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

Amir M. Gazar[1,2], Chloe Jackson[3], Georgia Mavrommati[3], Rich B. Howarth[4], Ryan S.D. Calder[1,2,5 *]

[1] Department of Population Health Sciences, Virginia Tech, Blacksburg, VA, 24061, USA
[2] Global Change Center, Virginia Tech, Blacksburg, VA, 24061, USA
[3] School for the Environment, University of Massachusetts Boston, Boston, MA 02125, USA
[4] Environmental Program, Dartmouth College, Hanover, NH, 03755, USA
[5] Department of Civil and Environmental Engineering, Duke University, Durham, NC, 27708, USA
* Contact: rsdc@vt.edu.

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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 PHASE (Probabilistic Hourly Assessment of System Electricity), 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 mitigation strategies in the United States and internationally (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). Meeting this demand while reducing emissions has stimulated planning and construction of diverse generation and transmission assets. In the U.S., the policy landscape governing the relative viability of various 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. U.S.-Canada trade tensions have created uncertainty over the political viability of long-term power purchase agreements and even the tariff regime applicable to spot-market imports. In response, the governors of all six New England states issued a bipartisan statement committing to explore advanced nuclear technologies including small modular reactors, a striking reversal in a region that has historically opposed new nuclear development.

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. Currently available CEMs are imperfectly suited to the emerging technical and social features of the energy transition because: (1) many are deterministic and hence cannot capture inherent uncertainties in a system increasingly dependent on variable renewable energy (VRE) generation (IRENA, 2017; Ringkjøb et al., 2018); (2) where probabilistic extensions exist, treat pathway uncertainties as independent, thereby overestimating uncertainty around inter-scenario differences (which are the quantities that drive investment and policy decisions) (Calder et al., 2019; Reichert & Borsuk, 2005); (3) many do not simulate the spatial and temporal distribution of costs and benefits of alternative scenarios, for example simulating a “sample day” or aggregating generation at the regional level (Gacitua et al., 2018; Poncelet et al., 2016); and (4) available models generally do not support exploration of a diverse range of scenarios beyond those emerging from optimizations with relatively narrow objective functions and hence may not reflect the full option space now requiring 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 scenarios (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 equity) (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. This gap is particularly consequential in the current moment, when the rapid destabilization of incumbent planning assumptions requires rapid screening of a wider and more diverse pathway space than existing tools support.

Opposition to renewable energy projects has been animated by claims about the electrical system that is not easily tested with existing models. This includes claims about intra-regional distribution of (1) the environmental impacts of transmission infrastructure, which would disproportionately affect rural areas (Cotton & Devine-Wright, 2013), and (2) benefits of displaced fossil fuel generation, which may disproportionately benefit denser urban areas (Buonocore et al., 2016; Campos Morales et al., 2024). These tensions are acute in New England, where rural New Hampshire and Maine are perceived as bearing land and landscape costs while denser population centers drive demand (perceived as driving demand for renewable energies) (Gazar et al., 2024; Kroot, 2020; Nolan & Rinaldi, 2020). There has also been a perception that scenarios formally evaluated by grid operators may not fully characterize the range of available pathways and their tradeoffs (Calder et al., 2024).

We present PHASE (Probabilistic Hourly Assessment of System Electricity) 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 (1) it is highly exposed to federal policy such as offshore wind permitting and tariffs on electricity imports; and (2) its common grid operator requires coordinated planning despite divergences in state energy goals and perceptions of differential impacts and benefits of alternative pathways. Key features responsive to 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 representation of social costs associated with Canadian hydropower, either based on import costs or on costs associated with operation and construction of reservoirs in Canada; 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. The framework is fully generalizable: PHASE uses nationally available datasets, and we release alongside this paper 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.

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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 scenarios 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.

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 Table 1. 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 ecological impacts of interest screened in Section 2.4. No third party influenced any modeling choice or the decision to report on any scenario or outcome. In Section 2.1.1 we describe the range of build-out scenarios we consider, and in Section 2.1.2., we describe our methodology for scheduling capacity expansion and retirements over the model period. All pathways assume the same hourly demand profile to 2050 (Section 2.2.1).

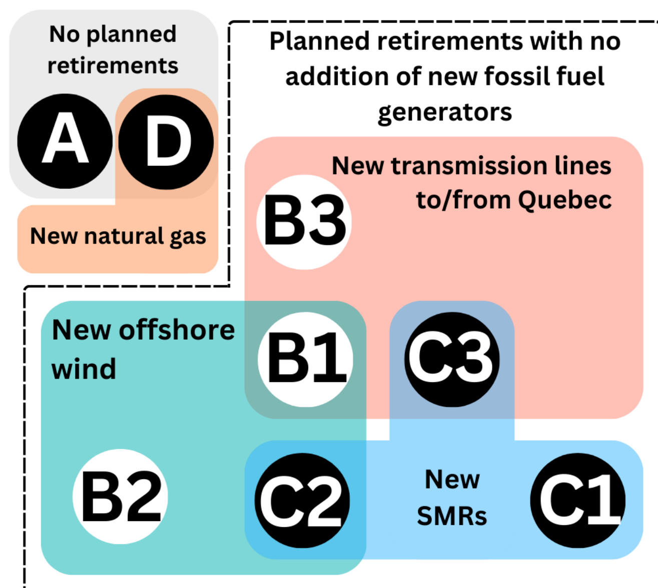

Figure 1: Euler diagram showing decarbonization pathways (circles) corresponding to different combinations of technologies (shaded rectangles). White circles show pathways considered by ISO-NE. Black circles show pathways unique to this study.

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 in B3 (Commonwealth of Massachusetts, 2020).

Table 1: Build-out/retirement by 2050 of technologies under each decarbonization pathway (yearly schedule provided in Supplemental Information (SI) Table S1).

Technology	Pathway							
	A	B1	B2	B3	C1	C2	C3	D
New interties with Quebec	None	+4.1 GW	None	+6 GW	None	None	+4.1 GW	+4.1 GW
New hydropower reservoirs in Quebec	None	None	None	~9 GW reservoir	None	None	None	None
New offshore wind	None	+33 GW	As required to balance 10 GW growth in demand by 2050 (>41 GW)	+28.5 GW	None	+33 GW	+28.5 GW	+1.5 GW
New small modular reactors	None	None	None	None	+42 GW	+4.2 GW	+2.1 GW	None
New natural gas power plants	None	None	None	None	None	None	None	+20 GW
Forced coal retirements	None	All retired by 2030	All retired by 2030	All retired by 2030	All retired by 2030	All retired by 2030	All retired by 2030	None
New solar	None	+64 GW	+64 GW	+64 GW	None	+64 GW	+64 GW	+ 14 GW
New onshore wind	None	+12 GW	+12 GW	+12 GW	None	+12 GW	+12 GW	+ 5 GW
Battery storage	None	+16.4 GW	+16.4 GW	+16.4 GW	None	+16.4 GW	+16.4 GW	+16.4 GW

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 2.2.1.

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. *Capacity additions and retirements*

2.1.2.1. Scheduling of 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 S2.

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 considered that 75% of oil-fired units (5,250 MW) would be retired by 2030 by filtering facilities using oil as their primary fuel type, calculating the 75th percentile of their real average capacity factor, identifying those at or below that threshold, and assigning them a 2030 retirement date, thereby ensuring less-utilized (higher marginal cost) facilities are retired first.

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 S3.

All eGRID, NREL, and EIA data used are archived on storage managed by Virginia Tech Advanced Research Computing (ARC) and are available in the supplemental information (see Section 5).

2.1.2.2. Build-out of new assets

Pathways B1 (new transborder transmission, new offshore wind), B2 (transborder transmission constrained, expanded offshore wind), and B3 (offshore wind constrained, expanded transborder transmission) are scenarios 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

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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.

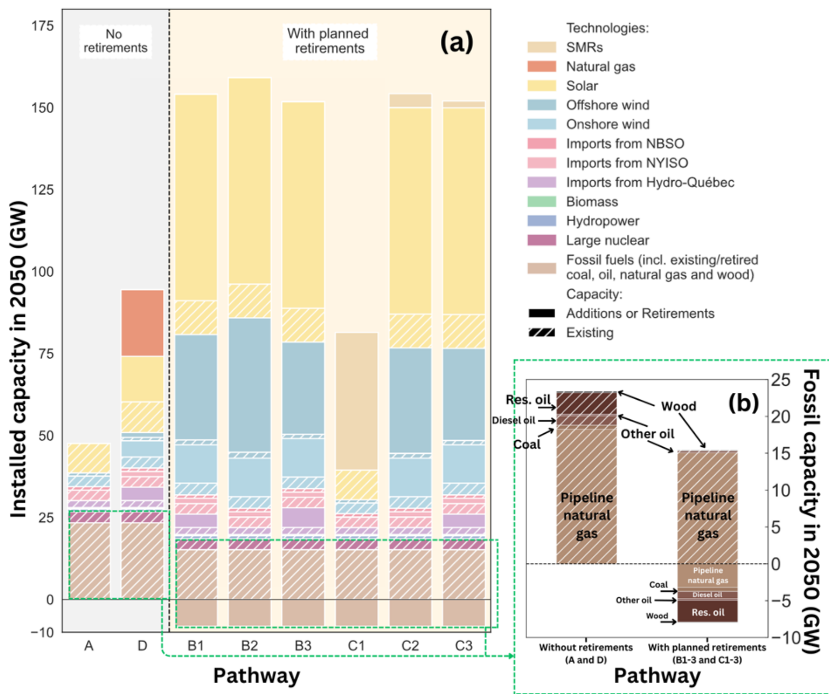

Figure 2: (a) Technology-specific installed capacities (status quo plus capacity additions and minus retirements) for pathways of interest for New England in 2050; (b) Fossil fuel capacities in 2050 for pathways B1, B2, B3, C1, C2 and C3 (scenarios with planned retirements) and A and D (scenarios with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

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 2(a), and the breakdown of fossil fuel generation is represented in Figure 2(b).

2.2. Generation model

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). Here, we describe how we calculate over the model period: electrical demand (Section 2.2.1); output of wind and solar assets (Section 2.2.2); output of nuclear and domestic hydropower facilities (Section 2.2.3); charging and discharging of batteries (Section 2.2.4); imports from other jurisdictions, notably, transborder trade with Quebec, Canada (Section 2.2.5); fossil fuel generation (Section 2.2.6); and curtailment of excess wind and solar and penalties for unmet demand (Section 2.2.7). Inputs, functionality, and outputs

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of the dispatch curve model are represented in Figure 3. Details of externally derived parameters for the GEM and monetized costs are provided in SI Tables S4 and S5, respectively.

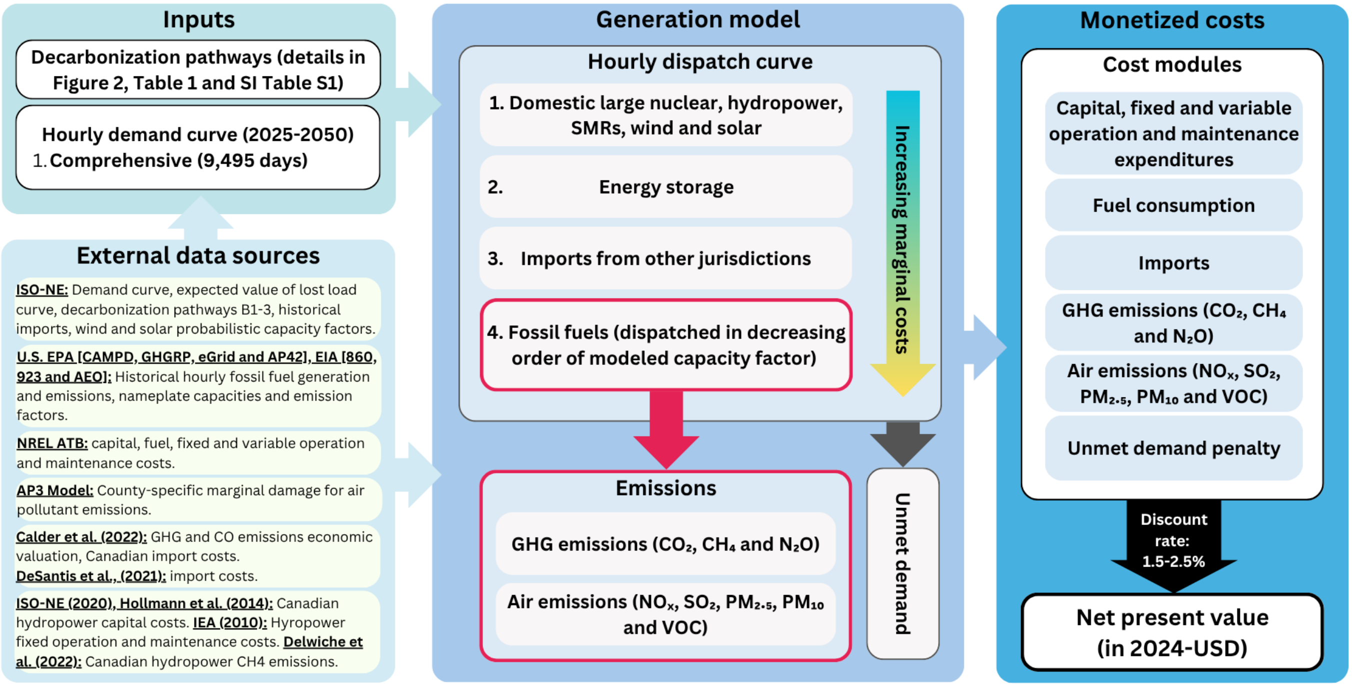

Figure 3: Relationships between data sources, decarbonization pathway and demand curve inputs, mathematical generation model, and monetized cost categories. Fossil fuel generators and air emissions are spatially resolved. Scenarios are also cross-referenced with select other ecological impacts (Section 2.4). The modular setup of the 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.

2.2.1. *Demand forecasts*

Hourly demand forecasts for New England were obtained from the Commonwealth of Massachusetts via request under the Massachusetts Public Records Act. These data support the publicly available decarbonization roadmap (Commonwealth of Massachusetts, 2020) and correspond to the ISO-NE 2025-2050 "High Electrification" scenario. This scenario assumes a medium level of flexibility in end-use loads, including incentivized consumer behavior to reduce consumption during peak demand (e.g., 53,715MW on January 24th,2050 and total demand in 2050 of 203 TWh). Raw data for all demand scenarios are provided in the SI to allow for reanalysis under alternative forecasts.

We implement a load duration curve approach utilizing the full hourly demand profile, totaling 227,880 timesteps for the period from 2025 to 2050, consistent with the methodology used by other recent GEM models (Dagoumas & Koltsaklis, 2019). The model can also be run using less computationally demanding representative demand curves or individual time slices if required.

2.2.2. *Wind and solar generation*

Contribution of wind (onshore and offshore) and solar resources is determined by multiplying installed capacity (increasing between 2025 and 2050 according to the Pathway retained as described in Section 2.1) by a capacity factor. Capacity factors are described by probability distributions specific to each hour within a calendar year and are calculated using simulated capacity factors supplied by ISO-NE (ISO-NE, 2024).

ISO-NE calculates hourly capacity factors for years with different cumulative levels of wind generation at the yearly 1^{st}, 5^{th}, 10^{th}, 50^{th}, 90^{th}, 95^{th}, and 99^{th} percentiles (e.g., mean annual net capacity factor for offshore wind in 99^{th} percentile year is 0.32 vs. 0.29 in 1^{st} percentile year). We resample this data to generate hour-specific probability distributions for net capacity factor, which we apply to all timesteps in our model period. The model can be run deterministically using the 50^{th} percentile value or stochastically as described in Section 2.8.

The dispatch model has perfect knowledge of uncertain future renewables generation to allow for optimized fossil fuel ramping (Section 2.2.6) and to minimize unmet demand penalties (Section 2.2.7). 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).

Wind and solar generation are dispatched first, multiplying installed capacity by the stochastic (or deterministic) capacity factor, given low marginal costs and to avoid curtailment (Section 2.2.7). At timesteps where renewables exceed demand, surplus generation is used to charge batteries (Section 2.2.4) or is curtailed (Section 2.2.7).

For Pathway B2, investments in wind power lead to the 50^{th} 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).

2.2.3. *Nuclear, domestic hydropower, and biomass generation*

Data from the National Renewable Energy Laboratory's Annual Technology Baseline (NREL ATB) 2024 are used as capacity factors for large nuclear (0.93), domestic hydropower (0.56), and biomass (0.60) generators (NREL, 2024). These are dispatched following wind and solar due to low marginal cost at timesteps where renewables alone cannot satisfy demand (Commonwealth of Massachusetts, 2020). Similarly, we selected the 300 MWe SMR with capacity factor of 0.9 since this is currently the only SMR in the NREL portfolio projected to be available from 2030 (NREL, 2024).

Across scenarios, existing large nuclear generation accounts for 27.29 TWh per year by 2050 (13% of annual demand), domestic hydropower accounts for 4.42 TWh (2% of demand), and biomass accounts for 2.10 TWh (1.03% of demand). In pathways C1, C2, and C3, investments in SMRs lead to potential maximum generation of 331.12 TWh, 33.11 TWh, and 16.56 TWh per year (representing 163%, 16%, and 8% of annual demand) by 2050, respectively.

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2.2.4. *Commercial battery storage*

We model the operation of commercial lithium-ion battery storage systems by utilizing surplus renewable energy to charge the batteries during timesteps when generation exceeds demand. We assume a round-trip efficiency of 85%, meaning that 85% of the input energy is effectively stored and later available for use (NREL, 2024). Thus, the batteries are discharged during timesteps when renewable generation and imports are insufficient to meet demand. To determine the maximum charge and discharge rates, we adopt an inverter-to-storage ratio of 1.67 (i.e., fast charging and discharging), as recommended by the NREL in the 2024 ATB (NREL, 2024).

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).

2.2.5. *Imports from other jurisdictions*

ISO-NE imports energy from Hydro-Québec, New York ISO, and the New Brunswick System Operator (NBSO). Decarbonization pathways B1, B3, C3 consider increased imports from Quebec with (B3) or without (B1 and C3) expanded generation in Quebec. Recently negotiated import agreements between Quebec and New York/Massachusetts commit to a constant transmission schedule with fixed prices for a period of approximately 20–25 years (see NECEC's 20-year fixed-price contracts (Central Maine Power Company, 2019; Hamlen & Lenzen, 2024) and CHPE's 25-year benefit framework (CHPExpress, 2021; Naldal, 2022)). Once agreed, the marginal price of these imports is zero, and so the model dispatches these resources ahead of fossil fuels. In these scenarios, long-term contracts are to account for the all-new imports, therefore subject to a fixed capacity factor. We assume all new imports from Quebec under all pathways are under a fixed-price contract.

For other imports negotiated on the short-term spot market with variable costs, we use historical data for the period 2011 to 2023 to simulate hourly transmission and prices. We calculate capacity factors by dividing real imports by available transmission capacity and apply that to the available transmission capacity available in the period 2025–2050. Transmission capacity for spot-market imports (unlike for long-term contractual imports as described above) is held constant for all scenarios considered here. Historical data are used to develop prior distributions, which are randomly sampled. In the event that fossil fuel generation (Section 2.2.6) when added to the other available capacity is not adequate to satisfy hourly demand, imports are resampled (within the constraints of historical maxima). Posterior distributions are saved and analyzed.

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For Pathways B1, C3, and D, investments in transborder infrastructure lead to average imports up to 60.54 TWh per year (30% of annual demand) by 2050, respectively. For Pathway B3 these investments lead to average imports up to 76.35 TWh (38% of annual demand). For other Pathways (including "status quo" Pathway A), average imports from other jurisdictions account for 26.42 TWh per year (13% of annual demand).

2.2.6. *Fossil fuel generation*

The difference between hourly demand (Section 2.2.1) and generation from wind and solar (Section 2.2.2), domestic hydropower, nuclear, and biomass (Section 2.2.3), battery discharges (Section 2.2.4), and imports from neighboring jurisdictions (Section 2.2.5) is accounted for by fossil fuel generation. The importance of potential fossil fuel generation by 2050 depends on the pathway considered as described in Section 2.1.1 and is as high as 107.6 TWh (representing 53% of annual demand) for pathways A and D and as low as 73.7 TWh (representing 36.2% of annual demand) for all other pathways. Additionally, in pathway D the potential generation of newly built natural gas plants account for 151.6 TWh (74.6% of the annual demand) by 2050.

The hourly fossil fuel demand in a given timestep is the sum of (1) demand unmet by renewables and other low-marginal-cost generation and imports described above and (2) increased generation necessary to respect ramping constraints to meet future demand. Ramping is carried out in accordance with each generating unit's ramping constraints. Each unit maintains a minimum generation level at all times, from which it ramps up as needed when demand increases. By using the look-ahead approach, if an upcoming demand is observed, we begin ramping sooner so the unit can reach maximum capacity precisely when the peak occurs.

Excess energy produced in ramping hours is balanced by (1) charging batteries (if available), (2) selling to neighboring jurisdictions up to the maximum historical exports for that hour using data from the period 2011–2023, and, (3) curtailing wind and solar for that hour if (1) and (2) are not sufficient to dissipate excess energy.

We developed a database of 4,633 generating units at 1,379 electric utility generating facilities across the United States cross-referenced to hourly generation and CO_2, NO_x, and SO_2 emissions data for the period from 2013 to 2023, inclusively, from the U.S. EPA Clean Air Markets Program Data (CAMPD) API (U.S. EPA 2024). Emissions of CO, N_2O, PM_{10}, $PM_{2.5}$, and VOC are determined by technology-specific emissions factors tabulated in SI Table S6. For all generating units and all generation and emissions variables, synthetic hourly probability distributions were fitted to the data for the period 2011 to 2023 to calculate 1st to 99th percentiles to be stochastically sampled (or run deterministically at the 50th percentile). Hourly generation in New England is cross-referenced with nameplate capacities from the EPA's CAMPD, and if the resulting capacity factor exceeds 1 (indicating a misreported capacity), we correct it using EIA 860 or eGrid data (U.S. EIA 860, 2023; U.S. EPA CAMPD, 2024; U.S. EPA eGrid, 2022). This has been completed for all generators in the database across all regions of the U.S. All relevant data has been archived in storage managed by Virginia Tech ARC and is accessible via the supplemental information.

In New England, approximately 7% of generating units accounting for 1.81% of all installed capacity were not represented in the CAMPD database we used to develop hourly generation and

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emissions distributions. For these facilities, distributions were developed by pooling units of the same technology and, where nameplate capacity was reported, of the same nameplate capacity range (± 20 MW). Technology groups were defined as combinations of unit types (e.g., “boiler”, “combined cycle”), and primary fuel type (e.g., “coal”,” natural gas”). This approach was also used to fill in emissions factors for CO_2, NO_x and SO_2 (3.24%, 1.81% and 8.98% of all installed capacity in New England respectively).

Hour-specific historical generation data is evaluated to ensure that it is mathematically possible to satisfy demand at a given timestep within historical maxima for that hour. Ensuring that historical maxima are not exceeded ensures that the model implicitly captures constraints such as within-grid bottlenecks or other technical constraints not explicitly modeled. If available fossil fuel resources cannot satisfy demand at a given timestep when added to previously sampled sources, then all generators are assigned generation corresponding to the historical maximum for the corresponding hour, and batteries are discharged subject to the discharge constraint. If these are not sufficient to meet demand, then imports from other jurisdictions (Section 2.2.5) are resampled (after verification that historical hourly maximum, when added to allocated generation and battery discharge, will satisfy demand). If historical hourly maximum fossil fuel generation and imports, when added to maximum battery discharge and available renewable supply, is insufficient to meet demand, then imports are also assigned the maximum historical hour-specific value, and an unmet demand penalty is applied (Section 2.2.7). Posterior distributions for all generation (and imports) are saved.

2.2.7. *Curtailments and unmet demand*

When renewable energy generation exceeds the system’s ability to use or store the energy (either by satisfying demand or charging batteries), output must be curtailed. Curtailments are calculated as the portion of renewable energy left unused after meeting demand and accounting for available battery storage capacity. We do not assign a monetary penalty for curtailment, consistent with most other models (Frew et al., 2021).

When all available generation and import capacity is inadequate to satisfy hourly demand, an unmet demand penalty is applied. This approximates the economic costs of demand curtailment and/or brownouts and has been used by ISO-NE, specifically we consider a variable cost curve (Section 2.3.4) used by ISO-NE to estimate unmet demand penalties (Potomac Economics, 2024).

2.3. Direct costs and monetized impacts

2.3.1. *CAPEX, FOM and VOM costs*

We calculate the capital expenditures (CAPEX), fixed operations and maintenance (FOM), and variable operations and maintenance (VOM) costs associated with the pathways described in Section 2.1. For all technologies except SMRs, these calculations leverage annual data from the 2024 NREL ATB, using mature market rates with a 30-year recovery period, pooled (uniform distribution) across different ATB technology cost scenarios (“conservative”, “moderate” and “advanced”). For SMRs, we use the 2024 NREL ATB nascent market rate, with a 30-year

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recovery period pooled across different ATB technology cost scenarios starting in 2030. Details of all externally derived parameters for cost calculations are provided in SI Table S5.

This method of calculating CAPEX includes direct land acquisition costs. However, we separately tabulate land use (and select other ecological impacts) by technology and by pathway as a proxy for the potential complexity of land acquisition, stakeholder engagement, environmental assessment, and other features that have slowed decarbonization. These impacts are described in Section 2.4.

CAPEX accrues in the year of deployment of a new generation or transborder transmission asset in each Pathway. FOM and VOM recur in every year of operation of a new or existing generation asset. FOM and VOM are not calculated for existing transmission assets because these do not vary across scenarios. Costs are actualized to a net present value (NPV) at a discount rate of 2% (U.S. EPA, 2016) with all costs reported in 2024-USD.

In this study, costs for new transmission infrastructure focus solely on lines connecting New England with other regional transmission organizations, notably cross-border connections with Quebec. CAPEX and FOM costs associated with transmission infrastructure are modeled based on the total capacity of the line ($ per MW). Therefore, we use CAPEX ($0.7 - $1.0 million per MW) and FOM ($700 - $1,000 per MW) values based on cost estimates for the New England Clean Energy Connect (roughly $950 million for a 1200 MW line) reported by Calder et al. (2022) adjusted to 2024-USD. To capture uncertainty, following industry guidelines (e.g., Association for the Advancement of Cost Engineering International recommended practices for "Class 3" cost estimates), total CAPEX and FOM costs are drawn from a normal distribution with 95% confidence interval ±20% around the mean reported figure (Dysert, 2016).

As we describe in more detail in Section 2.3.6, there are conceptual disagreements on whether and how to account for Canada-side costs in U.S. decarbonization pathways that increase imports of Canadian hydropower. For the sensitivity analysis in which we apportion a fraction of Canada-side costs to a hydropower-dependent pathway (CAPEX and FOM costs incurred from new large Canadian hydropower plants in Quebec for Pathway B3(2)), we use benchmarks from ISO-NE reports, indicating an average cost of $7,144 kW^{-1} (2024-USD) (Commonwealth of Massachusetts, 2020). Scaled to a class 5 dam, this equates to a range of 8.3 to 19.7 million-USD MW^{-1} (2024-USD) (Hollmann et al., 2014). This cost range reflects the variability in project locations, regulatory requirements, and construction complexities. Moreover, IEA (2010) estimates that hydropower FOM costs are 1.5% to 2.5% of CAPEX annually which is 0.12-0.49 million-USD MW^{-1} year^{-1} (2024-USD).

All costs are easily changed via user input to adapt this generalizable framework to other regions or countries.

2.3.2. *Greenhouse gas emissions costs*

We use the U.S. EPA estimates for social cost of GHG emissions at 2% discount rate in 2025 as $253.71 tonne-$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). These costs are applied to fossil fuel GHG emissions

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described in Section 2.2.6. In the sensitivity analysis where methane emissions from new Canadian hydropower are valued (Pathway B3(2)), these costs are also applied to reservoir methane emissions calculated as described in Section 2.3.6.

2.3.3. *Air pollutant emissions costs*

Economic valuations for NO_x, SO_2, $PM_{2.5}$, PM_{10} and VOC were derived using county-specific and stack-height specific values from the APEEP (AP3) model (Muller, 2022). This model calculates premature fatalities associated with marginal increases in emissions and a corresponding economic value based on a prescribed Value of a Statistical Life (VSL). We used EIA Form 860 data to determine stack height and county for each facility. Damages are also reported in terms of premature fatalities (i.e., without consideration of the VSL retained). 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 social costs of air emissions are provided in SI Table S7.

2.3.4. *Unmet demand penalty costs*

During conditions of capacity scarcity, where supply fails to meet demand, the market cost of electricity experiences a substantial increase. This rise is influenced by market dynamics and significant fines imposed by ISO-NE (Potomac Economics, 2024) on electricity suppliers that are unable to fulfill their obligations as part of a pay-for-performance mechanism (see SI Figure S1). Our generation expansion model incorporates a perfect-foresight demand curve, enabling estimation of unmet demand throughout the simulation. Consequently, this approach facilitates the calculation of total shortage penalties, using the ISO-NE pay-for-performance rate of \$3,500 MWh^{-1} (Potomac Economics, 2024).

2.3.5. *Costs of fuel and imports from other jurisdictions*

We calculate the fuel and import costs using the generation expansion model results summed for annual generation and imports for each facility and jurisdiction. We utilized the 2024 NREL ATB data for large nuclear and biomass fuel costs, applying mature market rates with a 30-year recovery period and pooling results across various ATB scenarios. For SMRs, we employed the 2024 NREL ATB nascent market rate with a similar 30-year recovery period, also pooled across different ATB scenarios beginning in 2030. We derived the fossil generation fuel costs from the NREL ATB data (2021), pooling mature market rates with a 30-year recovery period across multiple ATB scenarios.

We estimated import costs from NYISO to be between 0.78¢ to 2.41¢ kWh^{-1} (2024-USD) (uniform distribution) within the U.S. (DeSantis et al., 2021). For imports from Canada, using the CHPE (339 miles) as a reference, we estimate delivery costs to be approximately 2.12¢ kWh^{-1} (2024-USD) (Calder et al., 2022). Notably, this figure represents an upper bound estimate, while a similar uncertainty range as applied for NYISO yields a lower bound estimate of 0.78¢ kWh^{-1} (2024-USD). These import costs apply to new and existing infrastructure, and we apply these as standardized levelized import costs from other jurisdictions.

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2.3.6. *Accounting for costs of increased imports of Canadian hydroelectric power*

There is debate about how to value direct and indirect costs associated with increased imports of Canadian hydroelectric power to the U.S. (Calder et al., 2022; Gazar et al., 2024). Within the U.S., direct costs are those associated with investments in new transmission infrastructure plus costs of imported power (either purchased on the spot market or negotiated in a long-term contract). If imports to one U.S. market have the effect of reducing exports to another U.S. market, then increased fossil fuel generation in that other market can be counted as indirect costs. Costs in Canada derive from direct expenses in building and operating reservoirs and impacts from environmental and social effects of reservoir construction (e.g., global climate impacts from reservoir methane emissions, local impacts on Indigenous food systems, etc.). Recent uncertainty over how and whether different energy imports may be restricted or tariffed highlight the need for greater clarity on how benefits and costs can be valued.

Pathway B3 specifically assumes that new hydroelectric generation in Canada would be necessary to sustain the level of increased exports to the U.S. (Commonwealth of Massachusetts, 2020). From a "consequentialist" perspective (Calder et al., 2022; Curran et al., 2005; Earles & Halog, 2011; Ekvall, 2019), it is therefore necessary to account for the generation-side impacts of that hydroelectric development, i.e., costs in Canada. We retain two alternative accounting methods corresponding to two unique pathways: (1) U.S. costs only, i.e., costs of U.S. infrastructure plus costs of imports (a lower bound estimate of the costs of generation in Canada), corresponding to Pathway B3(1), described in Section 2.3.1; and (2) total social costs, accounting for costs of infrastructure in the U.S. and Canada (Section 2.3.1), plus indirect costs from reservoir methane (CH4) emissions, proportionally to the power exported to the U.S., corresponding to Pathway B3(2) (Section 2.3.2). Method (2) excludes the value of the imports/exports because this is not a cost to society from the energy system but rather a payment between actors. Figure 4 illustrates how direct (U.S. infrastructure, power purchase) and indirect (fossil displacement, reservoir CH_4) costs are captured under the two cost-accounting methods (U.S.-only vs. total social cost).

Other pathways consider that Canadian hydroelectric resources are leveraged without stimulating new hydroelectric development in Canada, and therefore, from a consequentialist perspective, do not require consideration of impacts associated with existing reservoirs. While "attributional" analyses that apportion impacts of all existing infrastructure to incremental transmission expansion are common, they are known to overestimate total costs in comparison with alternatives when there is no causal connection between, for example, new transmission and new generation (Calder et al., 2020, 2022; Curran et al., 2005; Gazar et al., 2024).

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Delwiche et al., (2022) reported emissions ranging from 5,685 to 16,744 mg CH_4-C day^{-1} for three existing reservoirs in Quebec, Canada (Eastmain, Robert-Bourassa, and LaForge-1). These reservoirs span a range of trophic statuses, ages, surface areas, and other parameters believed to be important in determining the time course of CH_4 emissions. Because of uncertainties in (1) how these variables combine to determine emissions and (2) the location and characteristics of a hypothetical future reservoir, we estimate CH_4 emissions from a new hydroelectric facility in Quebec by pooling the above range of values into a uniform distribution and scaling by the generation demanded in Scenario B3 (up to 126.2 TWh per year or 62% of demand). The Eastmain reservoir powers turbines at Eastmain-1 (480 MW), Eastmain-1-A (768 MW) and Sarcelle (150 MW), while Laforge-1 (878 MW) and Robert-Bourassa (878 MW) are each associated with one dam for a total of 7,892 MW at an estimated average capacity factor of 0.65 (Hydro-Québec, 2025). Thus, we consider CH_4-C emissions using a uniform distribution of 0.16 to 1.22 kg CH_4-C per MWh imported. Details of facility specific methane emissions from Canadian reservoirs are provided in SI Table S8.

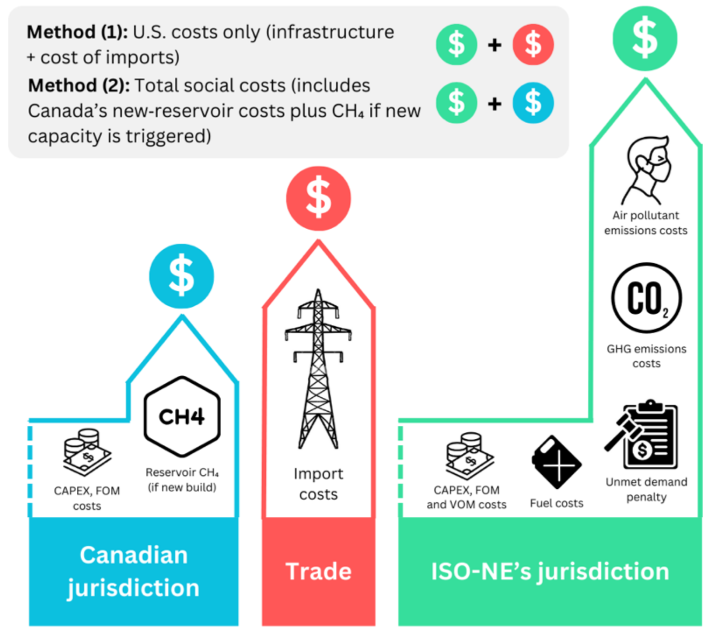

Figure 4: Illustration of how direct and indirect costs are allocated for imports of Canadian hydropower under two accounting methods. Method (1) ("U.S. costs only") includes U.S. infrastructure plus payments for imports. Method (2) ("total social costs") additionally includes new reservoir construction costs and methane (CH_4) emissions in Canada if new hydropower capacity is triggered. Payments for imports are treated as transfers within the overall system and not net social costs. Where imports to one U.S. region displace exports that would have gone to another, any increased fossil generation in that second region can be counted as an additional indirect cost.

2.3.7. *Total costs tabulation and presentation of results*

We compile NPVs (2024-USD) associated with various decarbonization pathways, including CAPEX, FOM, VOM, fuel, imports, GHG emissions, air pollutants, and unmet demand penalty. We use the consumer price index (CPI) to ensure all cost valuations represent 2024-USD using the latest Bureau of Labor Statistics CPI data (U.S. Bureau of Labor Statistics, 2024). The baseline analysis presented here considers a discount rate of 2% for all future costs. Select alternative discount rates that are included in the SI. The model dynamically updates the Social Cost of Carbon schedule as a function of user-supplied discount rate by interpolating between the schedule supplied by U.S. EPA (ref). Results are visualized using R and (R Core Team, 2025) Python (Van Rossum & Drake Jr, 1995).

2.4. Non-monetized ecological impacts

Beyond GHG and other air emissions with robust, widely used tools for monetization (described in Section 2.3), we screened scenarios 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 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 2 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.

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Table 2: 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 S8
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	≤ 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). 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.

All data, code, and a comprehensive guide (Reproduction Information) for reproducing the study are provided in the SI; see Section 5 for details.

3. Results and discussion

3.1. Proposed GEM accurately represents the dynamics of a decarbonized power system

Our proposed GEM effectively captures the operational complexities and dynamics of a decarbonized power system (with a computation time of 15 minutes per simulation), as illustrated in Figure 5. 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 GEM'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.

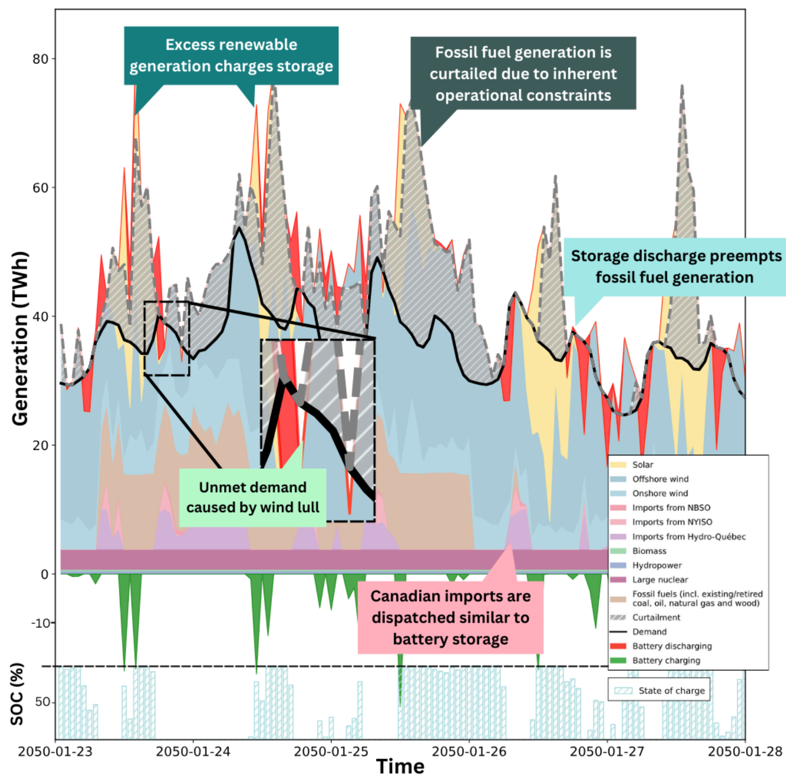

Figure 5: Winter wind lull and peak annual demand GEM results for pathway B1 (Simulation #1, 23rd to 28th January 2050).

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 GEM 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 S2.

During the wind lull, the GEM 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).

The GEM'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 GEM 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).

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

Scenarios analyzed here and by ISO-NE (e.g., B1, “All Options”) have similar mean direct costs to those calculated by ISO-NE. However, ISO-NE considers different discount rates for different cost categories as opposed to the uniform (and lower) discount rate of 2% considered here. Total direct categories are overlapping but somewhat higher here than as reported by ISO-NE (e.g., $355 vs. our mean of $343 2024-bUSD; see SI Table S12 for details on ISO-NE estimates). Overall, however, the areas of overlap with ISO-NE’s previous modeling suggest that PHASE is able to reproduce those findings.

Figure 6 illustrates the NPVs of different decarbonization pathways for New England under a 2% discount rate. Scenario A (“status quo”) is not represented because, without additional capacity, unmet demand levels become excessively high, resulting in unreliable grid performance and rendering the scenario unrealistic due to prohibitive total costs. Nevertheless, full breakdowns of all costs by category for each decarbonization pathway (including scenario A) are provided in SI Tables S9, S10 and S11. Moreover, we consider diverse indirect cost categories (e.g., GHG and air pollutant impacts) not monetized by ISO-NE.

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Figure 6 demonstrates that deviations from ISO-NE's identified least-cost pathway (B1) lead to different total social costs. Notably, pathway C3, characterized by SMRs technologies and limited new offshore wind development, emerges as having lower 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.

Pathway D has the highest mean NPV at approximately $740 billion, reflecting significant environmental and social costs, including substantially greater emissions costs. Conversely, the ISO-NE least-cost pathway, B1, has a much lower mean NPV of $477 billion at a 2% discount rate, presenting a balanced trade-off between cost, reliability, and emissions reductions. Pathway B1 thus remains optimal when broader cost metrics are considered compared to pathway D.

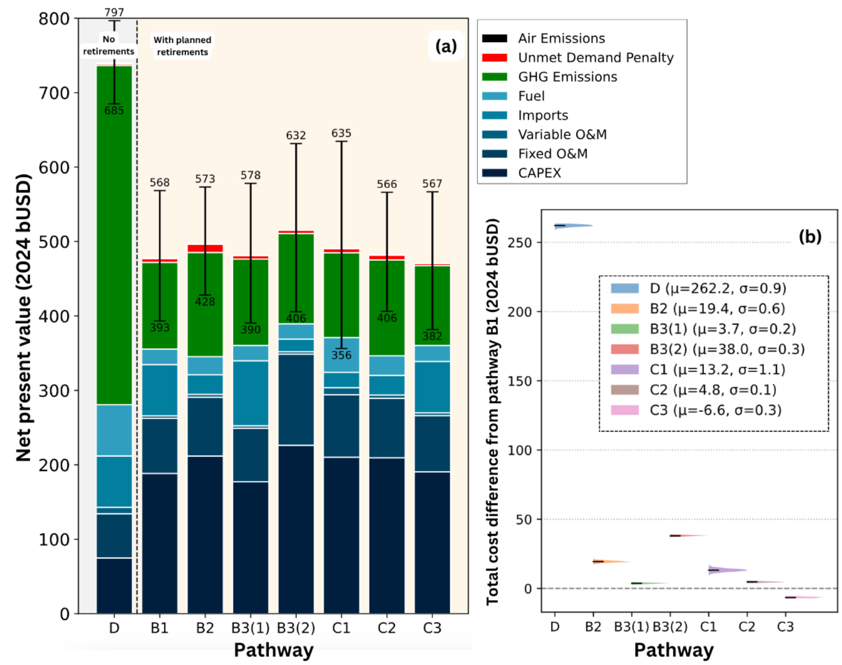

Figure 6: **a)** Comparison of NPVs across all decarbonization pathways in New England (discount rate 2%). B3(1) corresponds to Pathway B3 with import costs and B3(2) corresponds to Pathway B3 with prorated CAPEX costs (see Section 2.3.6). The whisker lines represent the 90% CI. **b)** Horizontal ridgeline 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.

Pathway C1, relying heavily on emerging SMR technologies, emerges slightly more expensive 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 notably increases, highlighting sensitivity to accounting methodologies.

GHG emission outcomes vary across pathways, reflecting distinct strategic decisions within the decarbonization scenarios. Pathway D, the most expensive option under a 2% discount rate, incurs 290% higher GHG emissions costs relative to pathway B1, making it environmentally detrimental and incompatible with New England's emission reduction goals. Conversely, Pathway C3 achieves the greatest emissions reductions, with GHG emission costs approximately 30% lower than those of Pathway A at the same 2% discount rate.

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.

Comparing panels (a) and (b) of Figure 6 demonstrates how tracking correlated uncertainties enhances decision support: absolute cost intervals overlap substantially across pathways in panel (a), yet pairwise difference distributions in panel (b) are strikingly tight and in no case 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 demonstrates that NPV uncertainty derives primarily from parameters shared across pathways (e.g., fuel prices, weather-driven generation variability, Social Cost of Carbon assumptions, etc.) rather than from pathway-specific uncertainties (e.g., costs of small modular nuclear).

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

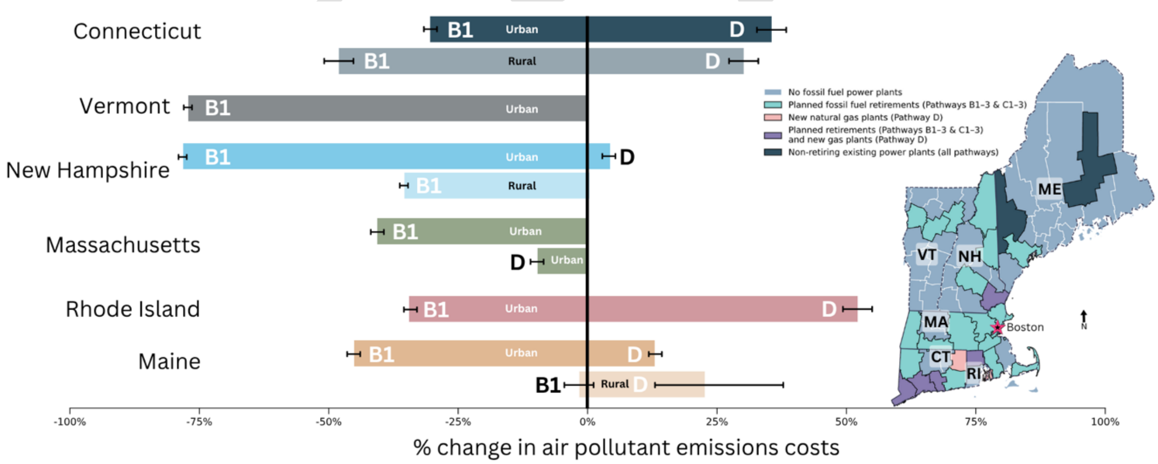

Figure 7: Intraregional distribution of benefits from air emission NPV reductions (or increases for pathway D) comparing pathways B1 and D with pathway A, using a discount rate of 2%. Each bar represents the percentage change in the average air pollutant emissions NPV relative to pathway A for either 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 7 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 S13, S14 and S15 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 7 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.

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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.

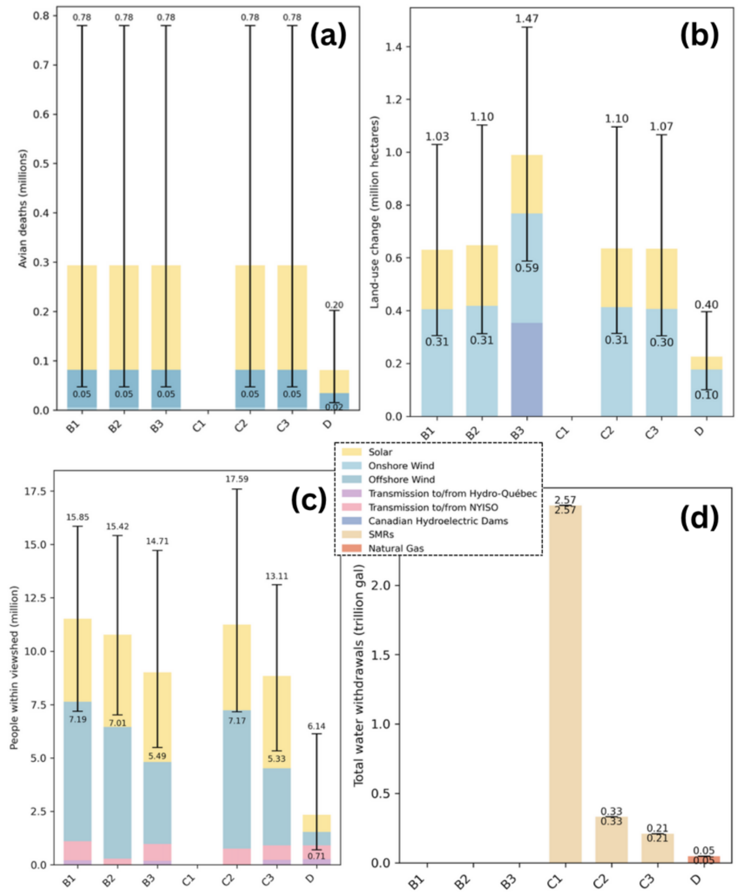

Figure 8: Ecological impacts across decarbonization pathways: (a) additional forest area impacted (million hectares), (b) total land-use change (million hectares), (c) population residing within affected watersheds (million people), and (d) total water withdrawals for thermal generation (trillion gallons). The horizontal bars in all panels show the 90% CI.

Furthermore, as shown in Figure 8 (and SI Table S16), 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 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 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.

3.4. 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 6 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.

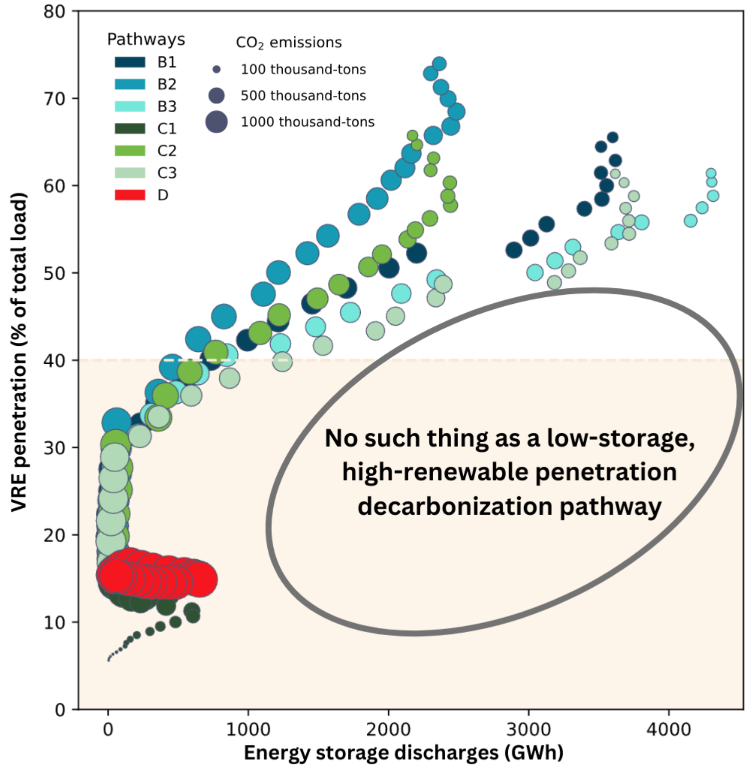

Figure 9: VRE penetration versus energy storage utilization across different pathways. Each bubble shows mean VRE penetration, storage discharge and CO_2 emissions for a specific pathway and year across all simulations. Note that hydro is not included in the renewables category because it's not uniformly 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 9). 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 9, 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 GEM 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.

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. 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).

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 estiamates 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

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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, 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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