Probabilistic analysis of ecological, economic, and health tradeoffs of decarbonization pathways for New England, USA

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Abstract

Advocates, researchers and policymakers seek characterizations of tradeoffs from diverse decarbonization pathways beyond outputs of optimization models and robust quantification of uncertainties. We develop and apply to New England, U.S.A. an hourly-scale probabilistic model accepting portfolio decisions and electricity demand as inputs and simulating costs and impacts through 2050. A pathway incorporating small modular reactors lowers total social costs but increases cost uncertainties compared to the reference "High Electrification" pathway currently pursued by policymakers ($470 ± 97 billion vs. $477 ± 87.5 billion by 2050). All decarbonization pathways have costs and uncertainties in the same order of magnitude but vary dramatically across the ecological and health impacts that drive public attitudes (e.g., land use varies from negligible to 9,890 km^2). Tracking uncertainties correlated across pathways improves decision support (e.g., >90% confidence that constraining transmission with Canada increases costs by ≥ $19.4 billion despite overlapping 90% CIs for absolute costs).

Keywords

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

1. Introduction

Decarbonization of the electrical sector by 2050 is a key component of plans to constrain global temperatures to within 2ºC of preindustrial averages (IEA, 2021; NASEM, 2021). Meanwhile, population growth and electrification of other sectors such as transportation is likely to increase energy demand by roughly 900 to 2700 TWh $year^{-1}$ over the same period in the United States alone (NREL, 2018). In the U.S. and elsewhere, decarbonization is stimulating the planning and construction of diverse generation and transmission assets. Yet, controversies and opposition at the project scale have demonstrated a need for better information on local, regional, and global tradeoffs and the spatial distribution of costs and benefits of alternative pathways (Calder et al., 2024; Mongird & Rice, 2024).

Capacity expansion models (CEMs) generally seek to identify generation portfolios that satisfy future demand while minimizing direct costs subject to technology-specific constraints and other criteria such as capping greenhouse gas (GHG) emissions. Yet, currently available CEMs are imperfectly suited to the emerging technical and social features of the energy transition because they variously (1) represent storage using temporally aggregated chronologies or simplified operating constraints, which can misrepresent the reliability value of storage and multi-day scarcity dynamics (Kuepper et al., 2022; Levi et al., 2023; Levin et al., 2023; Mantegna et al., 2024; Matz, 2023); (2) are generally deterministic and hence cannot capture inherent uncertainties in a system increasingly dependent on variable renewable energy (VRE) generation (e.g., wind and solar) (IRENA, 2017; Ringkjøb et al., 2018); (3) do not simulate the spatial and temporal distribution of costs and benefits of alternative pathways, for example, simulating a "sample day" in the future or aggregating generation at the regional level (Gacitua et al., 2018; Poncelet et al., 2016); and (4) do not support exploration of a diverse range of pathways beyond those emerging from optimizations with relatively narrow objective functions that focus primarily on cost minimization rather than probabilistic trade-off evaluation (Dagoumas & Koltsaklis, 2019; DeCarolis et al., 2017; Trutnevyte, 2016). There have thus been recent calls for tools detailed enough to provide insights into tradeoffs at the local, project scale while using publicly available data and allowing for uptake by a broad range of researchers, advocates, and policymakers (Calder et al., 2024; Levin et al., 2023; Pfenninger, 2017).

Recent work has coupled the results of CEMs with open-source impact screening models such as the CO-Benefits Risk assessment, Health Impacts Screening and Mapping Tool (COBRA) (Rodgers et al., 2018, 2019), Environmental Benefits Mapping and Analysis Program (BenMAP) (Campos Morales et al., 2024), or AVoided Emissions and geneRation Tool (AVERT) (Kan et al., 2020). However, such coupled approaches provide an incomplete basis for decision-making because they do not (1) control for uncertainties correlated across decision pathways (thereby overestimating uncertainties if run probabilistically or underestimating uncertainties if run deterministically) (Calder et al., 2019; Reichert & Borsuk, 2005); (2) characterize the distribution of benefits and costs at the local, intra-regional level (Campos Morales et al., 2024; Pfenninger et al., 2014); or (3) describe how project-scale interventions (e.g., new or decommissioned facilities or changes to operational regimes of individual facilities) may affect the energy system as a whole (i.e., regional equality) (Sasse & Trutnevyte, 2020). In general, there is a gap between (1) regional-scale capacity expansion models, which calculate costs and

benefits aggregated across time and/or space, and which guide procurement and planning decisions, and (2) the need for characterizations of tradeoffs associated with individual projects and with diverse portfolios, which often generate disagreement and which delay decarbonization.

In this work, we present the Probabilistic Hourly Assessment of System Electricity (PHASE) model, a novel probabilistic multi-impact assessment framework to analyze economic, environmental, and health tradeoffs of hypothetical decarbonization pathways for the electrical system over the period 2025-2050. This model propagates correlated uncertainty in generation, imports, and impacts to compare prescribed decarbonization pathways rather than perform cost-minimizing optimization. Other key features 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, for example, both prior and posterior distributions of future hourly capacity factors of the existing generating fleet; (3) tracking of uncertainties that are correlated across pathways to reduce uncertainty around pathway comparisons (Reichert & Borsuk, 2005); (4) flexible representation of social costs associated with Canadian hydropower such as environmental externalities (either within the U.S. based on import costs or globally based on costs associated with operation and construction of reservoirs in Canada); and (5) a focus on comparing tradeoffs across prescribed pathways that may have small or localized differences in technical performance but large differences in social acceptability or viability.

This work complements traditional CEMs by characterizing absolute and relative impacts probabilistically, modeling a wider array of outcomes of interest, and providing granular spatial resolution, for example, calculating generator-specific air pollutant emissions. Several existing CEMs (e.g., GenX, PyPSA, Switch 2.0) endogenously model generator operations, including dispatch and unit commitment, but typically rely on exogenously specified, deterministic availability limits for generators, which may overlook forced outages, weather-linked unavailability, and correlated availability uncertainty (Brown et al., 2018; Johnston et al., 2019; Sepulveda et al., 2018). By contrast, our framework differs by explicitly representing probabilistic, generator-specific hourly availability to preserve correlated uncertainty across pathways based on historical performance data. Likewise, integrated assessment models (IAMs) and general-equilibrium models (GEMs) calculate, respectively, cross-sector tradeoffs (Weyant, 2017) and economy-wide feedbacks (including demand responses) (Nasirov et al., 2020) but often operate at coarse sectoral/temporal/spatial resolution relative to power-system operations. Unlike GEMs, this work treats demand forecasts as stable inputs, following the methodology of most CEMs. Recent work has demonstrated the benefits of coupling CEMs and GEMs (Nishiura et al., 2024); this work seeks to advance this literature by (1) expanding the range of impacts considered; (2) leveraging empirical generation data to characterize uncertainties in simulation of counterfactual grid configurations; and (3) demonstrating the decision support benefits of tracking correlations in uncertainties across and within pathways. Stochastic optimization has been applied in capacity-expansion contexts such as the GenX fusion-energy study; our contribution extends these probabilistic methods using a stochastic framework that jointly quantifies uncertainty across economic, ecological, and health impacts.We apply this model to

the setting of the six U.S. states of New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont). New England is served by a common grid operator, ISO New England (ISO-NE), but states vary significantly in renewable energy targets, demographics, etc. For example, Massachusetts has legally mandated net-zero emissions by 2050 alongside a steadily increasing renewable portfolio standard with no set final end date, which is one of the region's most ambitious climate targets (ISO-NE, 2025). In contrast, New Hampshire has no statutory net-zero commitment and a renewable portfolio standard that plateaus at 10% (Adams, 2025). These contrasting energy policies have contributed to inter-state disagreements described above, making New England a compelling case study for a model that can elucidate the intra-regional distribution of costs and benefits of diverse energy pathways. This adds to a growing body of work that uses spatially confined case studies to demonstrate the insights that can be gained from probabilistic, multiobjective analyses (Goteti et al., 2025; Haas et al., 2025; Khayambashi et al., 2025; Sundar et al., 2024). New England also has unique features such as increasing energy integration with eastern Canada, which this model supports.

2. Methods

This analysis expands on the methodology published by Calder et al. (2022). That work screened indirect costs (greenhouse gas and air pollutants) and direct costs (upfront, operational, and variable expenditures) of grid pathways by coupling a dispatch model for fossil fuel generators with economic data for all technologies. While that model featured annual resolution and focused on cost-benefit analysis of long-term transborder hydropower purchase agreements, here, we develop an hourly-scale model allowing for analysis of a more diverse range of granular policy interventions and featuring more realistic technical and operational constraints for generators. We also add support for energy storage and alternative methods to value costs associated with Canadian hydropower.

Section 2.1 describes the development of decarbonization pathways. Section 2.2 describes how the generation model forecasts demand and satisfies it with new and existing generation. Section 2.3 describes how generation forecasts are cross-referenced with direct costs and other monetized impacts. Section 2.4 describes how other non-monetized impacts are screened. Section 2.5 describes the organization of the probabilistic modeling framework and the computational and other resources used for this work. A full mathematical formulation of the model including constraints, and equations implemented in the code is included in the supplemental information (SI). The subsections below provide a conceptual overview of all model components.

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 SI Table S1. These pathways 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 ecological impacts of interest screened in Section 2.4, but no external organization influenced model design, parameterization, or reporting decisions. No third party influenced any modeling choice or the decision to report on any pathway or outcome. Pathway A represents a status quo case with no new buildouts. In Pathway B2, investments in wind power lead to a 50th percentile generation level of 211.46 TWh per year (representing 104% of annual demand) by 2050. Pathways B1 and C2 each produce 175.35 TWh (86% of annual demand). Pathways B3 and C3 achieve slightly lower wind power generation of 158.73 TWh per year (78% of annual demand). For Pathway A and C1, wind accounts for 12.90 TWh per year (6% of annual demand), while Pathway D reaches 33.18 TWh (16% of annual demand).

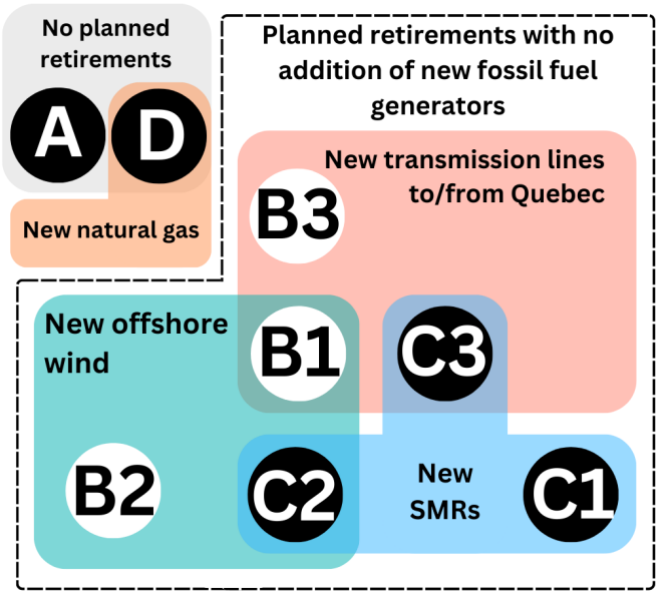

Figure 1: Euler diagram showing decarbonization pathways (circles) corresponding to different combinations of technologies (shaded rectangles). White circles show pathways considered by ISO-NE. Black circles show pathways unique to this study.

Detailed build-out and retirement schedules are provided in SI Section 1 and correspond to (or are based on) the assumptions retained by ISO-NE. All pathways assume the same hourly demand profile to 2050 (Section 2.2).

2.2. Generation model (PHASE)

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 the SI. A diagram of how all model inputs and outputs fit together is provided in Figure 2.

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.

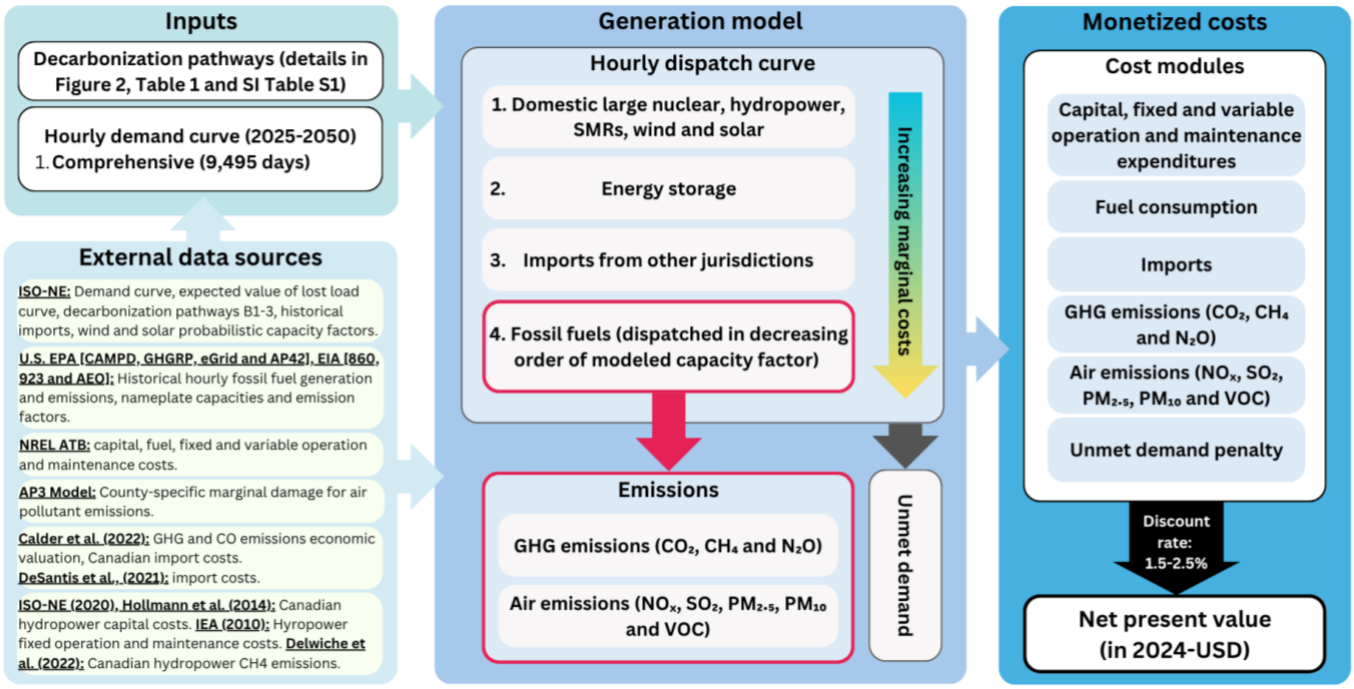

Figure 2: Relationships between data sources, decarbonization pathway and demand curve inputs, mathematical generation model, and monetized cost categories. Fossil fuel generators and air emissions are spatially resolved. Pathways are also cross-referenced with select other ecological impacts (Section 2.4). The modular setup of the PHASE 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.

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 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). If battery charging cannot dissipate available energy, then the excess is exported to neighboring

jurisdictions within the limits of historical ranges or, if these ranges would be exceeded, then wind and solar are curtailed (SI Section 2.7). 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.

Uncertainty in future hourly utilization of fossil fuel, wind, and solar assets is modeled by way of Monte Carlo anaylsis. 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.

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.

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 2.10.

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). Facility-specific marginal emissions costs are included in SI Section 2.11.

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, clean generation and imports serve demand first, storage discharges only when clean plus imports are insufficient, and (with charging restricted to surplus

clean and imports) storage charges only from curtailment rather than from thermal output. 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. Because the generation model has perfect foresight, it ramps up fossil fuel generators to minimize total unmet demand. Unmet demand is explained in more detail in SI Section 2.12.

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 calclulate 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.

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 (α=0.20, loc=0, θ=2.54) Gamma (α=1.538, loc=0, θ=4.160)	bird deaths MW^{-1} $year^{-1}$ bat deaths MW^{-1} $year^{-1}$	(Allison & Butryn, 2020b) (Allison & Butryn, 2020a)
Solar	Lognormal (μ=log(1.214), σ=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 (α=3.695, θ=9.382)	hectares MW^{-1}	(Denholm et al., 2009)
Small modular nuclear	0.017[b]	hectares MW^{-1}	(ENTRA1 Energy, 2025)
Solar	Gamma (α=4.25, θ=0.82)	hectares MW^{-1}	(Ong et al., 2013)
View shed			
High-voltage transmission	$\leq$ 27[a]	km	(Sullivan et al., 2014)
Off-shore wind	$\leq$ 40[a]	km	(Sullivan et al., 2013)
Solar	$\leq$ 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, 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.

3. Results and discussion

3.1. Build-out of new assets

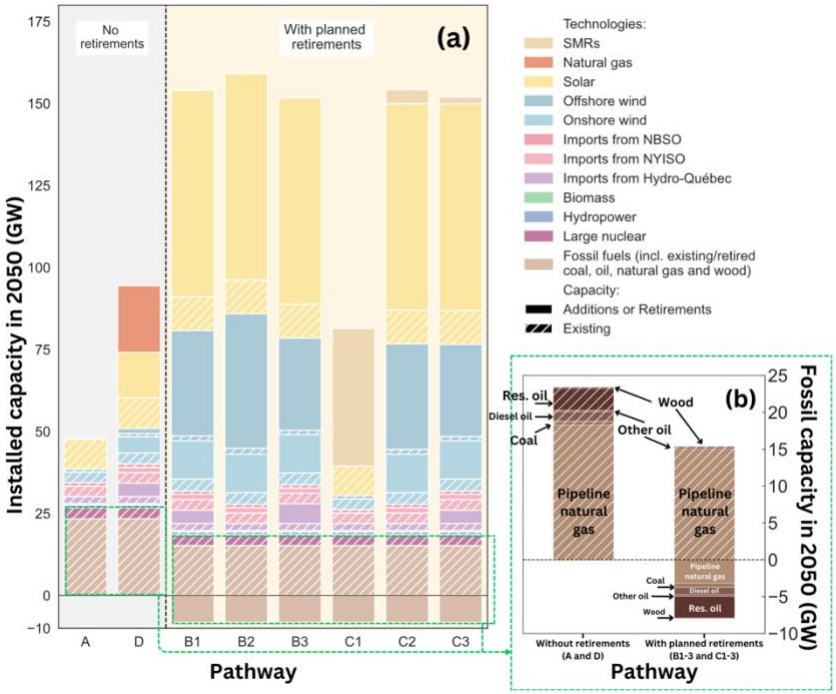

Figure 3: (a) Technology-specific installed capacities (status quo plus capacity additions and minus retirements) for pathways of interest for New England in 2050; (b) Fossil fuel capacities in 2050 for pathways B1, B2, B3, C1, C2 and C3 (pathways with planned retirements) and A and D (pathways with no retirements or new natural gas plants).

Pathways B1 (new transborder transmission, new offshore wind), B2 (transborder transmission constrained, expanded offshore wind), and B3 (offshore wind constrained, expanded transborder transmission) are pathways already considered by ISO-NE (Commonwealth of Massachusetts, 2020). We consider the same build-out for Pathways B1, B2, and B3, which all include 12.05 GW of onshore wind, 16.37 GW of battery storage, and 64.28 GW of solar. The key differences lie in the expansions of offshore wind and transborder transmission: Pathway B1 adds 32.64 GW of offshore wind alongside 4.1 GW of new transborder transmission; Pathway B2 increases offshore wind to 41.80 GW but does not expand transborder transmission; and Pathway B3 expands offshore wind capacity to 28.43 GW and increases transborder transmission capacity by 6.0 GW. This pathway specifically includes the construction of new hydroelectric reservoirs in Canada to supply electricity exports to New England. According to ISO-NE estimates, approximately 9 GW of new hydro capacity will be constructed in Canada, following a linear development schedule from 2025 through 2045. We calculate the associated capital expenditure (CAPEX) and fixed operational expenditure (FOM) costs for these reservoirs based on ISO-NE's proposed linear build-out timeline, proportionally scaled according to the maximum added transmission capacity to account for actual imports to New England.

Pathway C1 mirrors the retirement schedule of B1 but substitutes all other new capacity and transmission development with SMRs. We designed this pathway to explore the full range of possible SMR deployment parameters. Pathways C2 and C3 (based on SMRs) mirror B2 and B3, substituting SMR generation for expanded transborder transmission and offshore wind, respectively. Best available estimates for timelines of SMR development suggest this is technically feasible starting from 2030 (NREL, 2024). According to the NREL, SMRs could be online by 2030, which aligns with typical lead times for large-scale renewable and infrastructure

projects. This is consistent with international plans for the deployment of SMR technology. For instance, Ontario Power Generation plans to deploy a grid-scale SMR at its Darlington site by 2028 (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 (entered service in 2018). For the purposes of the New England case study presented here, 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. New natural gas generation faces significant hurdles in Massachusetts and Vermont under recent state laws (e.g., MA 2024 Climate Act, VT 2024 Climate Superfund Act and Renewable Standard Overhaul Act) and is comparatively less likely in those states. Many counties in Maine are served by the Maritime & Northeast Pipeline (M&NP), but Maine faces more transmission bottlenecks and lower in-state demand and may not represent an optimal location for a new large gas generator. By contrast, Rockingham and Strafford Counties in New Hampshire have access to the Tennessee Gas Pipeline (TGP) and the M&NP, a favorable regulatory environment, and better integration with the regional grid. Likewise, Rhode Island and Connecticut are served by diverse pipelines and have existing gas generators facilities in Fairfield, Hartford, Middlesex, New Haven, New London, and Windham (CT) and Newport, Providence, and Washington (RI) counties. We consider these counties to be the likeliest locations for new natural gas generation and calculate impacts of new gas generation probabilistically across these "candidate counties".

The composition of generation portfolios of all Pathways by 2050 is represented in Figure 3(a), and the breakdown of fossil fuel generation is represented in Figure 3(b).

3.2. Proposed PHASE model accurately represents the dynamics of a decarbonized power system

The proposed PHASE model effectively captures the operational complexities and dynamics of a decarbonized power system as illustrated in Figure 4. This figure highlights the system's response to a winter wind lull and peak annual demand during January 2050 under pathway B1 (Simulation #1 out of 1,000). Each feature shown in the figure demonstrates the proposed model's capability to model a decarbonized or low-carbon power system. Costs are calculated by pooling all 1,000 simulations for the simulation period 2025–2050.

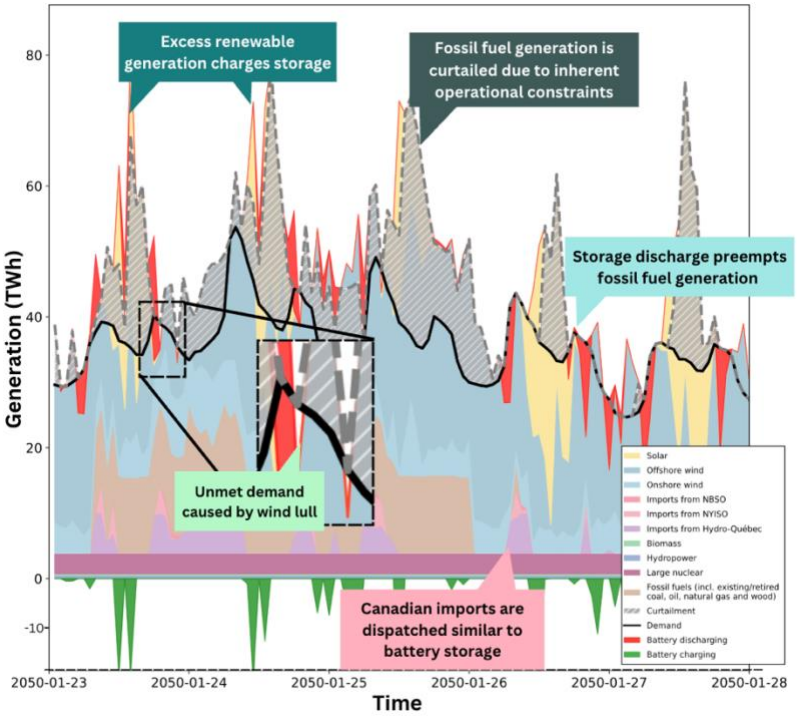

Figure 4: Winter wind lull and peak annual demand PHASE model results for pathway B1 (Simulation #1, 23rd to 28th January 2050).

The figure shows that fossil fuel generation is curtailed due to inherent operational constraints, emphasizing the model's ability to simulate realistic generator-specific limitations using prior and posterior distributions of future hourly capacity factors of the existing generating fleet. Meanwhile, during periods of excess renewable generation, the system charges storage to manage surplus energy, demonstrating how the model integrates renewable generation. Moreover, storage discharges prevent fossil fuel generation during low renewable output, underscoring its critical role in maintaining grid reliability while minimizing emissions. These trends are illustrated in greater detail in SI Figure S3.

During the wind lull, the model tracks how unmet demand caused by insufficient wind generation is mitigated (or not) through other resources, including imports and storage. The model also highlights how Canadian imports are dispatched similarly to battery storage (constrained by explicit representation of intra-regional hourly transmission capacity), supporting the grid when renewable generation is insufficient. This ability to integrate imports reflects the model's explicit representation of intra-regional transmission constraints and trade dynamics (e.g., long-term baseload contracts versus dispatch for demand).

Pathway B1 modeled here overlaps with ISO-NE's "High Electrification" pathway (reported in the Massachusetts Decarbonization Roadmap) (Commonwealth of Massachusetts, 2020), which we retain as a benchmark by which to validate our model's results (details provided in SI Section 4). As described in Section 2.1, other pathways evaluated here are not comparable to pathways

previously modeled by ISO-NE. The model developed here exhibits excellent agreement with the ISO-NE model. ISO-NE has released annual generation data from its model, reported at five-year intervals between 2025 and 2050, available through this project's GitHub repository. Plotting these annual values for total renewable generation for our model and the ISO-NE model reveals a coefficient of determination (R^2) of 0.97. By 2050, our model projects a median (across simulations) of 275 TWh of renewable generation (90% of simulations fall between 272.8 and 276.4 TWh), compared to 289 TWh suggested by ISO-NE (SI Figure S4(a)). Likewise, for total annual generation and imports, we have $R^2 = 0.89$, with 382 TWh in our model (90% of simulations fall between 379.0 and 384.9 TWh per year) relative to 358 TWh forecasted by ISO-NE (SI Figure S4(b)). Therefore, our model closely reproduces ISO-NE results when run for the median case and captures a wider range of outcomes when input parameters are allowed to vary probabilistically. In particular, our model suggests that a slightly higher total generation capacity may be required to meet the same net demand under real-world weather uncertainty.The PHASE model's probabilistic framework and detailed representation of hourly operational constraints enable us to gain insights into the tradeoffs between technical performance and other impacts of interest. The model reduces uncertainty when comparing different pathways by tracking the correlations of uncertainties (1) across model parameters (e.g., low wind is correlated with high sun) and (2) across pathways (e.g., all pathways have uncertainties deriving from unknown future wind conditions, but these are not pathway-dependent; hence, this contributes to uncertainty in *absolute* costs but not to uncertainty in *differences between* pathways).

3.3. Monetized social costs of decarbonization pathways

The clearest difference in monetized costs is between Pathway D and all others; D has lowest direct costs but by far highest indirect costs driven by GHG emissions. Overall, we calculated costs similar to those calculated by ISO-NE for those pathways analyzed both here and by ISO-NE (e.g., our B1 vs. ISO-NE's "High Electrification"). The range of estimates across pathways for total direct costs include those reported by ISO-NE where our pathays overlap, with our median result being slightly higher than the point estimate reported by ISO-NE (e.g., $355 in our pathway B1 vs. $343 2024-bUSD for ISO-NE pathway "High Electrification"; see SI Table S12 for details on ISO-NE estimates). We note that ISO-NE considers different discount rates for different cost categories as opposed to the uniform (and lower) discount rate of 2% considered here.

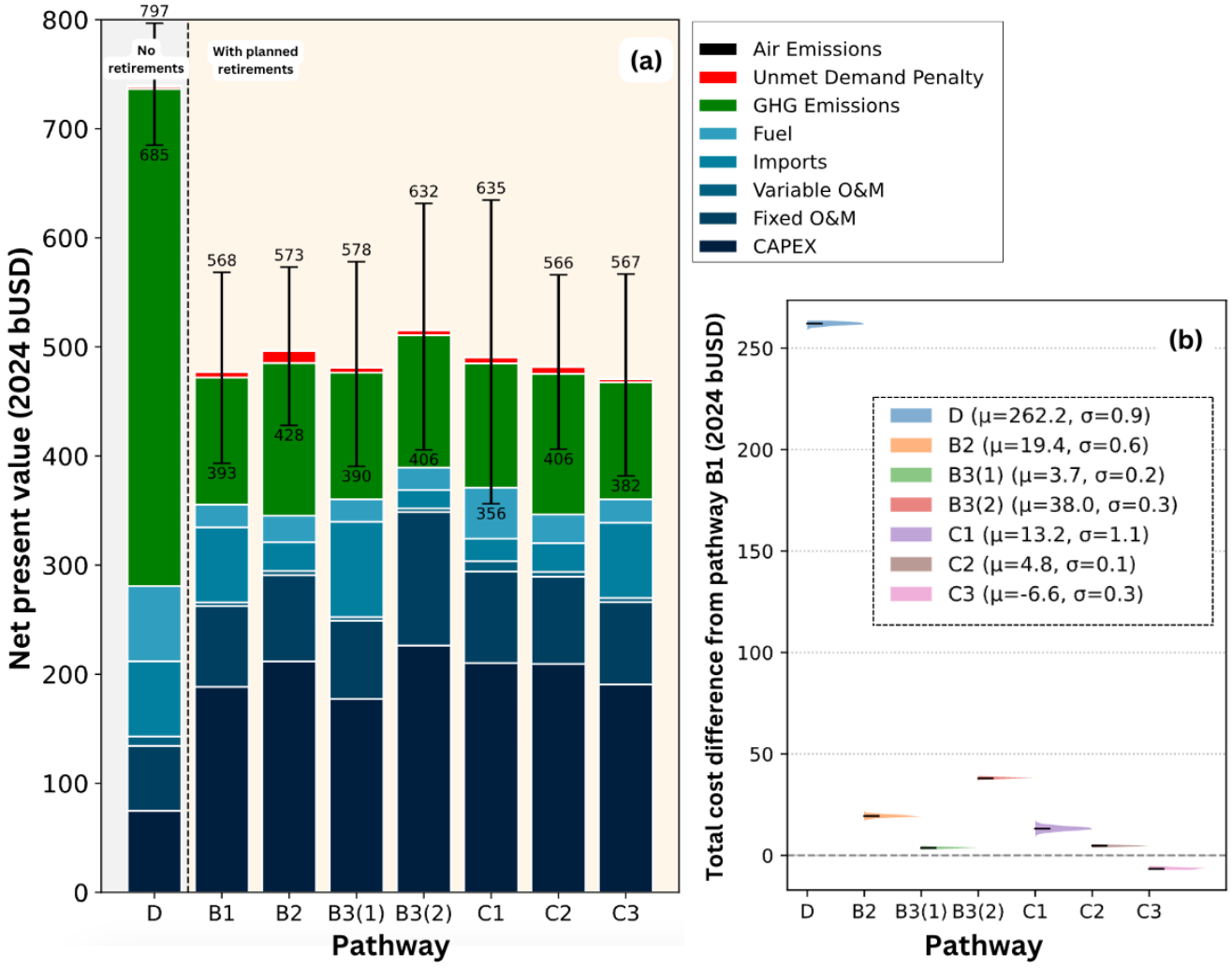

Figure 5: **a)** Comparison of NPVs across all decarbonization pathways in New England (discount rate 2%). B3(1) corresponds to Pathway B3 with import costs and B3(2) corresponds to Pathway B3 with prorated CAPEX costs (see SI Section 5). The whisker lines represent the 90% confidence interval, defined by the empirical 5th and 95th percentiles across uncertainty draws. **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.

Figure 5a illustrates the NPVs of different decarbonization pathways for New England under a 2% discount rate. Error bars in represent the 5th–95th percentile range across Monte Carlo runs. Pathway A ("status quo") is not represented because, without additional capacity, unmet demand levels become excessively high, resulting in unreliable grid performance and rendering the pathway unrealistic due to prohibitive total costs. Nevertheless, full breakdowns of all costs by category for each decarbonization pathway (including pathway A) are provided in SI Tables S10, S11 and S12.

Pathway C3, characterized by SMRs technologies and limited new offshore wind development, emerges as having lowest total social costs (but slightly higher direct costs) than pathway B1, with a mean NPV of approximately $471 billion. Thus, C3 is identified as the least-cost pathway for monetized costs in our study. This is slightly lower than the pathway emerging as least-cost from ISO-NE's analysis ("High Electrification", corresponding to our Pathway B1), for which we calculate an NPV of $477 billion.

While simulations of Pathways B1–C3 result in overlapping distributions for monetized costs, the distribution of the *differences* in total monetized costs relative to Pathway B1 are more tightly distributed, and none spans zero (Figure 5b). This tightening arises because uncertainties are correlated across pathways through shared Monte Carlo draws, such that common sources of uncertainty (e.g., fuel costs, demand, and weather-driven generation variability) affect all pathways simultaneously and cancel out in relative comparisons. As a result, variance in pairwise differences is substantially lower than variance in absolute costs. This demonstrates that tracking correlated uncertainties enables more statistically robust comparisons between pathways, even when absolute uncertainty ranges overlap. This is achieved by tracking the correlations in the uncertainty structure of the model (as described in Section 3.2) and demonstrates that we can improve the decision support value of model output by reducing uncertainty around the differences *between* pathways by controlling for sources of uncertainty that affect *multiple* pathways.

Pathway C1, relying heavily on emerging SMR technologies, emerges as having higher total social costs than B1, with a mean NPV of approximately $491 billion and substantial uncertainty due to the evolving economics of SMRs (ranging from $356 to $635 billion). Pathways B2 and C2, characterized by constraints on imports from Quebec and supplemented by offshore wind capacity (B2) and increased SMRs (C2), show mean NPVs of approximately $497 billion and $338 billion, respectively. Additionally, pathway B3 is accounted for using the two accounting methods described in Section 2.3.6. Thus, B3(1) and B3(2) demonstrate mean NPVs of $481 billion and $516 billion, respectively. When CAPEX, fixed O&M, and methane emissions from Canadian hydroelectric dams replace import costs in B3(2), the mean NPV increases, highlighting sensitivity to accounting methodologies. Pathway C3 has lower mean costs than C1 because it assumes fewer SMRs, reducing exposure to capital-cost uncertainty. The broader cost interval for C1 (SI Table S12) reflects the higher variance in SMR cost assumptions. Monetized damages from air emissions are included in Figure 5 but are small relative to other cost categories. They are described in more detail in Section 3.5. Air-emission costs are tabulated in SI Tables S14–S16.

3.4. Sensitivity of results to discount rate

As described in Section 3.3 we have used a single discount rate across all monetized cost categories, which we harmonize with the Social Cost of Carbon cost schedule. That is, the same discount rate used to actualize future costs is used to value all monetized impacts.

Crucially, the choice of discount rate dramatically influences the comparative economic viability of pathways. For example, the difference between the total cost NPVs for pathways D and B1sits at $132 (2.5% discount rate), $262 (2% discount rate) and $502 (1.5% discount rate) billion

2024-USD. This significant difference implies that higher discount rates diminish the economic disparity between previously divergent pathways, potentially shifting policy decisions toward pathways with higher emissions, like D, when evaluated strictly by discounted costs. This underscores the critical role of selecting an appropriate discount rate for cost of carbon in planning, as it can significantly alter perceptions of optimal decarbonization strategies.

We tested discount rates of 1.5 %, 2.0 %, and 2.5 % across all pathways. While absolute NPVs shift with rate choice, the relative ranking of pathways remains stable.

Finally, uncertainty analysis reveals that variability in NPVs primarily arises from inherent uncertainties in cost estimates rather than from the model itself. This demonstrates a high-resolution temporal-spatial model reduces uncertainty relative to representative-day simulations, underscoring the importance of load duration curve modeling in accurately capturing potential economic variability across decarbonization pathways.

More importantly, we explicitly tracked correlated uncertainties across both model parameters and pathways using a covariance-based framework (SI Figures S5 and S6). SI Figure S5 presents the Spearman correlation matrix showing pairwise relationships among uncertain parameters and outputs. Positive correlations (green) indicate parameters that tend to increase together, while negative correlations (red) indicate inverse relationships. Hierarchical clustering in SI Figure S5 highlights groups of interdependent parameters, such as the strong positive correlation between GHG and air-emission costs, and moderate correlations between fuel, CAPEX, and demand. These patterns confirm that key sources of variability are not independent and that the model captures realistic co-variation across pathways rather than random noise. SI Figure S6 quantifies the relative importance of each uncertainty source for total system cost. It shows that GHG and air-emission uncertainties dominate the overall NPV variability, while fuel prices, capital costs, and operational costs contribute comparatively little. Together, these figures confirm that the model's correlated-uncertainty structure reproduces realistic dependency patterns, enhances the interpretability of Figure 6, and ensures that observed differences among pathways arise from structural contrasts rather than sampling artifacts. This approach is consistent with recent work showing that incorporating correlations among uncertain parameters, such as between fuel prices and technology costs, can fundamentally change long-term energy strategy outcomes (Rodriguez-Matas et al., 2025). It also aligns with probabilistic frameworks that combine hierarchical Monte Carlo sampling and surrogate-based global sensitivity analysis to identify dominant epistemic uncertainties and preserve realistic parameter dependencies (Khayambashi et al., 2025).

3.5. Pathways with small differences in total costs and technical performance can exhibit distinct intraregional distribution of tradeoffs

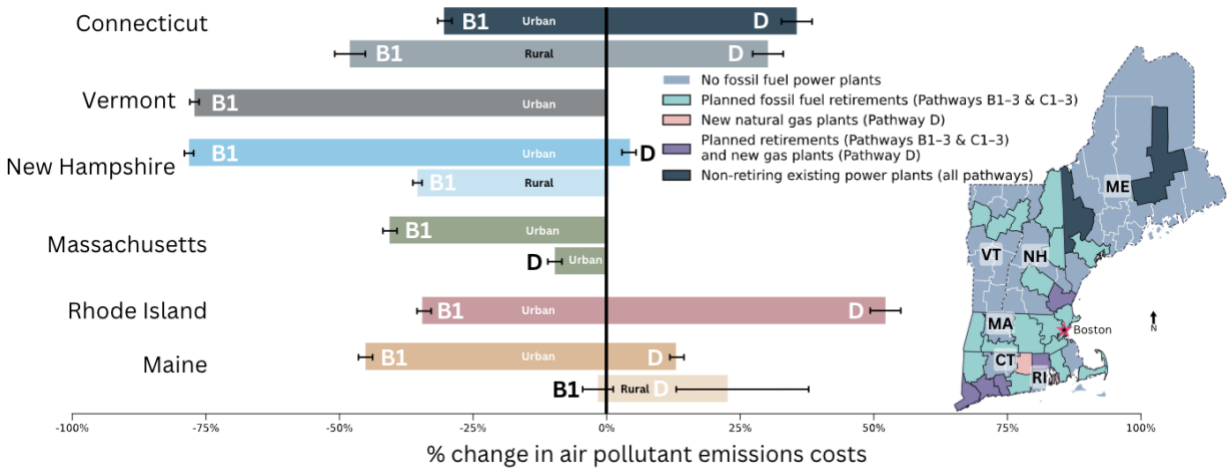

Figure 6: Intraregional distribution of benefits from air emission NPV reductions (or increases for pathway D) comparing pathways B1 and D with pathway A, using a discount rate of 2%. Each bar represents the percentage change in the average air pollutant emissions NPV relative to pathway A for either rural or urban areas in each state. The horizontal bars show the 90% CI. We used U.S. Department of Agriculture's Rural-Urban Continuum Codes dataset to identify rural versus urban regions (USDA, 2024). Monetized costs are calculated using the AP3 model as described in Section 2.3.3.

Figure 6 compares the intraregional distribution of air pollutant emission cost changes for pathways B1 and D relative to the "status quo" pathway A, highlighting nuanced tradeoffs within New England. Each bar represents the percentage change in air pollutant emission NPVs relative to pathway A for rural versus urban areas in each state, illustrating intraregional disparities in benefits and costs. SI Tables S14, S15 and S16 present county-level air emission NPVs (millions 2024-USD) discounted at 1.5%, 2% and 2.5%, respectively, further highlighting these intraregional variations in air pollutant emission costs under different discount assumptions. We observe that, across New England, rural states see greater relative reductions in air quality impacts under decarbonized pathways, challenging the perception that these benefits accrue to more urbanized Massachusetts (Kroot, 2020).

The spatial distribution depicted in Figure 6 underscores significant intraregional disparities between rural and urban areas across New England states. For instance, in Maine, rural and urban areas experience increases in emission costs 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 costs 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 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), underscoring the uneven effects of pathway choices. This indicates that technological choices distinctly affect rural and urban regions differently, emphasizing the need for spatially differentiated strategies within states.

These spatially variegated results align with insights from recent literature. Calder et al. (2022) emphasized that regional transmission infrastructure investments can notably alleviate 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 GEMs.

Furthermore, as shown in Figure 7 (and SI Table S17), ecological impacts vary distinctly across decarbonization pathways (estimated using built capacity of various technologies between 2025-2050), 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 sitting 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. These findings illustrate how technological composition distinctly shapes ecological outcomes, underscoring the importance of carefully balancing ecological considerations in decarbonization planning. We underscore that these

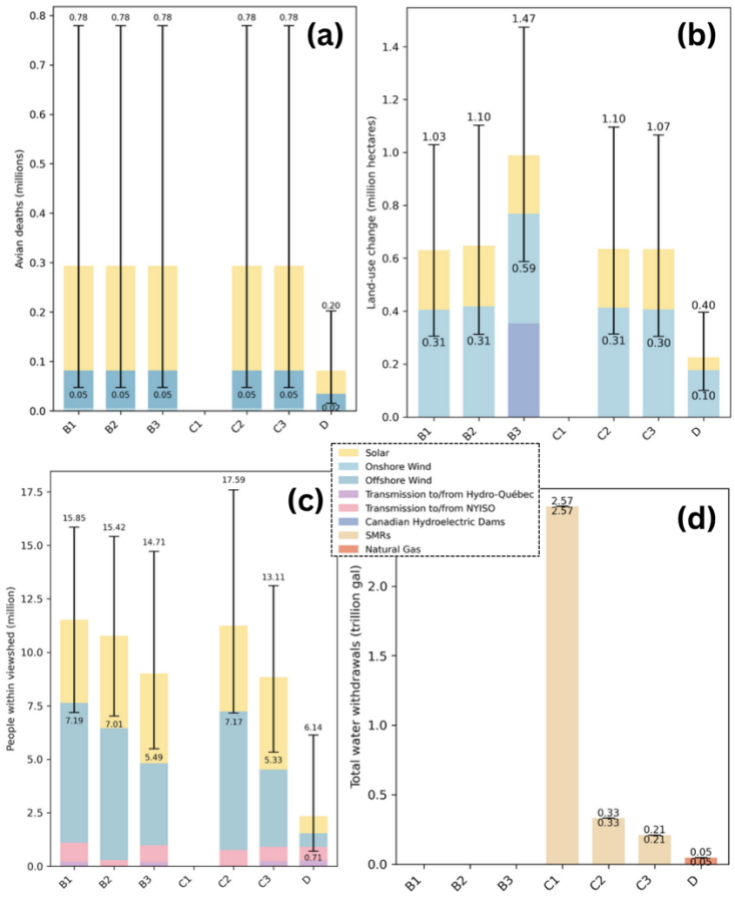

Figure 7: Ecological impacts across decarbonization pathways: (a) additional forest area impacted (million hectares), (b) total land-use change (million hectares), (c) population residing within affected watersheds (million people), and (d) total water withdrawals for thermal generation (trillion gallons).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

results are intended as a first-order screening of the plausible range of impacts for generic projects as reflected in the relatively wide uncertainties. Consideration of specific design and/or siting decisions would narrow these uncertainties significantly.

Collectively, these findings underline that a nuanced, spatially aware approach in evaluating decarbonization strategies is essential. Understanding these intraregional tradeoffs enables more informed policy decisions, promoting equitable transitions to clean energy while ensuring environmental justice goals are effectively prioritized.

3.6. Energy storage plays a vital role in enabling decarbonization pathways with high VRE penetration

Recent literature argues that energy storage is essential for stabilizing grids dominated by renewable generation and managing the variability introduced by weather-dependent resources (de Sisternes et al., 2016; Levi et al., 2023; Levin et al., 2023). This is further evidenced by the ability of storage systems to mitigate emissions during high-demand periods, underscoring their dual role in operational flexibility and emissions reduction.

In Figure 8 for pathway B1, we demonstrated that the deployment of utility-scale storage systems effectively addressed operational challenges posed by wind lulls and peak demand events. During periods of surplus renewable generation, storage systems were charged, and during supply shortages, they effectively discharged energy, reducing the reliance on fossil fuels.

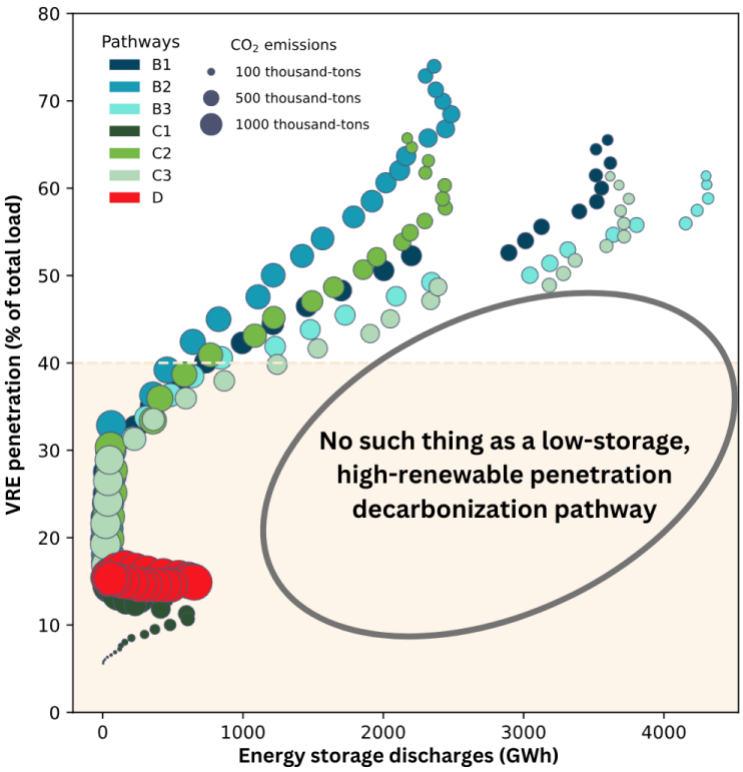

Figure 8: VRE penetration versus energy storage utilization across different pathways. Each bubble shows mean VRE penetration, storage discharge and CO_2 emissions for a specific pathway and year across all simulations. Note that hydro is not included in the renewables category because it's not uniformly classified as renewable across the six New England states.

Our results further confirm that achieving high VRE penetration (i.e., renewables greater than 40% of total supply (Zhao et al., 2024)) without significant storage deployment is not feasible (see Figure 8). This finding aligns with Levin et al.'s (2023) assertion that storage utilization scales with renewable energy, reinforcing the integral relationship between storage and renewables in building reliable, low-carbon electricity systems.

Pathways lacking adequate storage exhibited more frequent instances of unmet demand and curtailment, highlighting the limitations of renewables without complementary storage capacity.

Moreover, Levin et al. (2023) also underscore the importance of diversifying the energy mix and incorporating emerging technologies to enhance grid resilience and flexibility. Our analysis demonstrates that SMR deployment can complement renewable generation by filling supply gaps during prolonged wind lulls, thereby reducing dependence on imports and fossil-based peaking plants. For example, in Figure 8, pathway C2 shows reduced storage discharge compared to B2, indicating that SMRs effectively fulfilled a storage-like function. Conversely, in pathway C1, where VRE penetration is minimal, we still observe emissions reductions despite the lack of storage. In this pathway, SMR serves as a stable baseload source, while battery storage balances the limited VRE resources.

The financial and operational characteristics of storage and SMRs underscore their complementary roles. Battery storage, despite higher upfront capital expenditures, substantially reduces renewable curtailment and mitigates peak demand charges, thereby effectively lowering overall system costs. SMRs, benefiting from modular construction and rapid deployment timelines, offer viable solutions in regions facing renewable integration challenges or transmission limitations, enhancing system resilience.

Finally, our findings reinforce the importance of advanced modeling techniques advocated by Levin et al. (2023), particularly modeling frameworks that accurately represent the dynamics of state-of-charge for storage systems and operational integration of emerging technologies. Our model effectively captures these interactions, providing a robust foundation for capacity planning and policy development. This modeling approach demonstrates the transformative role energy storage and SMRs play in shaping resilient, cost-effective, and sustainable electricity systems across New England.

3.7. Future directions

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 pathways. As described in Section 2.2.6, we have developed and included in the SI (see 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 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).

Economic feedbacks such as energy-price responses or induced investment effects are not represented. Costs reported here therefore reflect engineering-system outcomes rather than general-equilibrium responses. This distinction confines interpretation to technical and ecological trade-offs rather than broader economic welfare. Therefore, future work could integrate PHASE within a hybrid bottom-up/top-down equilibrium framework (e.g., Böhringer & Rutherford, 2008) to capture macroeconomic feedbacks and endogenous price responses.

This analysis has demonstrated that incumbent models that represent costs and impacts deterministically overlook (1) the uncertainties attached to alternative decarbonization pathways and (2) the major differences in the magnitude of those uncertainties between pathways. 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.

Our analysis indicates that within-pathway uncertainty magnitudes can rival or exceed differences between pathways. Variability in SMR capital costs, for example, produces cost ranges comparable to the spread between SMR-based and wind-dominant pathways. This underscores the value of probabilistic modeling rather than deterministic least-cost comparisons.

Limitations include simplified hydropower variability, omission of market-price feedbacks, and fixed climate-insensitive demand. Future work should couple this framework with economic-equilibrium or policy-uncertainty modules to assess dynamic behavioral responses.

The framework does not model dynamic expectations or agent behavior as in dynamic-stochastic-general-equilibrium (DSGE) models. Instead, it evaluates stylized policy pathways under exogenous assumptions. Coupling with macro-economic or market-behavior modules could extend the analysis but lies outside this study's scope.

Although the results are region-specific to New England, the underlying probabilistic framework is generalizable. Substituting local demand profiles, generator fleets, and ecological data allows direct application in other jurisdictions (see SI Tables S5 and S6 for parameter structure).

4. Ethics declaration

The authors declare no competing interests.

5. 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.

6. 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, manuscript development (reviewing, and editing).

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

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

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