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Correlated uncertainty propagation enables multi-impact decision support for electrical system decarbonization

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Abstract

Decarbonization planning requires comparing diverse pathways across economic, ecological, and health dimensions under uncertainty. Capacity expansion models generally treat pathway uncertainties as independent, overestimating uncertainty around inter-scenario differences, which drive decisions. U.S.–Canada trade tensions and abrupt federal termination of offshore wind permits threaten key planks of regional decarbonization plans and illustrate the need for models spanning a wider pathway space. We present PHASED (Probabilistic Hourly Assessment of Scenarios for Electrical Decarbonization), propagating correlated uncertainties across prescribed pathways through hourly dispatch over a 26-year horizon and generating joint posterior distributions across modeled outcomes. Applied to eight New England pathways, correlated uncertainty tracking yields >90% confidence in pairwise cost differences despite overlapping absolute cost intervals. Pathways with similar monetized impacts (roughly $470–477 billion by 2050) diverge on land use, avian mortality, and air quality. Rural areas receive greater relative air quality benefits than urban areas, cutting against assumptions that shape siting politics.

Keywords

integrated assessment model; discount rate; capacity expansion model; decarbonization; renewable energy; energy policy; cost-benefit analysis

1. Introduction

Decarbonization of the electrical sector is a central component of climate change mitigation strategies in the United States and internationally (IEA, 2021; NASEM, 2021). In the U.S., the policy landscape governing the relative viability of plausible energy pathways has faced unprecedented volatility since January 2025, requiring the development of more flexible approaches to screening a wider variety of technologies. Federal permitting for offshore wind has been disrupted through stop-work orders, permit rescissions, and a freeze on new approvals (The White House, 2025). U.S.-Canada trade tensions have created uncertainty over the political viability of long-term power purchase agreements and the tariff regime applicable to spot-market imports (Hernandez, 2025; United States Congress, 2026). In 2026, the governors of all six New England states issued a statement committing to explore advanced nuclear technologies including small modular reactors, marking a shift in regional attitudes toward nuclear power (Office of Connecticut Governor, 2026).

Capacity expansion models (CEMs) are widely used to identify generation portfolios that satisfy future demand while minimizing costs under technical and policy constraints such as emissions limits. However, even when extended or coupled with open-source impact screening tools such as COBRA, BenMAP, or AVERT, current approaches remain imperfectly suited to the emerging technical and social features of the energy transition. Many are deterministic and cannot capture uncertainties inherent to systems increasingly dependent on variable renewable energy (VRE) (IRENA, 2017; Ringkjøb et al., 2018). Probabilistic extensions typically treat pathway uncertainties as independent, mischaracterizing uncertainty in inter-scenario differences (the quantities most relevant for decision-making) (Calder et al., 2019; Reichert & Borsuk, 2005). Many approaches aggregate costs and benefits across space or time, limiting insight into intra-regional distributions of impacts (Gacitua et al., 2018; Poncelet et al., 2016). Finally, existing frameworks often do not support exploration of sufficiently broad, policy-relevant scenario spaces or capture how project-scale interventions propagate through the system to shape regional outcomes (Dagoumas & Koltsaklis, 2019; DeCarolis et al., 2017; Trutnevyte, 2016). Recent work has also argued that an over-reliance on decarbonization or renewable-portfolio targets in capacity expansion modeling can obscure broader socio-environmental trade-offs across competing energy pathways, motivating tools that explicitly screen these trade-offs alongside cost and reliability (Fitzgibbon, 2025). There have thus been recent calls for tools able to provide insights into tradeoffs at the local, project scale while using publicly available data, and for harmonized U.S.–Canada modeling capacity given the deep integration of the two systems (Calder et al., 2024; Fitzgibbon, 2025; Levin et al., 2023; Pfenninger, 2017).

We present an energy pathway impact screening model called PHASED (Probabilistic Hourly Assessment of Scenarios for Electrical Decarbonization) and apply it to the six-state New England region served by ISO New England (ISO-NE). New England is a timely case study because of (1) high exposure to policy instability (e.g., offshore wind permit cancellation, uncertain tariff environment) requiring greater capacity to rapidly screen costs and benefits of alternative energy scenarios and (2) intra-regional disagreement and debate over the magnitude and distribution of benefits and impacts of alternative energy pathways; the energy transition has been delayed by perceptions that rural regions bear environmental and cultural costs while urban

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areas receive disproportionate benefits from displaced fossil fuel generation (Buonocore et al., 2016; Campos Morales et al., 2024; Gazar et al., 2024; Kroot, 2020; Nolan & Rinaldi, 2020).

Key features of PHASED responsive to modeling gaps identified above include (1) the explicit representation of intra-regional hourly transmission and generator-specific operational constraints via generator-specific hourly capacity factors; (2) probabilistic representation of model inputs and outputs, including prior and posterior distributions of future hourly capacity factors of the existing generating fleet; (3) tracking of uncertainties correlated across scenarios, reducing uncertainty around inter-scenario differences rather than absolute costs; (4) flexible accounting of social costs associated with Canadian hydropower; and (5) a focus on comparing tradeoffs across prescribed scenarios that may have small differences in technical performance but large differences in social acceptability or viability. PHASED uses nationally available datasets, and we include here a U.S.-wide database of hourly probabilistic generation characteristics for fossil fuel generators derived from two decades of EPA Clean Air Markets Program data allowing application to other regions.

2. Methods

In previous work (Calder et al. 2022), we presented a model to screen an array of direct and indirect costs associated with alternative decarbonization pathways in New York State, which we used to evaluate the reasonableness of the price of electricity used in State cost-benefit models. We adapt that model here to include hourly rather than yearly temporal resolution, more realistic dynamics and operational constraints of the existing generation fleet, energy storage, and a wider array of ecological endpoints of interest.

2.1. Decarbonization pathways

We evaluate stylized alternative decarbonization pathways for New England to explore the bounds of likely costs and benefits over the period 2025 to 2050, summarized in Figure 1 and detailed in Supplemental Information (SI) Tables S1 (total build-out and retirement by 2050) and S2 (yearly schedule). These scenarios emerged from an iterative process of simulation and presentation/discussion with community groups (e.g., Clean Energy New Hampshire, Concord, NH) and academic audiences (Gazar, 2024a, 2024b). These discussions also informed our selection of

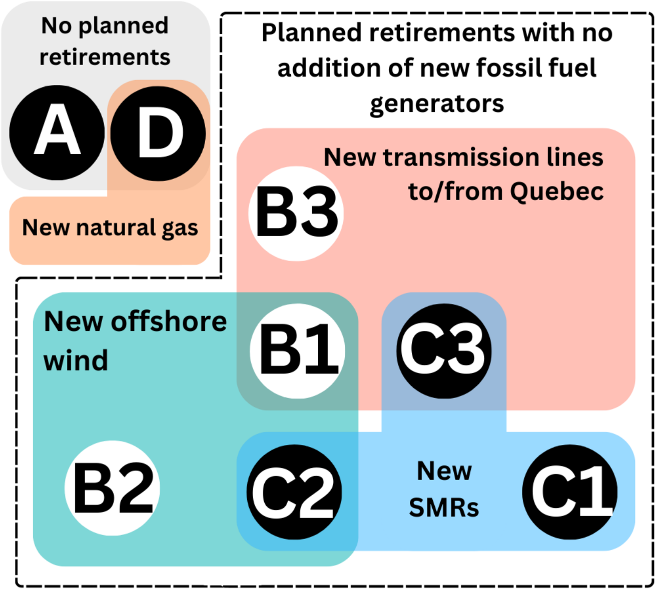

Figure 1: Euler diagram showing decarbonization pathways (circles) corresponding to different combinations of technologies (shaded rectangles). White circles show pathways considered by ISO-NE. Black circles show pathways unique to this study.

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ecological impacts of interest screened in Section 2.4. The authors retained ultimate authority on all modeling choices and inclusion or exclusion of scenarios and outcomes. All pathways assume the same hourly demand profile to 2050 (SI Section 2.2).

2.1.1. *Decarbonization pathway definitions*

We model select scenarios already proposed and evaluated by ISO-NE in order to (1) validate our methodology by comparing select endpoints shared between this analysis and analysis previously undertaken by ISO-NE and (2) provide more detailed information on the spatial and temporal distribution of costs and benefits for scenarios already known to be of interest. We also model scenarios not previously considered by ISO-NE but of interest to local stakeholders and/or the research community (e.g., implementation of small modular nuclear reactors).

Pathway A represents "status quo" where no new generation or transmission assets are built and demand is satisfied by dispatching existing resources. No generators are retired over the period of analysis. Pathways B1, B2, and B3 were proposed by ISO-NE as alternative pathways based on increased intertie capacity with Canada (constrained in B2) and increased offshore wind (constrained in B3). ISO-NE considers that new construction of hydroelectric generation capacity in Quebec (on the order of ~9 GW, according to recent estimates by ISO-NE) would be necessary to provide the level of exports from Quebec to NE in B3 (Commonwealth of Massachusetts, 2020).

Pathways C1, C2, and C3 are based on deployment of small modular nuclear reactors (SMRs), a pathway not currently envisioned by ISO-NE but of increasing interest to the public, advocacy organizations, policymakers, and other stakeholders. Recent developments such as partial reactivation of Three Mile Island in Pennsylvania to supply energy for a Microsoft data center and interest by other companies such as Amazon and OpenAI point to a likely future for SMRs, but these are not widely considered in other studies or in state/utility energy plans (Bowman, 2024; Castelvecchi, 2024; Gazar, 2023; L'Her et al., 2024; Vanatta et al., 2024). Scheduling of new generators is described in Section 2.1.3.

Pathway D considers construction of new natural gas plants and is not a scenario retained by ISO-NE but may nonetheless be plausible under certain changes in energy policy, for example, rescission or expiry of credits or incentives under the Inflation Reduction Act (Gerrard, 2024; Osaka, 2024; U.S. EIA AEO, 2023). We assume the following capacity build-up for this pathway includes 1.5 GW offshore wind, 5 GW onshore wind and 14 GW of solar PV. This pathway assumes addition of 20 GW of natural gas capacity with technical specifications drawn from CPV Towantic Energy Center combined cycle power plant located in Oxford, CT (nameplate capacity 565.5 MW), the most recently (operating started in 2018) constructed natural gas facility in New England.

2.1.2. *Scheduling of capacity retirements*

Across all pathways, we assume that existing large nuclear power plants and natural gas plants will be maintained through 2050. Pathways A and D have no retirements, following the U.S. EIA "No IRA [Inflation Reduction Act] Scenario". Details from this U.S. EIA scenario are included in SI Table S3.

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Pathways other than A and D consider likely retirements of existing generators over the period 2025 to 2050, including those already scheduled. This includes a complete phase-out of coal-fired power plants and the retirement of 75% of conventional oil-fired units, including dual-fuel facilities. This corresponds to the schedule established in ISO-NE's modeling assumptions in (Commonwealth of Massachusetts, 2020). We implemented the planned retirement of 75% of oil-fired units (5,250 MW) by 2030 by selecting the generators within the bottom 75% of annual capacity factors, likely corresponding to those with highest marginal costs, and taking them out of the mix at the end of 2030.

Additionally, plants are retired when they reach the end of their economic lifetime: 75 years for coal-fired plants, 45 years for wood-fired plants, and 55 years for other fossil fuel plants based on NREL's end of lifetime estimates for these plants (NREL, 2024). These ages are calculated based on data reported to the United States Environmental Protection Agency (U.S. EPA) Emissions & Generation Resource Integrated (eGRID) database and to the U.S. Energy Information Agency (EIA) via U.S. EIA Form 860 (U.S. EIA 860, 2023; U.S. EPA eGrid, 2022). Facility-specific retirement details are included in SI Table S4.

All eGRID, NREL, and EIA data used are available in the the GitHub repository.

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2.1.3. *Build-out of new assets*

Pathways B1, B2, and B3 are scenarios previously considered by ISO-NE (Commonwealth of Massachusetts, 2020). All include 12.05 GW of onshore wind, 16.37 GW of battery storage, and 64.28 GW of solar, but differ in offshore wind and transborder transmission assumptions: B1 adds 32.64 GW of offshore wind and 4.1 GW of new transborder transmission; B2 increases offshore wind to 41.80 GW without new transborder transmission; and B3 adds 28.43 GW of offshore wind and 6.0 GW of new transborder transmission. B3 also assumes construction of approximately 9 GW of new hydroelectric capacity in Canada to supply exports to New England, following ISO-NE's proposed linear development schedule from 2025 through 2045. We calculate associated CAPEX and FOM costs for these reservoirs using this schedule, scaled to imports to New England. The accounting boundaries for the two B3 hydropower variants are illustrated in SI Figure S1, and reservoir methane assumptions are provided in SI Table S9.

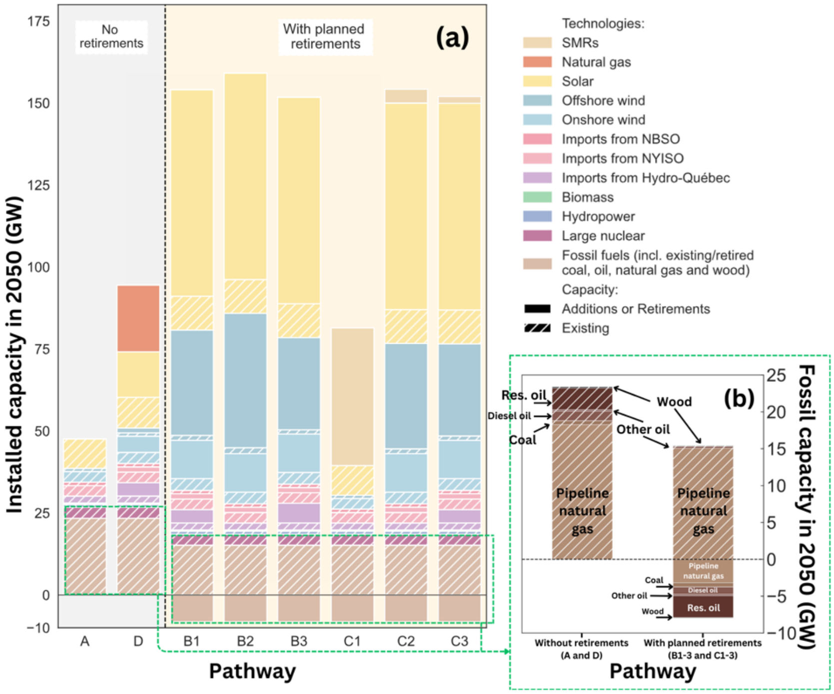

Figure 2: (a) Technology-specific installed capacities (status quo plus capacity additions and minus retirements) for pathways of interest for New England in 2050; (b) Fossil fuel capacities in 2050 for pathways B1, B2, B3, C1, C2 and C3 (scenarios with planned retirements) and A and D (scenarios with no retirements or new natural gas plants).

Pathways C1, C2, and C3 evaluate SMR-based alternatives to B1, B2, and B3. C1 follows B1's retirement schedule but substitutes SMRs for all new non-SMR capacity and transmission development, while C2 and C3 substitute SMR generation for expanded transborder transmission and offshore wind, respectively. We assume SMRs can enter service beginning in 2030, consistent with NREL technology assumptions and current deployment plans such as Ontario Power Generation's Darlington SMR project (NREL, 2024; OPG, 2025).

New pipeline natural gas generation in Pathway D is scheduled to come online in 2033 based on the timeline of CPV Towantic Energy Center. We consider that new natural gas must be developed in proximity to existing pipeline natural gas infrastructure, in an area well served by the existing electrical grid, and in a state without significant legal barriers. This analysis suggests that development is most likely within the counties of Fairfield, Hartford, Middlesex, New

Haven, New London, and Windham (CT); Newport, Providence, and Washington (RI); and Rockingham and Strafford (NH). We calculate impacts of new natural gas in Pathway D probabilistically, drawing from county-specific marginal air pollutant damage tables (Section 2.3.2) across these counties with a uniform distribution.

The composition of generation portfolios of all Pathways by 2050 is represented in Figure 2(a), and the breakdown of fossil fuel generation is represented in Figure 2(b).

2.2. Generation model (PHASED)

We developed a mathematical framework to calculate how generation resources are dispatched under each Pathway described in Section 2.1. Hourly utilization of each generator is then cross-referenced with direct costs and certain monetized impacts (Section 2.3) and other non-monetized environmental impacts (Section 2.4). Because the core of the generation model was previously published in Calder et al. (2022), we provide here a conceptual description and include full lists of equations and tables of parameters and intermediate outputs in SI Sections 2.1–2.7 and SI Table S5. A diagram of how all model inputs and outputs fit together is provided in Figure 3.

Hourly electrical demand through 2050 for results presented here is the “High Electrification” pathway from ISO-NE obtained pursuant to a request made under the MA Public Records Act. Hourly demand is represented as 227,880 timesteps for the period from Jan 1, 2025 to Dec. 31, 2050. The model supports less computationally intensive runs based on selected time periods, but results presented here are for the full model run. Details on demand forecast data are provided in SI Section 2.2.

For an hourly timestep, demand is satisfied first by available local low-carbon generation with near-zero marginal cost (hydropower, nuclear, small modular nuclear, biomass, solar, and onshore and offshore wind) (SI Section 2.3) or long-term imports from Quebec associated with increasingly common long-term purchase agreements with hourly import commitments (Pathway B3) (SI Section 2.5). If generation is less than demand, then fossil fuel resources are dispatched in increasing order of marginal cost, within the constraints of availability and ramping ability (SI Section 2.6). Perfect foreknowledge of demand by the model ensures that ramp constraints are respected. This model architecture emulates day-ahead pricing and week-ahead planning in electricity markets that consider factors such as weather conditions and other technical constraints (ISO-NE, 2024). If local low-carbon, long-term contractual imports (Pathway B3), and fossil generation together do not satisfy demand, then spot-market imports with higher

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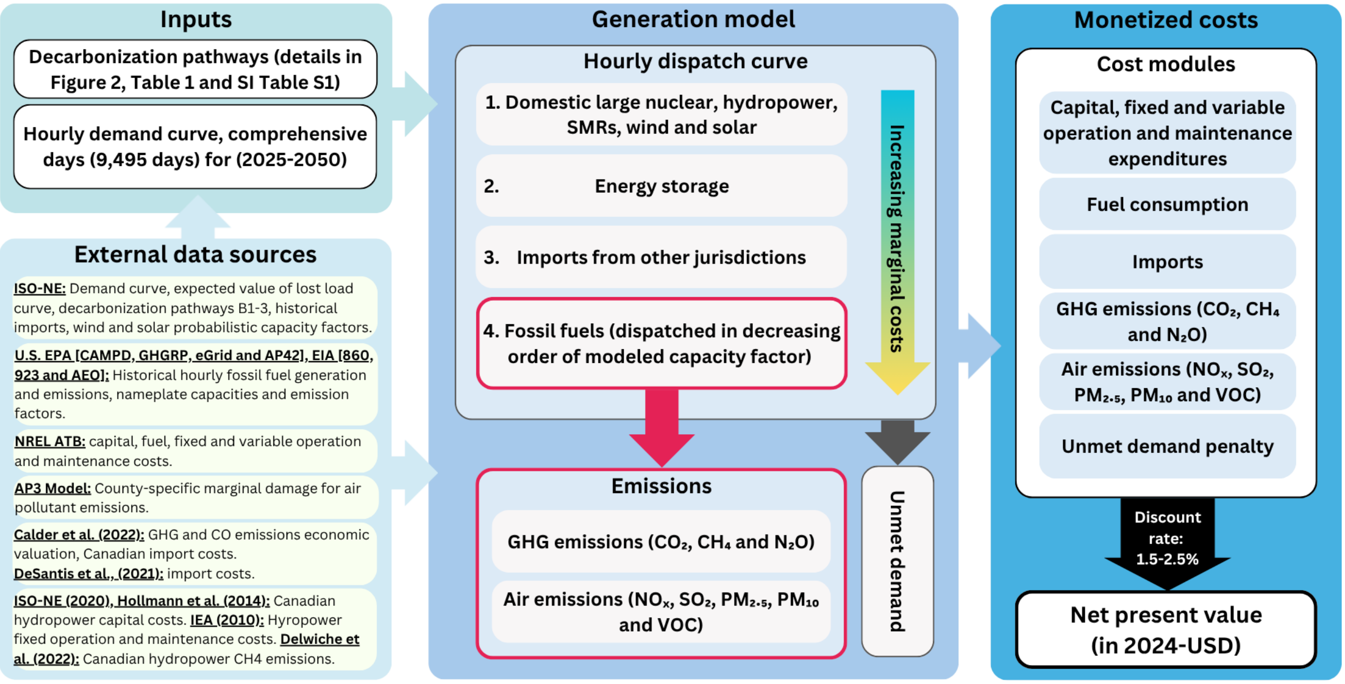

Figure 3: Relationships between data sources, decarbonization pathway and demand curve inputs, mathematical generation model, and monetized cost categories. Fossil fuel generators and air emissions are spatially resolved. Pathways are also cross-referenced with select other ecological impacts (Section 2.4). The modular setup of the PHASED model and use of nationally available data allows for other impacts to be added or for the model to be applied to other regions of the United States.

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marginal costs from other jurisdictions (ISO-NE, NYISO, Hydro-Québec) (SI Section 2.5) are introduced. If demand is exceeded by hourly generation, batteries are charged (SI Section 2.4). Modeling fossil fuel generation output and exchanges with other regions using historical ranges presents the advantage of capturing diverse transmission and availability constraints that are otherwise difficult to parameterize. The corresponding dispatch, storage, import, fossil-generation, curtailment, and unmet-demand equations are provided in SI Sections 2.3–2.7.

Uncertainty in future hourly utilization of fossil fuel, wind, and solar assets is modeled by way of Monte Carlo analysis. ISO-NE provides joint hourly probability distributions for capacity factors of solar and offshore and onshore wind on its territory, accounting for correlations between them and across time. Likewise, we create hourly probability distributions for capacity factors and CO_2, NO_x, and SO_2 emissions fossil fuel generators using the U.S. EPA Clean Air Markets Program Data (CAMPD) for the period 2013–2023. We do this for 4,633 generating units at 1,379 electric utility generating facilities across the United States, which we include here, but this model uses only data from 240 generators (90 facilities) in New England. CO, N_2O, PM_{10}, $PM_{2.5}$, and VOC emissions are determined by technology-specific (not generator-specific) emissions factors. Facility-level probabilistic sampling and the national fossil-fuel generator database are described in SI Sections 2.6.3 and 5.

Modeling battery storage is crucial for capturing the dynamics of decarbonized energy systems, yet it is not included in many capacity expansion models such as US-REGEN (Gacitua et al., 2018). However, an increasing number of models are recently integrating storage in their new releases. Recognizing this gap and emerging trend, we incorporate long-duration energy storage (LDES) to achieve zero-carbon grid goals by cost-effectively integrating renewables, enhancing grid reliability, and reducing overall system costs (Levi et al., 2023). Although we use specifications for an 8-hour lithium-ion battery, corresponding to a capacity factor of approximately 33.3%, we assume the storage system can retain its capacity for durations beyond 8 hours. This assumption enables the exploration of LDES potential but may lead to underestimating cost benchmarks and performance assumptions outlined in the ATB (Levi et al., 2023).

The dispatch model is described in more detail in SI Sections 2.3 (low-carbon generation), 2.4 (battery storage), 2.5 (imports), 2.6 (fossil fuel generation and emissions) and 2.7 (curtailments and unmet demand). Monte Carlo analysis is described in SI Section 3.

2.3. Direct costs and monetized environmental impacts

Build-out of new infrastructure (main text Section 2.1) and fixed operational and maintenance and marginal operational and fueling costs of all generation infrastructure are cross-referenced with direct cost tables (Section 2.3.1) and generator-specific emissions tables, which are then cross-referenced with emissions valuations (Section 2.3.2). Hours where available resources cannot satisfy demand are assigned an unmet demand penalty (Section 2.3.3). All costs are expressed in 2024-USD based on the Bureau of Labor Statistics Consumer Price Index (CPI) (U.S. Bureau of Labor Statistics, 2024). The model supports diverse discount rates, but results presented here use a discount rate of 2% based on the 2023 revisions to Office of Management and Budget (OMB) circular A-4 (Office of Management and Budget, 2023). This relatively low rate is appropriate because greenhouse gas emissions are valued using Social Cost of Carbon estimates, which are intended to reflect long-run climate damages and are commonly paired with relatively low discount rates in recent policy guidance. This approach is also consistent with prior state-level guidance used in decarbonization policy analysis, including New York State guidance (New York State Department of Environmental Conservation, 2021). We perform a sensitivity analysis using discount rates of 1.5% and 2.5%.

2.3.1. *Direct costs*

Direct costs include capital expenditures for new generation (CAPEX), fixed operations and maintenance (FOM), variable operations and maintenance (VOM) and fueling. CAPEX includes costs of land acquisition, though direct land requirements (in km^2) are also calculated separately as described in Section 2.4. Direct costs are based on the NREL ATB and are calculated probabilistically by pooling cost pathways into a uniform distribution. Costs for new interties with Quebec (Pathways B1, B3, C3 and D) are based on values pooled by Calder et al. (2022). Full methods for calculating direct costs for new and existing generation are provided in SI Section 2.8 and SI Table S6.

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2.3.2. *Greenhouse gases and air pollutants*

As described in Section 2.2, hourly fossil-fuel generation is linked to generator- or technology-specific emissions factors for greenhouse gases (CO_2, CH_4 and N_2O) and air emissions (SO_2, NO_X, VOC, $PM_{2.5}$ and PM_{10}).

Greenhouse gas emissions are monetized using the Social Cost of Carbon using rate schedules corresponding to the discount rate retained for the global analysis (default of 2% presented here). Nominal values for 2025 are \$253.71 tonne-CO_2^{-1}, \$2,423.48 tonne-CH_4^{-1} and \$72,126.48 tonne-N_2O^{-1} in 2024 USD, escalating over time (U.S. EPA, 2023). In a sensitivity analysis where methane emissions from new Canadian hydropower are valued (Pathway B3(2)), the value for CH_4 is also applied. Full methods for valuation of greenhouse gas emissions are supplied in SI Section 2.11 with fuel-specific emissions factors summarized in SI Table S7 and reservoir methane assumptions in SI Table S9. Alternative methods for accounting for Canadian hydropower are supplied in SI Section 2.10.

Air pollutant (NO_x, SO_2, $PM_{2.5}$, PM_{10} and VOC) emissions are cross-referenced with facility-specific monetary costs for marginal emissions from the APEEP AP3 model (Muller, 2022). This model calculates premature fatalities associated with marginal increases in emissions from stacks of different heights and calculates a corresponding economic value based on a prescribed Value of a Statistical Life (VSL). Results presented here use the default VSL value of \$11.4 million (2024-USD) per premature fatality (Office of Management and Budget, 2023). We used EIA Form 860 data to determine stack height and county for each facility. We also divide total cost by the VSL to determine total fatalities. Since the AP3 model does not provide economic valuations for CO, we used the estimates from Calder et al. (2022), which range from \$2.5 to \$2,400 tonne^{-1} (uniform distribution) (2024-USD Air-pollution damage calculations are described in SI Section 2.12; fuel-specific emissions factors are summarized in SI Table S7, and facility-specific marginal air-emission costs are reported in SI Table S8.

2.3.3. *Unmet demand penalty*

In our sequential (hour by hour) feasibility dispatch, renewable availability factors and import capability factors are drawn exogenously from the Monte Carlo random stream (one draw per hour for each technology and intertie) and are not adaptively increased in response to shortages; conditional on these realizations, carbon-free generation and imports serve demand first, storage discharges only when carbon-free generation plus imports are insufficient, and (with charging restricted to surplus carbon-free and importst) storage charges only from surplus low-carbon generation and imports; while the model supports optional grid charging from thermal output, all results presented here use curtailment-only charging. Fossil generation is then scheduled to cover any remaining residual demand subject to hourly capacity limits and ramp feasibility adjustments that can shift some fossil output earlier than the hour of need; any resulting must-run surplus is accounted for as curtailment in the energy balance (that is, it is not used to charge storage under our baseline assumptions). After all available resources have been dispatched, any excess demand is assigned an unmet demand penalty of \$3,500 based on ISO-NE guidance. The pay-for-performance rate and value-of-lost-load curve used to parameterize unmet-demand costs are shown in SI Figure S2. Because the generation model has perfect foresight, it ramps up fossil

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fuel generators to minimize total unmet demand. Unmet demand is explained in more detail in SI Section 2.13.

2.4. Non-monetized ecological impacts

Beyond GHG and other air emissions with robust, widely used tools for monetization (described in SI Section 2), we screened pathways by impact on several other ecological and land-use endpoints. These endpoints are identified as highly relevant to local decision-makers and the public emerging from stakeholder engagement activities described in main text Section 2.1 and include land use needs, avian mortality, and water use, and viewshed impacts. We did not identify widely used monetization or valuation frameworks for these endpoints, so we consider monetization to be beyond the scope of this work. Table 1 lists the range of impact for each technology with available references; where estimates are pooled from multiple studies, individual studies are tabulated in the indicated SI tables. Impacts that are unique to one technology studied (e.g., nuclear waste disposal) or whose outcomes cannot be reported in common units are not compared. The modular and extensible setup of the model allows for addition of other impacts, application to other geographic areas, or modifications to the assumptions retained here. While our method of calculating CAPEX (Section 2.3.1) includes direct costs of land acquisition for new generation and transmission, we calculate land use requirements separately here as a proxy for the potential complexity of land acquisition, stakeholder engagement, environmental assessment, and other features that have implementation of land-intensive projects.

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Table 1: Ecological impacts and resource requirements of selected energy generation technologies. Data reported in each citation are used to fit best representation of uncertainty.

Technology	Impact point estimate or distribution	Unit	Citations
Bird and bat mortality			
On-shore wind	Gamma ($\alpha=0.20$, loc=0, $\theta=2.54$) Gamma ($\alpha=1.538$, loc=0, $\theta=4.160$)	bird deaths MW^{-1} year^{-1} bat deaths MW^{-1} year^{-1}	(Allison & Butryn, 2020b) (Allison & Butryn, 2020a)
Solar	Lognormal ($\mu=\log(1.214)$, $\sigma=1.409$)	bird deaths MW^{-1} year^{-1}	(Kosciuch et al., 2020)
Land use			
Hydropower reservoirs	Uniform (43.1, 146.7)	hectares MW^{-1}	SI Table S9
Natural gas	0.032[a]	hectares MW^{-1}	(PowerTechnology, 2018)
On-shore wind	Gamma ($\alpha=3.695$, $\theta=9.382$)	hectares MW^{-1}	(Denholm et al., 2009)
Small modular nuclear	0.017[b]	hectares MW^{-1}	(ENTRA1 Energy, 2025)
Solar	Gamma ($\alpha=4.25$, $\theta=0.82$)	hectares MW^{-1}	(Ong et al., 2013)
View shed			
High-voltage transmission	≤ 27[a]	km	(Sullivan et al., 2014)
Off-shore wind	≤ 40[a]	km	(Sullivan et al., 2013)
Solar	≤ 5[a]	km	(Robert Sullivan & Jennifer Abplanalp, 2013)
Water withdrawals for thermal generation			
Natural gas (dry-cooled)	Uniform (15, 50)[b, c]	gal MWh^{-1}	(PowerTechnology, 2018; Wu & Peng, 2011)
Small modular nuclear (water-cooled)	740[d]	gal MWh^{-1}	(Idaho National Laboratory, 2018)

[a] Maximum visibility distance assuming flat terrain, visibility drops off sharply with terrain/vegetation

[b] Based on recently developed CPV Towantic Energy Center, Oxford, Connecticut

[c] 90% less that of wet recirculating [wet recirculating tower cooling estimate = 150-500 gal MWh^{-1} (Wu & Peng, 2011)]

[d] Based on recently tested NuScale technology in Oregon State University, Corvallis, Oregon

2.5. Modeling environment and infrastructure

The model was implemented in R (version 4.5.0) within the RStudio (version 2024.12.1+563) integrated development environment on Virginia Tech's ARC resources (ARC, 2025; R Core Team, 2025; RStudio Team, 2020). Model simulations were executed on ARC's shared high-performance computing cluster using a Singularity containerized R environment, with each run allocated a single compute node comprising 50 parallel tasks and a 24-hour wall-time limit. This configuration enabled efficient execution of the probabilistic simulation ensemble while ensuring reproducibility and consistent software dependencies across runs. High-resolution hourly outputs from the full ensemble of probabilistic simulations were archived using ARC project storage, with approximately 2.5 TB required at peak usage, enabling detailed post-processing, validation,

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and uncertainty analysis. Probabilistically distributed parameters described above were sampled within Monte Carlo simulations (1,000 trials for each decarbonization pathway, ~15 minute compute time for each trial) that tracked correlations in uncertainties (1) between model parameters (e.g., years with lower wind potential having higher solar potential); and (2) between pathways (e.g., a model run with relatively lower wind output has this lower wind output captured in all pathways, minimizing uncertainties in differences across pathways). This provides robust characterization of uncertainty while minimizing the uncertainty around output that drives decision-making (e.g., differences in total costs between pathways). Posterior distributions for all generation and imports as well as direct and indirect costs were saved for each pathway over the model timeframe 2025-2050. Input correlations are encoded in a covariance matrix spanning hourly load, wind, solar, and import priors. The mean vector, covariance matrix, and random-seed values are saved with each run, and a correlation heatmap and driver-attribution analysis are provided in the SI (SI Figures S5 and S6). Results are visualized using R (R Core Team, 2025) and Python (Van Rossum & Drake Jr, 1995). All data, code, and a comprehensive guide (Reproduction Information) for reproducing the study are provided in the SI. All eGRID, NREL, and EIA data used are archived on storage managed by Virginia Tech Advanced Research Computing (ARC) and are available in the SI.

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3. Results and discussion

3.1. PHASED model accurately represents the dynamics of a decarbonized power system

PHASED captures operational dynamics in a decarbonized power system at hourly resolution, illustrated in Figure 4 for a January 2050 winter wind lull and peak demand event under pathway B1. During this period, the model tracks how insufficient wind generation is mitigated or not through storage, imports, and remaining dispatchable generation. Canadian hydropower imports are dispatched similarly to storage, subject to explicit hourly transmission constraints and assumptions about long-term baseload contracts versus demand-responsive imports. Each simulation required approximately 15 minutes, and costs are summarized across 1,000 simulations over 2025–2050 using means and 90% confidence intervals, with additional model behavior shown in SI Figure S3. By representing hourly operational constraints and tracking correlated uncertainties across parameters and pathways, PHASED separates uncertainty in absolute outcomes from uncertainty in inter-scenario differences, which are more directly relevant to decision-making.

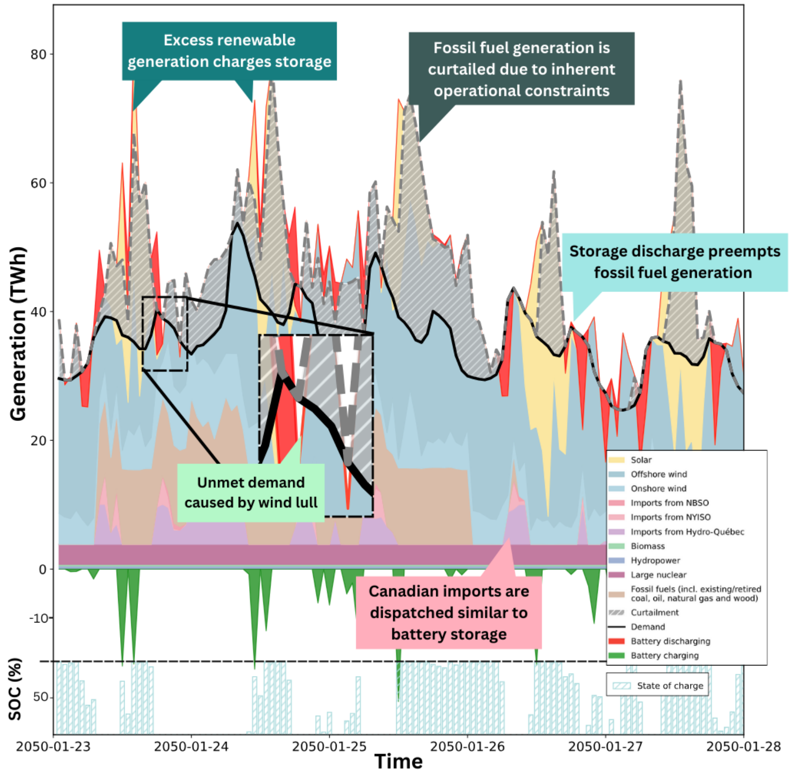

Figure 4: Winter wind lull and peak annual demand model results for pathway B1 (Simulation #1, 23rd to 28th January 2050).

3.2. Model validation, correlated uncertainty performance, and multi-impact monetization

PHASED broadly reproduces overlapping ISO-NE scenarios: deterministic validation against ISO-NE/MA Roadmap generation trajectories is shown in SI Figure S4, and for B1 ('All Options'), mean direct costs are similar despite ISO-NE's use of category-specific discount rates rather than the uniform 2% rate used here (e.g., ISO-NE \$355 billion vs. PHASED \$343 billion 2024-USD; SI Tables S11 and S13). Figure 5 reports pathway NPVs for New England at a 2% discount rate, including indirect cost categories not monetized by ISO-NE, such as GHG and air pollutant damages; full cost-category results, including scenario A ("status quo"), are provided in SI Tables S10–S12. Scenario A is omitted from Figure 5 because absence of new capacity produces prohibitive unmet-demand costs and unreliable grid performance.

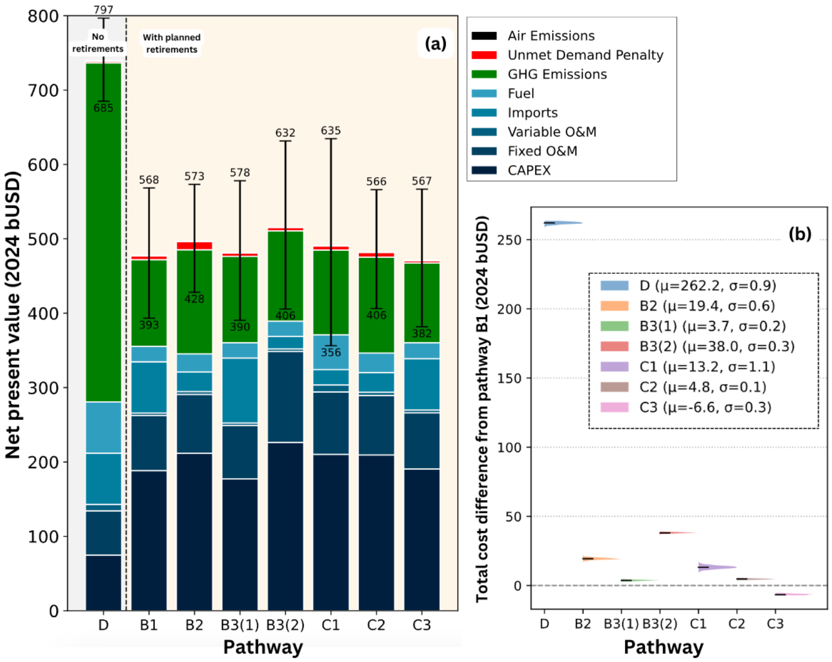

Figure 5: **a)** Comparison of NPVs across all decarbonization pathways in New England (discount rate 2%). B3(1) corresponds to Pathway B3 with import-cost accounting, and B3(2) replaces import costs with prorated Canadian hydropower CAPEX, fixed O&M, and reservoir methane damages (SI Section 2.10; SI Figure S1). The whisker lines represent the 90% CI. **b)** Horizontal ridgeline plot showing normalized distributions of NPV differences (2024 bUSD) for each pathway relative to B1, across all uncertainty draws. Horizontal bars marking the mean (μ) and standard deviation (σ) for each distribution.

Among monetized costs, C3 (SMR-based pathway) has the lowest mean NPV (\$471 billion), slightly below B1 (\$477 billion), while D has the highest mean NPV (\$740 billion). C1 is slightly more costly than B1 (\$491 billion; 90% range: \$356–\$635 billion), and B2 and C2 have mean NPVs of \$497 billion and \$482 billion, respectively. B3 is evaluated under the two accounting methods described in SI Section 2.10: B3(1) has a mean NPV of \$481 billion, while B3(2) rises to \$516 billion when import costs are replaced by CAPEX, fixed O&M, and methane emissions from new Canadian hydroelectric reservoirs. GHG outcomes also differ sharply: D has 290% higher GHG emission costs than B1, whereas C3 has the lowest GHG emission costs, approximately 30% below pathway A.

Discount-rate assumptions strongly affect pathway comparisons: the total-cost NPV difference between D and B1 is \$132 billion at 2.5%, \$262 billion at 2%, and \$502 billion at 1.5% (2024-

USD). Figure 5 further shows the value of tracking correlated uncertainties: absolute cost intervals overlap in panel (a), but pairwise difference distributions in panel (b) are narrow and never span zero (e.g., C3 vs. B1: μ = -\$6.6 billion, σ = \$0.3 billion; B2 vs. B1: μ = \$19.4 billion, σ = \$0.6 billion). This indicates that NPV uncertainty is driven mainly by parameters shared across pathways, such as fuel prices, weather-driven generation, and Social Cost of Carbon assumptions, rather than pathway-specific uncertainties such as SMR costs. The corresponding correlation structure and driver-attribution analysis are shown in SI Figures S5 and S6.

3.3. Pathways with small differences in total costs and technical performance can exhibit major differences in regional distribution of impacts and benefits

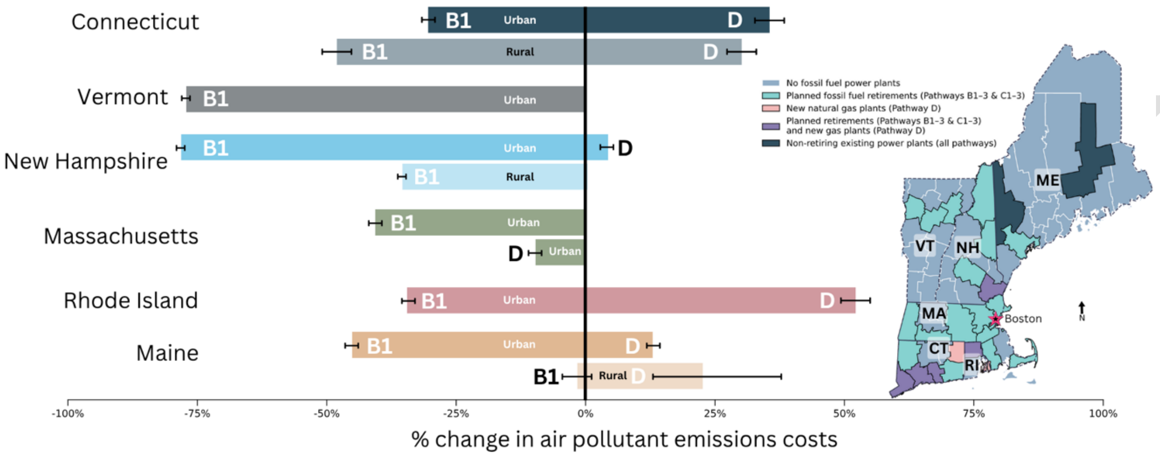

Figure 6: Intraregional distribution of changes in monetized air-pollution damages relative to pathway A. Damages are reported as NPV of future health damages using a 2% discount rate. Bars show percentage changes in average monetized air-pollution damages for rural and urban areas in each state; horizontal bars show 90% CIs. Rural and urban areas are classified using USDA Rural-Urban Continuum Codes (USDA, 2024). Monetized costs are calculated using the AP3 model as described in Section 2.3.2.

Figure 6 compares the intraregional distribution of monetized air-pollution damages for pathways B1 and D relative to pathway A. Emissions are translated into county-level health damages using AP3, monetized using a VSL-based framework, and reported as NPV under alternative discount rates. SI Tables S14, S15, and S16 present county-level monetized air-pollution damages (millions 2024-USD) discounted at 1.5%, 2%, and 2.5%, respectively.

We observe that, across New England, counties in rural states see greater relative reductions in monetized air-pollution damages under decarbonized pathways, challenging the perception that these benefits accrue to more urbanized Massachusetts (Kroot, 2020). For instance, in Maine, rural and urban areas experience increases in air quality impacts under pathway D, whereas we see significant benefits under pathway B1. Conversely, Massachusetts shows notable urban emission cost reductions under both pathways. For instance, Barnstable County, MA experiences a dramatic drop in air pollutant damages from \$20 million 2024-USD in pathway A to just \$5 million 2024-USD in pathway B1, whereas pathway D remains high at \$19 million 2024-USD, indicating substantial benefits from pathway B1. Moreover, Cumberland County in Maine

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experiences air pollutant cost reductions under pathway B1 (NPV from \$88 to \$36 million 2024-USD) but faces slightly higher costs under pathway D (NPV \$90 million 2024-USD).

These spatially variegated results align with insights from recent literature. Calder et al. (2022) emphasized that regional transmission infrastructure investments can reduce total social costs associated with air pollution and mortality, especially in counties historically burdened by these impacts. Similarly, Campos Morales et al. (2024) highlighted the necessity for spatially detailed retirement strategies that integrate social and environmental justice considerations, reinforcing the importance of using spatially explicit models.

Furthermore, as shown in Figure 7 (and SI Table S17), ecological impacts vary distinctly across decarbonization pathways, driven by differences in technological strategies. Pathways with higher reliance on solar and wind (e.g., B1-3) involve significant avian mortality area impacts (panel a) and overall land-use changes (panel b), whereas pathway C1, primarily leveraging SMRs exhibits the lowest ecological footprint across categories except for water withdrawals. Pathway B3 notably presents the highest land-use change (panel b), reflecting substantial siting requirements for new reservoirs. Conversely, water consumption (panel d) peaks dramatically under pathway C1 due to SMR deployment, emphasizing critical tradeoffs between land impacts and water resource demands. Consideration of specific design and/or siting decisions would narrow these uncertainties significantly.

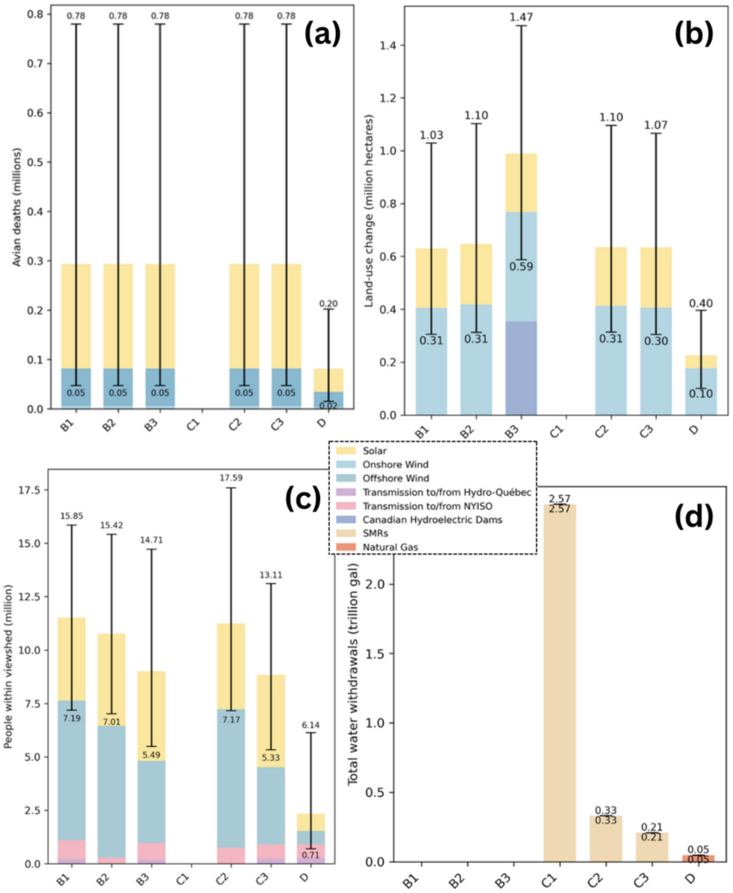

Figure 7: Ecological impacts across decarbonization pathways: (a) additional forest area impacted (million hectares), (b) total land-use change (million hectares), (c) population residing within affected watersheds (million people), and (d) total water withdrawals for thermal generation (trillion gallons). The horizontal bars in all panels show the 90% CI.

4. Conclusions

This work has developed an extensible model using nationally available data sets that can be expanded in scope and/or applied to other geographic regions. For example, as described in

Section 3.2, direct costs can be further elucidated by adding finer-scale investments in transmission infrastructure associated with different scenarios. To this end, we have developed and included in the SI (Section 5) a U.S.-wide database of fossil fuel generators with hourly-scale probabilistic generation characteristics.

The modular and probabilistic setup facilitates representation of hypothetical technologies represented here by analysis of SMRs. Future work may analyze tradeoffs associated with uptake of other rapidly emerging technologies such as long-duration energy storage or hydrogen-based energy systems. Likewise, this framework could be applied to different hourly-scale demand curves (for example, higher or more variable demand curves driven by proliferation of technologies such as data centers or quantum computing). Other tradeoffs or impacts can be considered, beyond those demonstrated by the select ecological and other impacts modeled in Section 3.3. Other nationally available models and datasets are available and can be added to this model setup, for example, NREL's Jobs and Economic Development Impact (JEDI) Models (NREL, 2015).

Many incumbent models overlook not only the uncertainties attached to alternative decarbonization pathways, but the correlated structure of those uncertainties. This analysis has shown that accounting for correlations in uncertainties provides much firmer estimates of the benefits of any one decision relative to a base case. More analysis is needed to understand how policymaker and public risk preferences intersect with these differences. Notably, SMR-based pathways appear to have overall direct and total social costs less than pathways analyzed by ISO-NE, but the uncertainties and maximum plausible (e.g., 90th percentile) costs are higher (e.g., pathway C3). As described in Sections 2.5 and 3.1, the model is set up to capture correlations across sources of uncertainty between pathways and between model parameters and hence provides a robust basis for such future analyses.

5. Ethics declaration

The authors declare no competing interests.

6. Data and computer code availability statement

Computer code, datasets, reproduction information document, national (U.S.-wide) database of hourly-scale probabilistic generation characteristics for fossil fuel power plants are available via GitHub. For the latest updates, visit this project's GitHub page.

7. Author contribution statement

A.M.G. contributed to conceptualization, data collection, data analysis, methodology, visualization, computer code development and manuscript development (drafting, reviewing, and editing).

C.J. contributed to manuscript development (reviewing, and editing),

G.M. contributed to funding acquisition, manuscript development (reviewing, and editing).

R.B.H. contributed to conceptualization, funding acquisition, manuscript development (reviewing, and editing).

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R.S.D.C. contributed to conceptualization, funding acquisition, data analysis, visualization, computer code development, manuscript development (drafting, reviewing, and editing), management and supervision.

8. Acknowledgements

The authors acknowledge U.S. Environmental Protection Agency (grant number RD840558 awarded to R.C.) for sponsoring this project. The authors thank Sam Evans-Brown at Clean Energy NH for engagement in scenario development. The authors acknowledge Advanced Research Computing at Virginia Tech for providing computational resources and technical support. URL: https://arc.vt.edu/

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