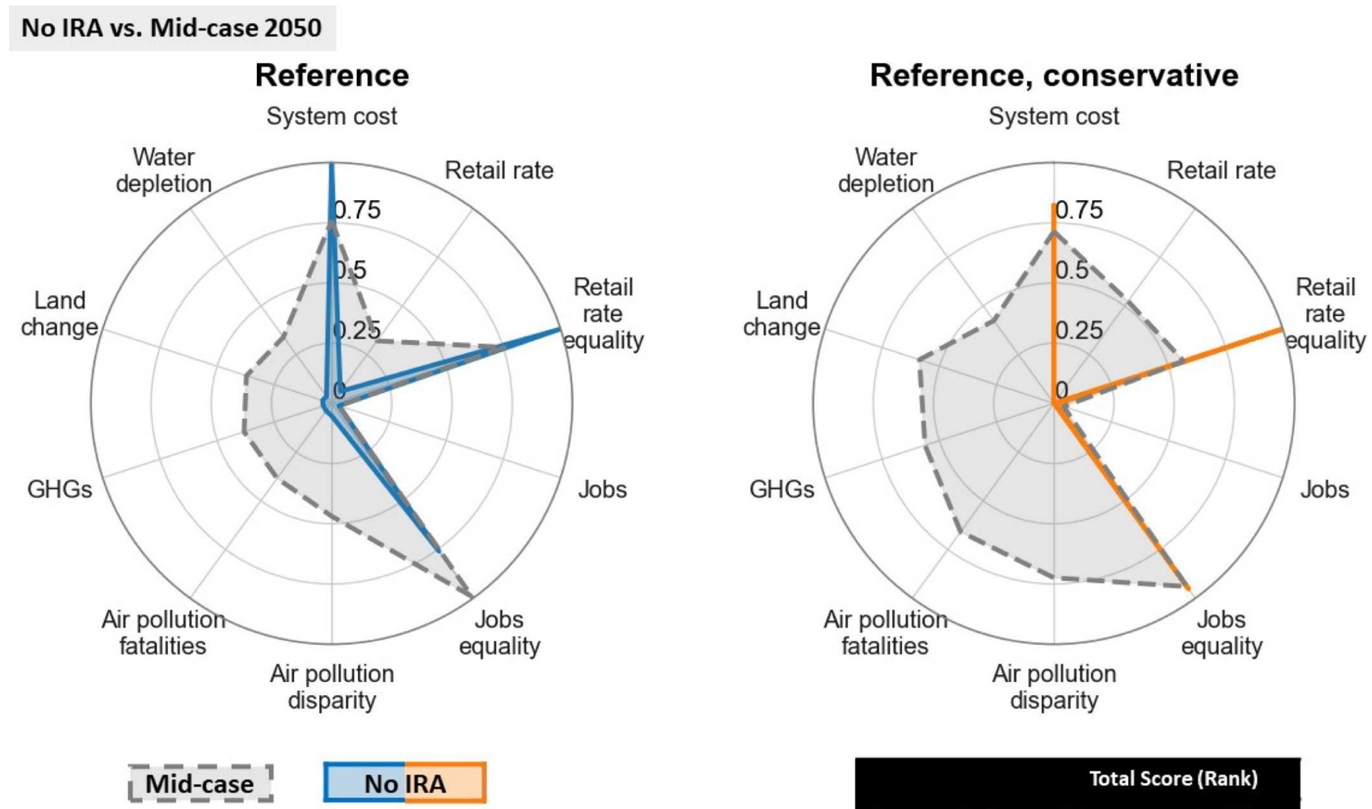
We investigated the trade-offs across different decarbonization scenarios across economic, environmental, and distributional equity criteria using a least-cost optimization capacity expansion model tied to a MCDA. We find trade-offs between system costs and environmental and air pollution disparity outcomes, where scenarios with higher system costs tend to have better environmental and air pollution disparity outcomes. Also, there are synergies (e.g., positive relationship) between most of the environmental and air pollution disparity criteria and high



Decarbonization scenario	Total Score (Rank) Mid-case	Total Score (Rank) Tax credit extension
Reference	4.81 (25)	6.99 (8)
Reference, conservative	5.75 (20)	7.06 (6)
100% CO_2 reduction 2035	6.39 (17)	7.29 (4)
95% CO_2 reduction 2050	6.47 (14)	7.99 (1)
95% CO_2 reduction 2050, conservative	6.59 (12)	7.61 (2)

***(a)** Tax credit extension*

Fig. 6. Comparison of Mid-case performance to (a) Tax Credit Extension policies and (b) No IRA policies. We only investigated pathways for the No IRA runs that did not implement additional carbon reduction goals through carbon caps. The Mid-case scores for each decarbonization scenario are shown in gray, and the Tax Credit Extension and No IRA scores are shown in colour.



	Total Score (Rank)	
Decarbonization scenario	Mid-case	No IRA
Reference	4.81 (25)	3.04 (29)
Reference, conservative	5.75 (20)	2.79 (30)

(b) *No IRA*

Fig. 6. (*continued*).

renewable energy penetration scenarios. We see that these results are consistent across scenarios with and without CCS systems, but there remains some uncertainty how much power plants with CCS systems would also reduce co-pollutant emissions, or cause other environmental or social risks [49,50].

We find that extending tax credits results in overall positive sustainability outcomes, with greater investments in renewable energy technologies, and result in better environmental, system cost, job, and air pollution disparities compared to the *Mid-case* pathways, which include all current policies. The *Tax Credit Extension, 95% CO_2 reduction* scenario is the top performing scenario under equal weighting but does not perform the best in any single criteria. This highlights the importance of simultaneously evaluating multiple criteria when choosing a system, because a single objective may miss pathways that are holistically beneficial. We also see that some social criteria (jobs equality and retail rate equality) are a trade-off to criteria within the same topic focus (jobs and national retail rates), which shows that using MCDA to quantify multiple aspects of sustainability may identify trade-offs within a given topic dependent on the goal or preference of outcome (e.g., maximize equality or prioritize national level outcomes). This outcome emphasizes a benefit of MCDA for stakeholders to understand more holistic perspectives of electricity system outcomes.

Under different preference scenarios, the top three scoring pathways under equal weighting score within the top three 66% of the time. These scenarios are robust in performance across many different potential stakeholder preferences. Across carbon cap scenarios, we find that the *100% CO_2 reduction by 2035* scenarios rank poorly (less than 16th) in economic and system cost focused preference scenarios because this system is the most expensive, but ranks well across environmental (e.g., environmental, climate, air quality, environmental-social) and jobs (e.g., jobs-jobs equality) preference scenarios. To better represent stakeholder preferences in reality, future work could consult with different energy stakeholders to determine preferences toward economic, environmental, and social criteria outcomes throughout the energy transition with the U.S., as some studies have done outside the U.S. and at smaller scales (city or local energy planning) [51–53].

As the U.S. continues decarbonizing its electricity system, there are many different priorities in planning a cost-effective, equitable, and environmentally sustainable electricity system, some of which may conflict with each other, as we have highlighted in our study. Capturing impacts across economic, environmental, and social sustainability helps to identify pathways that are beneficial across multiple aspects of sustainability. Several other metrics and impacts could be considered in future work and energy planning, like additional environmental or social sustainability criteria. Specifically, we define equity in this analysis as equality of distributional impacts, but equity and justice could be expanded to include other impacts, like impact on household or demographic group differences. Through a restorative justice lens, justice or equity criteria could account for cumulative impacts from the energy system. In conclusion, energy planning and transitions are complex with many different priorities and impacts to be balanced. It is important to consider distributional impacts of the energy transition to ensure that the future energy system has an equitable distribution of costs and benefits.

CRediT authorship contribution statement

Teagan Goforth: Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **Destenie Nock:** Conceptualization, Methodology, Writing – review & editing. **Maxwell Brown:** Formal analysis, Methodology, Software, Writing – review & editing. **Tapajyoti Ghosh:** Data curation, Formal analysis, Methodology, Software, Writing – review & editing. **Patrick Lamers:** Software, Writing – review & editing, Methodology.

Declaration of competing interest

The authors have no competing interests to disclose.

Data availability

Some data can be made available by request, other data cannot be shared due to being proprietary data.

Acknowledgements

We would like to acknowledge that this work has been supported in part by the National Science Foundation [grant number 2017789]. This work was authored in part by the National Renewable Energy Laboratory (NREL), operated by the Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. T. Ghosh and P. Lamers were supported by the Laboratory Directed Research and Development (LDRD) Program at NREL. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123376.

References

[1] The White House. A guidebook to the bipartisan infrastructure law for state, local, tribal, and territorial governments, and other partners. Accessed: Apr. 11, 2023. [Online]. Available: https://gfoaorg.cdn.prismic.io/gfoaorg/0727aa5a-308f-4ef0-addf-140fd43acfb5_BUILDING-A-BETTER-AMERICA-V2.pdf; 2022.
[2] The White House. Inflation reduction act guidebook. Accessed: Feb. 03, 2023. [Online]. Available: https://www.whitehouse.gov/wp-content/uploads/2022/12/Inflation-Reduction-Act-Guidebook.pdf; 2023.
[3] Mowers M, Mai T. An evaluation of electricity system technology competitiveness metrics: the case for profitability. Electr J May 2021;34(4):106931. https://doi.org/10.1016/j.tej.2021.106931.
[4] Young S, Mallory B, McCarthy G. The path to achieving Justice40. The White House; 2022. Accessed: Jul 07. [Online]. Available: https://www.whitehouse.gov/omb/briefing-room/2021/07/20/the-path-to-achieving-justice40/.
[5] Edmonds J, Wilson T, Wise M, Weyant J. Electrification of the economy and CO2 emissions mitigation. Environ Econ Policy Stud Sep. 2006;7(3):175–203. https://doi.org/10.1007/BF03353999.
[6] IPCC. Climate change 2014: synthesis report. Gian-Kasper Plattner; 2014. Accessed: Oct. 25, 2020. [Online]. Available: http://www.ipcc.ch.
[7] Araújo K. The emerging field of energy transitions: Progress, challenges, and opportunities. Energy Res Soc Sci Mar. 2014;1:112–21. https://doi.org/10.1016/j.erss.2014.03.002.
[8] Purvis B, Mao Y, Robinson D. Three pillars of sustainability: in search of conceptual origins. Sustain Sci May 2019;14(3):681–95. https://doi.org/10.1007/s11625-018-0627-5.
[9] Deng X, Lv T. Power system planning with increasing variable renewable energy: a review of optimization models. J Clean Prod Feb. 2020;246:118962. https://doi.org/10.1016/j.jclepro.2019.118962.
[10] Cole W, et al. Regional energy deployment system model 2.0 (ReEDS 2.0) [Online]. Available: https://www.nrel.gov/analysis/reeds/index.html; Nov. 2021.
[11] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sust Energ Rev May 2014;33:74–86. https://doi.org/10.1016/j.rser.2014.02.003.
[12] Krumm A, Süsser D, Blechinger P. Modelling social aspects of the energy transition: what is the current representation of social factors in energy models? Energy Jan. 2022;239:121706. https://doi.org/10.1016/J.ENERGY.2021.121706.
[13] Conlon T, Waite M, Wu Y, Modi V. Assessing trade-offs among electrification and grid decarbonization in a clean energy transition: application to New York State. Energy Jun. 2022;249:123787. https://doi.org/10.1016/j.energy.2022.123787.
[14] Costa-Campi MT, del Rio P, Trujillo-Baute E. Trade-offs in energy and environmental policy. Energy Policy May 2017;104:415–8. https://doi.org/10.1016/j.enpol.2017.01.053.
[15] Kumar P, Banerjee R, Mishra T. A framework for analyzing trade-offs in cost and emissions in power sector. Energy Mar. 2020;195:116949. https://doi.org/10.1016/j.energy.2020.116949.
[16] Volkart K, Weidmann N, Bauer C, Hirschberg S. Multi-criteria decision analysis of energy system transformation pathways: a case study for Switzerland. Energy Policy Jul. 2017;106:155–68. https://doi.org/10.1016/j.enpol.2017.03.026.
[17] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew Sust Energ Rev Dec. 2009;13(9):2263–78. https://doi.org/10.1016/j.rser.2009.06.021.
[18] Klein SJW, Whalley S. Comparing the sustainability of U.S. electricity options through multi-criteria decision analysis. Energy Policy Apr. 2015;79:127–49. https://doi.org/10.1016/j.enpol.2015.01.007.
[19] Nock D, Baker E. Holistic multi-criteria decision analysis evaluation of sustainable electric generation portfolios: New England case study. Appl Energy May 2019; 242:655–73. https://doi.org/10.1016/j.apenergy.2019.03.019.
[20] Estévez RA, Espinoza V, Ponce Oliva RD, Vásquez-Lavín F, Gelcich S. Multi-criteria decision analysis for renewable energies: research trends, gaps and the challenge of improving participation. Sustainability Jan. 2021;13(6). https://doi.org/10.3390/su13063515. Art. no. 6.
[21] Choi D, Ahn Y-H, Choi DG. Multi-criteria decision analysis of electricity sector transition policy in Korea. Energ Strat Rev May 2020;29:100485. https://doi.org/10.1016/j.esr.2020.100485.
[22] Danielson M, Ekenberg L, Komendantova N, Al-Salaymeh A, Marashdeh L. A participatory MCDA approach to energy transition policy formation. In: de Almeida AT, Ekenberg L, Scarf P, Zio E, Zuo MJ, editors. Multicriteria and optimization models for risk, reliability, and maintenance decision analysis: recent advances. International Series in Operations Research & Management Science. Cham: Springer International Publishing; 2022. p. 79–110. https://doi.org/10.1007/978-3-030-89647-8_5.
[23] Maxim A. Sustainability assessment of electricity generation technologies using weighted multi-criteria decision analysis. Energy Policy Feb. 2014;65:284–97. https://doi.org/10.1016/J.ENPOL.2013.09.059.
[24] Carley S, Konisky DM. The justice and equity implications of the clean energy transition. Nat Energy Jun. 2020;5(8):569–77. https://doi.org/10.1038/s41560-020-0641-6.
[25] Sasse JP, Trutnevyte E. Regional impacts of electricity system transition in Central Europe until 2035. Nat Commun 2020;11(1):1–14. https://doi.org/10.1038/s41467-020-18812-y.
[26] Goforth T, Nock D. Air pollution disparities and equality assessments of US national decarbonization strategies. Nat Commun Dec. 2022;13(1). https://doi.org/10.1038/s41467-022-35098-4. Art. no. 1.
[27] Sasse J-P, Trutnevyte E. A low-carbon electricity sector in Europe risks sustaining regional inequalities in benefits and vulnerabilities. Nat Commun Apr. 2023;14(1). https://doi.org/10.1038/s41467-023-37946-3. Art. no. 1.
[28] Bistline J, et al. Equity implications of net-zero emissions: a multi-model analysis of energy expenditures across income classes under economy-wide deep decarbonization policies. Energy Clim Change Oct. 2023:100118. https://doi.org/10.1016/j.egycc.2023.100118.
[29] Brown ML, et al. Tax credits for clean electricity: The distributional impacts of supply-push policies in the power sector. In: Working paper series. National Bureau of Economic Research; Aug. 2023. https://doi.org/10.3386/w31621.
[30] García-Muros X, Morris J, Paltsev S. Toward a just energy transition: a distributional analysis of low-carbon policies in the USA. Energy Econ Jan. 2022; 105:105769. https://doi.org/10.1016/j.eneco.2021.105769.
[31] Brown M, et al. Regional energy deployment system (ReEDS) model documentation: version 2019. Renew Energy 2020:140.
[32] Gagnon P, et al. 2022 standard scenarios report: a U.S. Electricity Sector Outlook. National Renewable Energy Lab; 2022.
[33] U.S. Energy Information Administration (EIA). Annual energy outlook 2022. Accessed: Mar. 06. [Online]. Available: https://www.eia.gov/outlooks/aeo/narrative/introduction/sub-topic-02.php; 2024.
[34] Mai TT, et al. Electrification futures study: scenarios of electric technology adoption and power consumption for the United States. NREL/TP–6A20–71500 Jun. 2018;1459351. https://doi.org/10.2172/1459351.
[35] Brown P, Gagnon P, Corcoran JS, Cole W. Retail rate projections for long-term electricity system models. NREL/TP-6A20–78224, 1840705, MainId:32135. Jan. 2022. https://doi.org/10.2172/1840705.

[36] Mayfield E, Jenkins J, Larson E, Greig C. Labor pathways to achieve net-zero emissions in the United States by mid-century. Energy Policy Jun. 2023;177: 113516. https://doi.org/10.1016/j.enpol.2023.113516.

[37] Tessum CW, Hill JD, Marshall JD. InMAP: a model for air pollution interventions. PLoS One Apr. 2017;12(4):e0176131. https://doi.org/10.1371/JOURNAL.PONE.0176131.

[38] Thind MPS, Tessum CW, Azevedo IL, Marshall JD. Fine particulate air pollution from electricity generation in the US: health impacts by race, income, and geography. Environ Sci Technol Dec. 2019;53(23):14010–9. https://doi.org/10.1021/ACS.EST.9B02527.

[39] Ghosh T, Chun SM, Upasani S, Lamers P. LiAISON (life-cycle assessment integration into scalable open-source numerical models) [SWR-24-01]. USDOE Office of Energy Efficiency and Renewable Energy (EERE), Energy Efficiency Office. Advanced Materials & Manufacturing Technologies Office (AMMTO); 2024 [Online]. Available: https://github.com/NREL/LiAISON/tree/LiAISON_ReEDS.

[40] ecoinvent. ecoinvent v3.8. Accessed: Dec. 17. [Online]. Available: https://ecoinvent.org/the-ecoinvent-database/data-releases/ecoinvent-3-8/; 2023.

[41] Stats Direct. Gini coefficient of inequality. Accessed: Aug. 17. [Online]. Available: https://www.statsdirect.com/help/default.htm#nonparametric_methods/gini.htm; 2021.

[42] Graham K, Knittel CR. Assessing the distribution of employment vulnerability to the energy transition using employment carbon footprints. Proc Natl Acad Sci Feb. 2024;121(7):e2314773121. https://doi.org/10.1073/pnas.2314773121.

[43] US Census Bureau. Census bureau data. Accessed: Feb 20. [Online]. Available: https://data.census.gov/; 2024.

[44] U.S. Energy Information Administration (EIA). Where our coal comes from. Accessed: Mar 05. [Online]. Available: https://www.eia.gov/energyexplained/coal/where-our-coal-comes-from.php; 2024.

[45] Steinberg D, et al. Evaluating impacts of the inflation reduction act and bipartisan infrastructure law on the U.S. power system. NREL/TP-6A20-85242, 1962552, MainId:86015, Mar. 2023. https://doi.org/10.2172/1962552.

[46] Bistline J, et al. Emissions and energy impacts of the inflation reduction act. Science Jun. 2023;380(6652):1324–7. https://doi.org/10.1126/science.adg3781.

[47] United States Department of Energy. Qualifying advanced energy project credit (48C) program. Energygov Accessed: Nov 13. [Online]. Available: https://www.energy.gov/infrastructure/qualifying-advanced-energy-project-credit-48c-program; 2023.

[48] The White House. FACT SHEET: inflation reduction act advances environmental justice. The White House; 2023. Accessed: Nov 13. [Online]. Available: https://www.whitehouse.gov/briefing-room/statements-releases/2022/08/17/fact-sheet-inflation-reduction-act-advances-environmental-justice/.

[49] Koornneef J, Ramirez A, van Harmelen T, van Horssen A, Turkenburg W, Faaij A. The impact of CO2 capture in the power and heat sector on the emission of SO2, NOx, particulate matter, volatile organic compounds and NH3 in the European Union. Atmos Environ Apr. 2010;44(11):1369–85. https://doi.org/10.1016/j.atmosenv.2010.01.022.

[50] Wilday J, Paltrinieri N, Farret R, Hebrard J, Breedveld L. Addressing emerging risks using carbon capture and storage as an example. Process Saf Environ Prot Nov. 2011;89(6):463–71. https://doi.org/10.1016/j.psep.2011.06.021.

[51] Simoes SG, et al. InSmart – a methodology for combining modelling with stakeholder input towards EU cities decarbonisation. J Clean Prod Sep. 2019;231: 428–45. https://doi.org/10.1016/j.jclepro.2019.05.143.

[52] Vögele S, et al. Robust assessment of energy scenarios from stakeholders' perspectives. Energy Nov. 2023;282:128326. https://doi.org/10.1016/j.energy.2023.128326.

[53] Weber J. Gridlock in compromise, or is multi-objective optimisation possible in renewable energy planning? A stakeholder analysis using scenario-MCDA. Int J Sustain Energy Dec. 2023;42(1):1538–68. https://doi.org/10.1080/14786451.2023.2275812.