ENVIRONMENTAL RESEARCH
INFRASTRUCTURE AND SUSTAINABILITY

ACCEPTED MANUSCRIPT • OPEN ACCESS

Causal inference to scope environmental impact assessment of renewable energy projects and test competing mental models of decarbonization

To cite this article before publication: Amir Mortazavi Gazar *et al* 2024 *Environ. Res.: Infrastruct. Sustain.* in press https://doi.org/10.1088/2634-4505/ad8fce

Causal inference to scope environmental impact assessment of renewable energy projects and test competing mental models of decarbonization

Amir M. Gazar[1,2], Mark E. Borsuk[3], Ryan S.D. Calder[1,2,3,4,5,*]

[1] Department of Population Health Sciences, Virginia Tech, Blacksburg, VA, 24061, USA
[2] Global Change Center, Virginia Tech, Blacksburg, VA, 24061, USA
[3] Department of Civil and Environmental Engineering, Duke University, Durham, NC, 27708, USA
[4] Faculty of Health Sciences, Virginia Tech, Roanoke, VA, 24016, USA
[5] Department of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA, 24061, USA

* Contact: rsdc@vt.edu.

Abstract

Environmental impact assessment (EIA), life cycle analysis (LCA), and cost benefit analysis (CBA) embed crucial but subjective judgments over the extent of system boundaries and the range of impacts to consider as causally connected to an intervention, decision, or technology of interest. EIA is increasingly the site of legal, political, and social challenges to renewable energy projects proposed by utilities, developers, and governments, which, cumulatively, are slowing decarbonization. Environmental advocates in the United States have claimed that new electrical interties with Canada increase development of Canadian hydroelectric resources, leading to environmental and health impacts associated with new reservoirs. Assertions of such second-order impacts of two recently proposed 9.5 TWh year^{-1} transborder transmission projects played a role in their cancellation. We recast these debates as conflicting mental models of decarbonization, in which values, beliefs, and interests lead different parties to hypothesize causal connections between interrelated processes (in this case, generation, transmission, and associated impacts). We demonstrate via Bayesian network modeling that development of Canadian hydroelectric resources is stimulated by price signals and domestic demand rather than increased export capacity per se. However, hydropower exports are increasingly arranged via long-term power purchase agreements that may promote new generation in a way that is not easily modeled with publicly available data. We demonstrate the utility of causal inference for structured analysis of sociotechnical systems featuring complex mechanisms that are not easily modeled mechanistically. In the setting of decarbonization, such analysis can fill a gap in available energy systems models that focus on long-term optimum portfolios and do not generally represent questions of incremental causality of interest to stakeholders at the local level. More broadly, these tools can increase the evidentiary support required for consequentialist (as opposed to attributional) LCA and CBA, for example, in calculating indirect emissions of renewable energy projects.

Keywords

Renewable energy, Causal inference, Cost benefit analysis, Life cycle assessment, Sociotechnical systems, Energy policy

1. Introduction

To limit global climate warming to within 1.5ºC of preindustrial averages, total greenhouse gas emissions will need to be offset by removal and sequestration ("net-zero") by 2050 (Dafnomilis et al., 2024; Huang & Zhai, 2021; United Nations, 2024; van Soest et al., 2021). This in turn will require investments in electrical generation and transmission infrastructure on the order of $4 trillion to $6 trillion beyond a business-as-usual scenario over the same period in the United States alone (National Academies of Sciences, Engineering, and Medicine, 2021). Yet, in the United States and internationally, governments, utilities, and other stakeholders have faced major obstacles in achieving the rate of build-out of renewable energies necessary to meet these targets. As we describe below, a significant fraction of projects proposed for development are challenged using Environmental Impact Assessment (EIA) legislation.

In this section, we recast EIA-centered debates as disagreements over causal "mental models" and describe how causal inference methodologies may be used to evaluate the extent to which competing mental models are supported by available data. We describe how this may complement existing energy systems models which are not designed to elucidate questions of incremental causality at the local scale, and how these methods add to the literature on sociotechnical analysis of energy systems. We introduce the case study of controversial electrical interties between the United States and Canada, which provides a timely setting for characterization of advantages and limitations of these methods. We introduce the central claim we test in this analysis, that new electrical interties stimulate new reservoir development in Canada, and we describe why this question cannot be answered with currently available energy systems models.

1.1. Local sociopolitical dynamics complicate decarbonization planning

Notwithstanding major recent developments such as the U.S. Inflation Reduction Act, the pace of build-out of wind, solar, storage, and associated transmission infrastructure remains highly uncertain in the United States and internationally. These uncertainties arise from (1) quantifiable differences in model assumptions in the national and international economic and technological parameters driving technology uptake and the range of projects that are proposed (e.g., future costs for battery storage, availability of tax credits, etc.) (Batel, 2020; Bistline et al., 2024; Moore et al., 2022); and (2) the cumulative effect of less predictable sociopolitical processes at the individual to global scales that determine (among other things) the pace at which proposed projects are actually built (Batel, 2020; Moore et al., 2022), which is the focus of this analysis.

Realization of climate targets is jeopardized by the cumulative effects of localized rejection of renewable energy projects. In the United States and Canada, 17% and 18% respectively of wind projects proposed between 2000 and 2016 faced significant opposition, with this fraction increasing over time (Stokes et al., 2023). Weise and Bhat (2024) report that 15% of U.S. counties have effectively halted new wind and/or solar projects, with half of solar bans having been passed in 2023 alone. Restrictions at the state level have more than doubled between 2023 and 2024 (Eisenson et al., 2024). Environmental protection legislation the most common vehicle for these challenges, accounting for 1,316 of the 2,328 legal challenges against U.S. renewable energy projects inventoried by the Sabin Center for Climate Change Law as of September 2024

(Sabin Center for Climate Change Law, 2024). Of these, challenges to under federal or state environmental impact assessment (EIA) legislation account for the majority (706 out of 1,316). The land-use needs of renewable energies suggest that EIA will play an increasing role in debates over decarbonization decisions. For example, Lovering et al. (2022) calculate future global land use requirements of roughly 207 Mha by 2050 to achieve the International Energy Agency's 2ºC warming scenario compared to 97 Mha in 2017, not counting land required for transmission infrastructure.

1.2. Disputes over Environmental Impact Assessment reflect conflicting beliefs about causal relationships in environmental, social, and technical systems

EIA provides a mechanism by which infrastructure and other projects will be evaluated in terms of foreseeable environmental impacts and is now required in some form for major generation, transmission, and many other types of projects in most countries (Glasson & Therivel, 2013; Morgan, 2012). In the United States, the National Environmental Policy Act (NEPA) requires evaluation of "reasonably foreseeable" environmental consequences with a "reasonably close" causal link to a federal action (e.g., permit issuance) even if these consequences fall outside the U.S., and even if they are second-order or indirect effects (*Border Power Plant Working Group v. Department of Energy*, 2003; Council on Environmental Quality, 2021). Recent updates to the regulations governing NEPA implementation reaffirm that relevant impacts may occur at a different time or place than the covered action while clarifying that simple "but-for" causation is generally an insufficient standard (Council on Environmental Quality, 2020). Executive agencies have broad discretion and latitude to apply their own judgments in scoping and interpreting environmental assessments and impact statements, even while their actions and findings under NEPA can be (and frequently are) reviewed by the courts (Colburn, 2016).

There is increasing interest in (1) the extent to which EIA, life-cycle analysis (LCA), and similar tools embed critical but subjective and often inadequately justified judgments of developers or regulators, notably, in decisions over the geographic, temporal, and causal scope of the analysis (Cederlöf & Hornborg, 2021; Das, 2024; Dubois-Iorgulescu et al., 2018); and (2) techniques to consider second- and higher-order effects in EIA, and particularly social effects or effects mediated through social responses (Börjesson Rivera et al., 2014; Nilsson et al., 2021; Pohl et al., 2019). These questions are becoming increasingly urgent as widespread disagreements around EIA scope and adequacy combine to slow progress to decarbonization, but methodologies to resolve these controversies or build consensus among stakeholders remain elusive (Dutta et al., 2021; Hall et al., 2022; Larsen et al., 2018; Zarzavilla et al., 2022).

This work reports on controversies over the scope of EIA for transmission projects proposed to increase U.S. import capacity of Canadian hydropower in terms of contested "mental models" and proposes causal inference methodologies as an avenue of resolution and consensus-building. Mental models encode beliefs about deterministic or probabilistic causal relations among physical and social phenomena and are increasingly deployed to analyze conflicts over environmental systems (Gaus et al., 2023; Khemlani et al., 2014; Kolkman et al., 2007; Olofsson et al., 2023). To our knowledge, this is the first work to evaluate how competing causal beliefs may be evaluated quantitatively in the setting of disputed EIA.

1.3. Debates over United States – Canada energy integration provide a case study for the use of Bayesian inference methodologies to address controversies in EIA

In the northeastern United States, state decarbonization plans have sought to leverage Canadian hydroelectric resources as firm lower-carbon capacity and to buffer intermittent wind and solar generation; however, of four (~1 GW) large intertie projects proposed since 2018, two have been cancelled (2018 and 2024) and one was suspended in 2021 before a legal challenge allowed construction to resume (*Appeal of Northern Pass Transmission, LLC & a.*, 2019; *NECEC Transmission LLC et al. V. Bureau of Parks and Lands et al.*, 2022; Dalton, 2024; Gronendyke, 2018; Maine Department of Environmental Protection, 2021; U.S. Department of Energy, 2017).

A key feature of the opposition to these transmission projects is the claim that *increased transborder transmission* will stimulate *increased generation* in Canada and hence increase the environmental, social, and health impacts of large-reservoir hydropower (Calder et al., 2016; Rosenberg et al., 1997); this has been the basis for legal filings to the U.S. Department of Energy and others during the EIA process for these projects (Appalachian Mountain Club, 2018; Birchard, 2017; Forest Society, n.d.; Natural Resources Council of Maine, 2018; Peggy Kurtz et al., 2018; Riverkeeper, n.d.). Thus, debate over transborder electrical interties is in effect a debate over how to understand the causal relationship between transmission and generation infrastructure and whether to construe generation-side impacts as causally downstream from decisions over transmission. This is an example of a much broader category of disputes over EIA which center on the range of impacts that can be plausibly attributed to the action under consideration which differ between parties according to the mental model of each.

1.4. Quantitative tools are needed to bridge the gap between technical and sociotechnical conceptions of the evolving energy system

Such questions are not easily addressed by currently available mechanistic energy systems models. Available capacity expansion models (at least in the transborder context) do not have the resolution to describe, for example, how a decision about a transmission corridor affects the probability of new generation (Calder et al., 2024). In general, energy systems research has tended to develop models that characterize optimal portfolios of assets without regard to contingencies or path-dependencies introduced at intermediate steps along the path to these portfolios (e.g., at the project-specific level) (Ba et al., 2024; Bouffard et al., 2018; Dimanchev et al., 2021; Rodríguez-Sarasty et al., 2021). This work may acknowledge social "barriers" to implementation and support characterization of uncertainties around economic (but usually not other social) constraints or trends (Geels et al., 2017; Sovacool et al., 2015).

Conversely, a socio-technical framing interrogates the political, perceptual, legal, and behavioral mechanisms that combine to constrain and determine the evolution of the energy system in ways that are often overlooked in quantitative research (Sovacool, 2009). In reality, the energy system evolves as a function of complex interdependencies between social (political, economic, etc.) and technical processes that are difficult to simulate mechanistically (e.g., as in traditional energy systems models) (Geels, 2005; Hess & Sovacool, 2020, 2020), though the present work posits that retrospective quantitative analysis may nonetheless be possible. At the same time, there is increased interest in understanding conflict over renewable energy projects in terms of the set of tools used by, and range of projects proposed by, governments, developers, and utilities, notably with respect to public priorities, values, and interests (Calder et al., 2024; van de Grift & Cuppen, 2022).

There is a need for tools that allow for structured analysis of alternative worldviews as they pertain to the evolution of sociotechnical systems (notably, the range of impacts to consider in EIA, as analyzed here) in a way that provides empirical evidence for or against competing mental models. Such tools can provide a transparent basis for regulators to justify decisions over (for example) the scope of an analysis and can help other actors decide whether they will support or oppose a given project (for example, transmission projects that are contentious given their uncertain range of impacts). Here, we propose a role for tools that (1) complement rather than imitate the range of disciplinary-specific tools available to understand the performance of technical systems (e.g., tools to simulate the current electrical grid that operates almost independently of social dynamics) and (2) leverage data to describe the range of social and technical systems and sectors that combine to describe the evolution of energy systems using a sociotechnical framing.

There is for example increasing interest in the application of statistical causal inference tools to scope the range of environmental impacts attributable to biophysical perturbations (Arif & MacNeil, 2022; Paul, 2011). We have however not identified work exploring the use of these methodologies in the setting of impacts mediated by social systems, for example, to arrive at consensus of the range of second-order impacts that can plausibly be attributed to renewable energy projects. We demonstrate by way of case study that Bayesian inference methodologies can bridge the gap between (1) energy systems analysis, which is overwhelmingly quantitative and focused on the optimization of select technical endpoints, and (2) analysis of controversies regarding the scope of social and environmental impacts to consider.

This responds to a growing call within sociotechnical systems research to integrate causal inference methodologies to examine the intricate cause-and-effect relationships inherent in energy transitions (Andersen & Geels, 2023; Geels et al., 2016; Köhler et al., 2019). By employing causal inference models, we can quantitatively assess how non-technical factors influence technical developments and vice versa, providing empirical evidence to support or challenge competing mental models (Pearl, 2000; Sovacool et al., 2021). This enables (1) a more nuanced understanding of contingencies and path dependencies (e.g. secondary impacts) that shape energy systems which is often neglected in mental models, and (2) the ability to curate effective and socially responsive energy policies by identifying critical causal relationships and potential intervention points to accelerate decarbonization (Kern & Rogge, 2016).

More broadly, we posit that such methods may be informative for understanding the evidence underpinning competing mental models in other types of disputes. Impacts mediated through social systems, i.e., those which are conditional on an unknown future individual or social response, are virtually never addressed in EIA due to a lack of integrated modeling capacity or efforts by project proponents to limit EIA scope. This includes results of economic phenomena such as the “rebound effect”, where projects improving efficiency accelerate rather than arrest depletion of natural resources or environmental degradation (Owens et al., 2022), and market actions of electricity suppliers following projects that increase transmission capacity, which is the focus of the present analysis (*Border Power Plant Working Group v. Department of Energy*, 2003).

2. Methods

2.1. Study area

Quebec, Canada has 37,590 MW of installed hydroelectric capacity (plus an exclusive power purchase agreement for 5,428 MW of generation at Churchill Falls in Labrador), accounting for 94% of total generation (Canada Energy Regulator, 2024a; Hydro-Québec, 2022a). These resources are a large and generally growing source of electricity for the northeastern United States across borders with Maine, New Hampshire, New York, and Vermont: net exports to the U.S. averaged 22.5 TW·h year^{-1} between 2018-2023, compared to 11.9 TW·h year^{-1} between 1998-2003, and accounted for roughly half of Canada's net electricity exports to the U.S. in that period (Canada Energy Regulator, 2024b). Energy systems models find that increased intertie capacity with Canada generally lowers overall costs of decarbonization in the United States, with Canadian hydropower either buffering intermittent supply of U.S. wind and solar or supplying base load (Calder et al., 2022; Dimanchev et al., 2021).

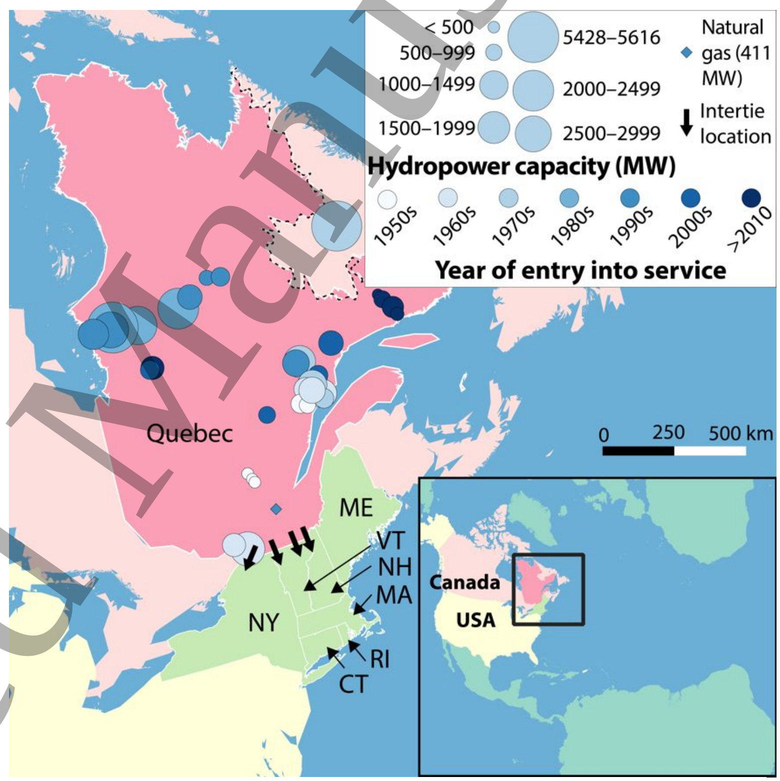

Figure 1: Large (>245 MW) generation and transborder transmission infrastructure in Quebec, Canada including Churchill Falls in Labrador due to exclusive power purchase agreement. New York (NY), New England states Connecticut (CT), Massachusetts (MA), Maine (ME), New Hampshire (NH), Rhode Island (RI), and Vermont (VT), and Quebec, Canada, are highlighted. Years of entry into service and installed capacity from Hydro-Québec (2023). Locations of infrastructure from Hydro-Québec (2020). Intertie locations represent 25 capacity expansion projects (~ 4300 MW) undertaken since 1979.

Development of large (>245 MW) hydroelectric facilities began with La Tuque (entry into service in 1955) and has continued to present day with Romaine-4 (2022). Locations of existing interties (corresponding to 25 incremental expansion projects undertaken since 1979) and large generation facilities are plotted in Figure 1. The U.S. accounts for the large majority (i.e., >70% over 2018-2023) (Canada Energy Regulator, 2024a; Hydro-Québec, 2018–2023) of net exports from Quebec and is the site of the most significant controversy regarding transmission infrastructure and is thus the focus of our analysis.

The six states of New England share a common transmission system operator, ISO New England, though each state has different renewable energy targets and has historically managed renewable energy procurements individually. The electrical grid in New York is managed by ISO New York. We refer to New England and New York collectively as the northeastern United States (NE USA). Historically, surplus generation from Quebec has been sold on the short-term spot market to neighboring states and provinces (i.e., 90% of exports between 2014-19). However, recently, longer-term export contracts tied to large purpose-built infrastructure have been pursued. This includes a 10.4 TWh year^{-1} (1.3 GW) corridor through New York recently completed, two 9.5 TWh year^{-1} (~1 GW) corridors to Massachusetts via New Hampshire (cancelled) and Maine (suspended), and a ~1 GW corridor through Vermont and New Hampshire (cancelled) (*Appeal of Northern Pass Transmission, LLC & a.*, 2019; *NECEC Transmission LLC et al. V. Bureau of Parks and Lands et al.*, 2022; Dalton, 2024; Gronendyke, 2018; Maine Department of Environmental Protection, 2021; U.S. Department of Energy, 2017).

Electricity trade between Quebec and Ontario display a balanced bilateral trade pattern that follows a seasonal cycle. Ontario's exports during the winter in Quebec help improve reliability and meet high electricity demands. In contrast, in the summer, there is a rise in exports from Quebec to Ontario due to the high demand for air conditioning (Independent Electricity System Operator, n.d.).

2.2. Model conceptualization

We conceptualize the Quebec–New England–New York electricity market as generation, demand, transmission, and price phenomena connected via a causal network with uncertain structure and test structures corresponding to alternative mental models of various stakeholders. We develop a rich dataset covering the period 1979 to 2021, which we use to evaluate the plausibility of alternative causal structures represented by Bayesian networks (BNs). BNs are directed acyclic graphs (DAGs) used to evaluate the evidential support for the presence and directionality of causation among system variables (Hernan & Robins, 2023; Nogueira et al., 2022; Pearl, 1995, 2000; Spirtes et al., 2001; Su et al., 2013).

Specifically, we interrogate the claim that transborder transmission infrastructure stimulates hydroelectric development in Canada. As described above, this claim has been the basis for legal filings arguing that DOE is required to consider generation-side environmental impacts in permitting transmission infrastructure and has contributed to opposition to these projects. We also characterize evidence for other asserted or hypothesized causal relations in this system and identify challenges inherent in the use of causal inference methodologies for complex sociotechnical systems more broadly.

As illustrated in Figure 2, alternative model structures are composed of diverse hypothesized relationships. In general, evaluation of BNs test entire model structures rather than one-way relationships as in classical statistical methods.

We developed a conceptual model for generation, demand, transmission, and price variables, representing assumed and disputed causal connections in the Quebec and NE USA electricity markets (Figure 2). Installed hydropower generation capacity is a function of current and projected demand and factors of safety to reflect uncertainties in future generation (governed by hydrologic conditions) and demand (Stedinger et al., 1984; U.S. Department of Energy, 2016). High-consequence dams require higher factors of safety for such uncertainties, increasing the probability of overdesign (Fell et al., 2005; Herza et al., 2018). Exports are meanwhile determined by generation capacity, price signals resulting from the balance of supply and demand domestically and in export markets, and the capacity of available transmission infrastructure. Investments are necessary for increases in both installed generation and transmission. To our knowledge, these basic dynamics are not in debate and we have represented them as "asserted relationships" in Figure 2.

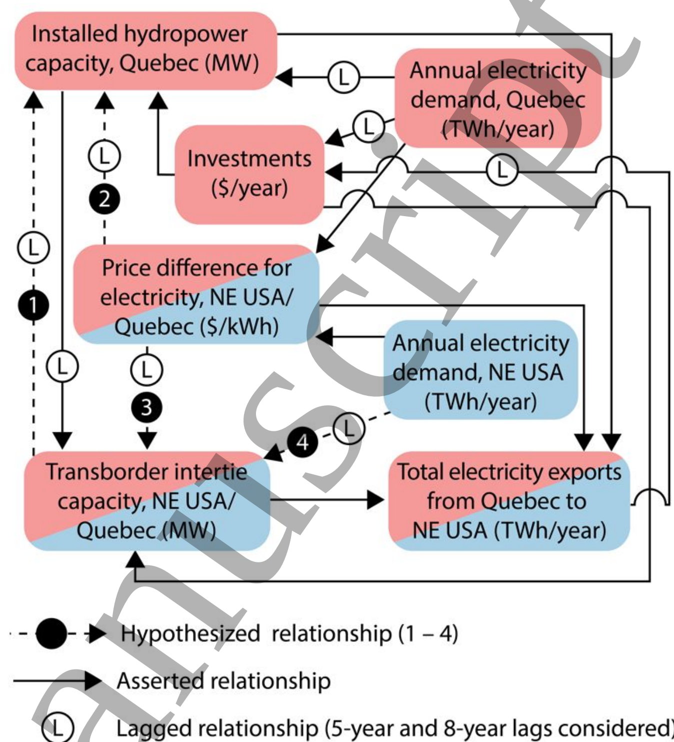

Figure 2: Conceptual diagram showing asserted and hypothesized relationships between generation, transmission, and demand variables in New York/New England (NE USA) and Quebec, Canada. Investments are a subset of revenues (omitted). Asserted and hypothesized relationships are described in the text. System variables are shaded red for Quebec, blue for the NE USA, and red/blue for transborder.

Development of transborder transmission capacity stimulated by U.S. electricity demand may accelerate the development of Canadian hydroelectric resources by enhancing opportunities for export. Historically, higher prices for electricity in the U.S. than in Canada have played a major role in the pursuit of export opportunities by Canadian utilities (Warner & Coppinger, 1999). These export opportunities continue to be acknowledged in decision-making around new projects, for example, coupling the Maritime Link transmission project with the 824-MW Muskrat Falls hydroelectric project in Newfoundland & Labrador, developed in the 2010s (Government of Newfoundland and Labrador, 2012). Meanwhile, public statements by Hydro-Québec, the government-owned utility that manages electrical generation and distribution in Quebec, Canada, suggest that the export market is necessary for profitability (Snyder, 2018).

However, it is not clear that investments in transmission infrastructure decisions are themselves stimulating new generation beyond key drivers such as domestic demand and the export opportunities allowed by existing transmission. It is therefore not understood if, in the context of proposed transmission projects, potential new generation (and its associated environmental and social effects) can be construed as second-order consequences within the meaning of environmental impact, life cycle, or cost benefit analysis. Likewise, it is not clear how opposition to transborder transmission infrastructure affects the viability of new generation projects in Canada. While capacity expansion models can simulate the economics of new hydroelectric generation under different transborder transmission scenarios, currently available tools do not have the resolution to allow for simulations conditioned on individual projects (Calder et al. in prep). Therefore, we apply causal inference to available data to better understand these questions.

The claim that increased transborder infrastructure leads to increased generating capacity in Canada is the central focus of this analysis and is represented as Hypothesis # 1 in Figure 2. An affirmative finding would support the argument that generation-side impacts are "reasonably foreseeable" consequences of transmission infrastructure and hence reviewable under environmental assessments and/or impact statements required by NEPA for federal permitting as previously argued to DOE (Birchard, 2017). Conversely, a negative (or null) finding may increase support among stakeholders who currently oppose transmission infrastructure on the basis of a supposed stimulating effect on generation (Webster, 2022).

Beyond this central question, we evaluate other, non-mutually-exclusive relationships. Relationship # 2 holds that installed hydroelectric capacity is instead stimulated by the price difference between Quebec and the northeastern U.S. Other relationships evaluated represent potential drivers of transborder intertie capacity: Relationship # 3 hypothesizes that intertie capacity is stimulated by the same price difference, and Relationship # 4 hypothesizes that intertie capacity is stimulated by U.S. demand. These alternative hypotheses have fewer immediate implications for EIA but may provide an alternative causal framework by which to understand the temporal evolution of this system.

2.3. Variable definition and data aggregation

Table 1 summarizes the raw variables aggregated for this analysis with reference to the original data sources. Some variables are then transformed to reflect likely lags (represented in Figure 2 and described in Section 2.3). We selected the period 1979–2021, which maximizes data availability for relevant variables while covering all periods of major expansion of transborder transmission capacity.

Hydro-Québec's annual reports were consulted to acquire information regarding the company's generation capacity, its sales to the domestic market, its exports to outside markets, its annual revenues, and its investments in transmission and generation infrastructure. We quantify the rated capacity of transmission infrastructure developed (in MW) as a measure of transmission rather than the power exported in a given year (MW·h) because this is more consistent with the physical properties of the infrastructure subjected to permitting and environmental review. Capacity of transmission lines was often reported in kV, which is not directly comparable to generation or transmission in MW. We converted transmission capacity to MW using the transmission line power-transfer capability curve commonly known as the St. Clair curve presented in supplemental information (SI) Figure S1 (Gutman et al., 1979), calibrated using eight available data points and applied to seven remaining points where capacity in MW was unknown (Equation 1). R^2 for the calibration curve was 0.998. Calibration and prediction data are included in SI Table S1. The calibrated St. Clair curve is written as:

$$P = \alpha_1 V^2 + \alpha_2 V + \beta \qquad \text{Eq. 1}$$

In Equation 1, P is the maximum loadability (capacity) in MW; V is the maximum voltage in kV; α_1 is a constant calculated via calibration as 0.004431; α_2 is a constant calculated via calibration as -0.5154; and β is a constant calculated via calibration as 20.82.

To represent the disparities in electricity prices between these regions, we calculated the retail price difference between Quebec vs. NE USA based on average electricity price per kWh from both regions. We used retail price difference as a proxy for wholesale price difference since data for wholesale market prices was not available for the full period of our study (1979–2021). This approximation is justified by the strong correlation between retail and wholesale prices (Castro Pérez & Flores, 2023). A causal connection between other variables in the proposed network (Figure 2) and retail price would thus very likely imply a causal connection with wholesale price (or vice-versa). We tabulated other data related to climate, hydrology, and electricity sales to explore possible other correlations and identify potentially overlooked variables. These variables are described in SI Table S2 but are not retained in the final causal model described below.

Table 1: Summary of data aggregated for causal analysis, 1979-2021. Bolded variables correspond to conceptual Figure 2 and include values derived from underlying data sources. Unbolded variables allow calculation of certain derived variables.

Variable name	Units	Description	References
EXPORTS	TWh $year^{-1}$	Hydro-Québec's total exports	Hydro-Québec (1979–2021)
DEMAND_QC	TWh $year^{-1}$	Hydro-Québec's electricity sales to the Québec's market; equates to generation net of transmission losses	Idem
DEMAND_US	TWh $year^{-1}$	Annual electricity sales to ultimate customers for NE USA (New England and New York).	U.S. Energy Information Administration (2022)
INVESTMENT	\$CAD $year^{-1}$	Total investments in generation and transmission infrastructure made by Hydro-Québec	Hydro-Québec (1979–2021)
INSTALLED	MW	Installed hydroelectric generation capacity in Quebec, Canada	Idem
INTERTIE	MW	Transborder intertie transmission capacity (see text for method to convert from kV)	U.S. DOE (1979–2021)
PRICE	\$CAD kWh^{-1}	Price difference between U.S. and Quebec [= PRICE_US × EX_RATE – PRICE_QC] – retail price used as a correlate for wholesale price	n/a
PRICE_QC	\$CAD kWh^{-1}	Annual average retail electricity prices for electricity in Quebec	(Hydro-Québec, 2022b)
PRICE_US	\$USD kWh^{-1}	Annual estimate of average electricity price in NE USA	U.S. Energy Information Administration (2022)
EX_RATE	\$CAD $\$USD^{-1}$	Exchange rate between Canadian and U.S. dollars	Federal Reserve Board (2023)

2.4. Variable transformations

Intertie capacity and installed generation capacity reflect large civil infrastructure projects with lead times of an average of 8.6 years between announcement and completion (Ansar et al., 2014). We therefore expect that responses in the form of infrastructure expansion may be lagged with respect to their predictor variables (as represented in Figure 2). However, infrastructure decisions are also made on the basis of forecasts and may be pursued in parallel with complementary components (intertie may expand in anticipation of new generation or vice versa). While many decades can elapse between first discussion of a hydroelectric project and its ultimate completion, the time between official sanction and project completion is substantially shorter; for example, the financing for Muskrat Falls was finalized in 2013 and the first power was generated in 2020. Therefore, for infrastructure outcomes, we consider lags in potential predictor variables of both 5 and 8 years. Because a lag period of *t* years reduces the size of the dataset by *t-1* years, consideration of longer lag periods interferes with the ability of the model algorithm to identify coherent networks; nevertheless we also explored the use of lag periods up to 15 years.

Furthermore, we expect many variables represented in Figure 2 to respond not necessarily to the absolute value of upstream nodes (i.e., their parents) but rather to changes in those variables over some preceding time period. For example, sudden increases in intertie capacity may stimulate expansion in generation (Hypothesis 1). Therefore, both generation and transmission were represented as the 5- or 8-year running average of changes (which serve as predictors lagged 5 or 8 years as described above). A lag is implemented for infrastructure variables serving as predictors but not when the same variable serves as an outcome. Thus, some variables may have more than one representation.

Table 2: Asserted and hypothesized causal relations indicating lagged (5 or 8 years), Box-Cox transformed and discretized variables. Relations are summarized in Figure 2. Expanded figure showing all representations of variables included in SI Figure S2A.

Response variable	Asserted causal (parent) variable(s)	Hypothesized causal (parent) variable(s)
INSTALLED[a,b]	DEMAND$_{QC}$[c], INVESTMENT[d,e]	INTERTIE[f,h,1], PRICE[g,b,2]
INTERTIE[a,h]	INVESTMENT[d,e], INSTALLED[i,e]	PRICE[g,b,3], DEMAND$_{US}$[c,4]
EXPORTS[j]	PRICE[j,b], INSTALLED[a,b], INTERTIE[a,h]	n/a
INVESTMENT[d,e]	EXPORTS[c,k], DEMAND$_{QC}$[c]	n/a
PRICE[j,b]	DEMAND$_{US}$[j,e], DEMAND$_{QC}$[j,e]	n/a

[a] Total expansion in 5- or 8-year period up to year *t*
[b] Box-Cox transformed variable
[c] 5- or 8-year lag of the 5 or 8-year moving average for the incremental expansion, i.e., value in year *t* minus value in year *t-1*
[d] Average total investment in 5- or 8-year period up to year *t*
[e] Discretized variable ("low", "medium", "high")

[f] 5- or 8-year lag of the total intertie capacity expansion in 5- or 8-year period up to year *t*
[g] 5- or 8-year lag of price difference in 5- or 8-year period up to year *t*
[h] Discretized variable (“non-significant”, “significant”)
[i] 5- or 8-year lag of the total installed capacity expansion in 5- or 8-year period up to year *t*
[j] Average expansion in 5- or 8-year period up to year *t*
[k] Discretized variable ("negative", "positive")
[1,2,3,4] Hypotheses 1, 2, 3 and 4

Finally, variables were transformed to respect the underlying assumptions for the structure and parameters of the BN approach used. BN models can be learned from data on continuous variables that are normally distributed, or on categorical variables. Therefore, if they are not already normally distributed, data may either be transformed to respect the assumption of normality or discretized. We thus evaluated each variable for normality using the Shapiro-Wilk test with a significance level of 0.05. Non-Gaussian variables (i.e., those that failed the Shapiro-Wilk test) were transformed using the Box-Cox method with the boxcox() function in the *MASS* package in R (Ripley & Venables, 2003) to achieve normality where possible in order to retain maximum information.

After transforming the non-Gaussian variables, we reapplied the Shapiro-Wilk test to evaluate the effectiveness of the transformation. Variables that failed the Shapiro-Wilk test post-transformation were then discretized. Discretization of variables was done manually using the ordered cut() function in R; this means that continuous variables were converted to ordinal discrete variables. We used histogram plots to determine the cutting points for each variable to ensure a roughly equal distribution of observations across variable levels. Depending on the variable’s definition (Table 1) and its histogram, we discretized the variables according to three different schema: 1. "low", "medium", or "high", 2. “non-significant” or “significant” and 3. “negative” or “positive”. Implementation of a manual discretization protocol helps ensure production of meaningful and interpretable BN models (Beuzen et al., 2018). All transformations are reported in Table 2. Code for all variable manipulations and transformations is included in the reproduction information (RI).

2.5. Bayesian network modeling and evaluation of causal relations

We used BN modeling to test alternative model structures against data in order to evaluate the plausibility of asserted and hypothesized causal relations (Section 2.1). BNs are probabilistic graphical models that represent sets of variables and their conditional dependencies in the form of DAGs (Scutari & Denis, 2021). Compared to alternative approaches like Vector Autoregression (VAR), BNs make weaker assumptions about linearity and stationarity and are better suited to analysis of smaller datasets (Righetti, 2022). DAG representation of these networks aids in illuminating possible causal relationships between variables, providing a clear illustration of how one variable or factor can affect others. BN models contain two major components: the network *structure,* which maps nodes and directed edges to create a DAG; and conditional probability distributions for each node, which are represented using *parameters*, describing the relative likelihood of values of response variables conditioned on the values of its direct causes.

Two types of data-training algorithms are available to evaluate network structures against a dataset: *score-based* and *constraint-based* (Su et al., 2013). *Score-based* methods calculate a score for alternative structures, and the score reflects the ability of that structure to explain the observed data. Score-based methods are commonly favored for datasets that are small and contain noise (Cheng et al., 2002). In score-based methods, the objective is to identify the configurations that yield high scores. Conversely, *constraint-based* methods seek to identify conditional independence (i.e., Markov condition) among variables. These methods use data to perform hypothesis testing regarding conditional independence to eliminate edges from a fully connected undirected graph. Subsequently, directions are assigned to edges in accordance with the *d-separation* criterion (Pearl, 2000). It is also common to use hybrid algorithms that integrate the two types of methods to capture the benefits of each as a function of the properties of the dataset and the strength of hypotheses (Tsamardinos et al., 2006).

We rely on a score-based method to evaluate the network structure against data because our dataset does not have a sufficient number of observations to effectively perform the hypothesis tests required of constraint-based methods. For example, many variables had to be discretized, resulting in a loss of information, and some variables were lagged, resulting in a loss of some years (described in Section 2.3 and summarized in Table 2). The score-based method employed uses the log-likelihood scoring criterion and employed a hill-climb (HC) algorithm using the hc() function in the *bnlearn* package for R to identify the highest scoring network (Scutari et al., 2023). Generally, the log-likelihood criterion is the least restrictive (will admit the most relations), enabling us to most confidently rule out hypothesized (or asserted) relations if they do not appear in the best-fitting model structures.

To further assess the degree of confidence in returned relations, we also applied alternative scoring criteria (Akaike information criterion, or AIC, and Bayesian information criterion, or BIC) that penalize for the number of edges in the network. AIC and BIC results are discussed in greater detail in the SI. In all cases, the algorithm was initialized using the hypothesized network presented in Table 2 and was constrained by a blacklist consisting of all illogical relations between variables (e.g., contemporary variables cannot influence lagged variables).

To interpret the network relations (i.e., assign a direction of effect) and measure the goodness of model fit for each variable in our DAG, we used the predict() function with the *bayes-lw* method (Needham et al., 2007). The *bayes-lw* method performs both causal prediction and noncausal Bayesian inference using Monte Carlo methods. Further likelihood weighting ensures that predictions account for all possible values of variables accounting for their relative likelihood. To assess goodness of fit for continuous numerical variables, we calculated the coefficient of determination (r squared), while for discretized variables we calculated the proportion of correct predictions as a measure of model accuracy.

Finally, to further interrogate specific relations of interest, we used the d-separation criterion. Informally, the d-separation criterion states that, "Each variable is independent of its non-descendants in the network given its parents" (Ding & Rebai, 2010). More formally, the d-separation criterion specifies the set of conditional dependences and independences that are implied by a particular graph and subject to statistical hypothesis testing. Specifically, we used our data to test the independence of pairs of nodes by conditioning each pair on the pair's parents. If the p-value for an independence test is greater than the high threshold of 0.95, then the two variables are interpreted as "Conditionally Independent". If the p-value is smaller than the low threshold of 0.05, then this is labeled "Potential Missing Link". If the p-value is between the low and high thresholds, then the analysis is inconclusive. All functions mentioned in this section are reported in RI, including the functions that were developed by authors.

3. Results and discussion

3.1. Model structures returned by Bayesian network analysis

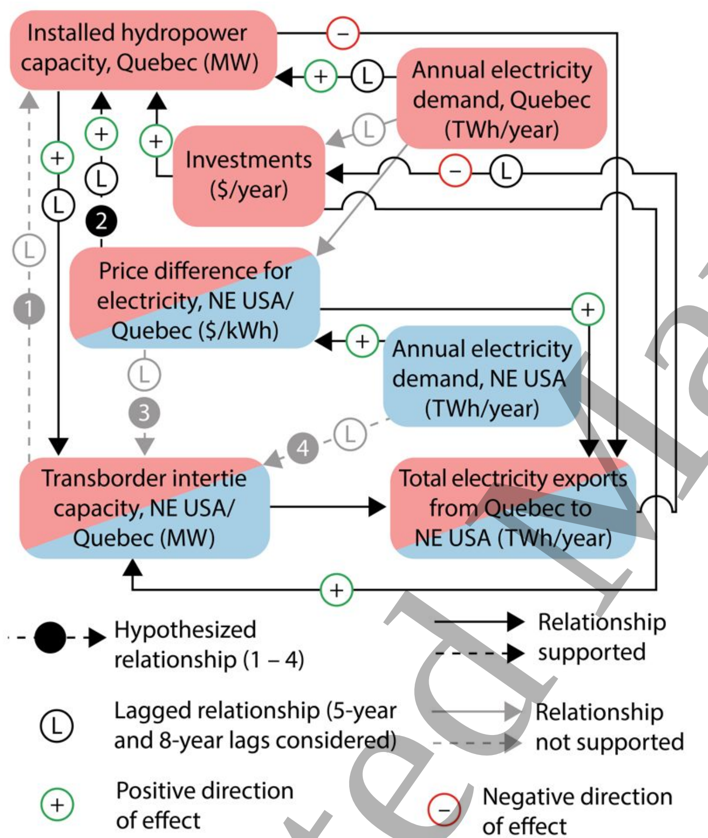

Figure 3: DAG that maximizes the log-likelihood scoring criterion (black lines) in comparison with the conceptual model in Figure 2 (including light grey lines). The same structure applies to both 5-year and 8-year models. Intertie → Exports has an ambiguous direction of effect as described in Section 3.2. Concept nodes are shaded red for Quebec, blue for the NE USA, and red/blue for transborder. Corresponding DAG is included in SI Figure S2B.

Using the log-likelihood criterion, the DAGs of the best fitting BNs were identical for the 5-year and 8-year formulations. Figure 3 shows the relations included in the best fitting BN (log-likelihood criterion) in comparison with the conceptual model presented in Figure 2, where relations not included in the fitted BN are greyed out. Table 3 provides an indication of the accuracy of the fitted relations. As described in Section 2.5, the log-likelihood criterion is generally more permissive than AIC and BIC and thus less likely to falsely rule out relationships. Thus, hypotheses rejected using the log-likelihood criterion are unlikely to exist. The identical model structure returned by both 5- and 8-year model formulations suggests that results are not sensitive to the averaging/lag period retained.

The best fitting BN does not indicate that installed generation capacity depends on intertie capacity (Hypothesis 1). The best fitting BN does indicate that price difference between the northeastern U.S. and Quebec has an influence on installed generation capacity (Hypothesis 2), but not on intertie capacity (Hypothesis 3). Intertie capacity also does not seem to be influenced by U.S. electricity demand (Hypothesis 4). D-separation results (Table 4) confirm the conditional independence between intertie capacity and installed generation (Hypothesis 1). Other results are the same as presented in Figure 3, with the exception of the relationship between electricity demand in Quebec and investments.

Therefore, the assertion that transborder intertie capacity directly "causes" expansion of hydroelectric generation in Quebec is not supported by our analysis. We note, however, that expanded intertie capacity does influence electricity exports, which influences investments, and investments in turn influence installed capacity. Thus, expanded transborder intertie capacity appears to be one part of a broader evolving technological system with mutual interdependencies rather than a trigger of installed hydropower capacity per se. Yet, as described below, the ambiguous direction of effect along the causal path does not necessarily support the interpretation that expanded generation capacity is even a second- or higher-order result of expanded transmission.

Table 3: Summary of our BN modeling results: fitted relationships and corresponding performance metrics. Results generated using the AIC and BIC criteria are available in SI Tables S3 & S4 (AIC), and S5 & S6 (BIC). Variables are transformed following footnotes in Table 2.

Response	Causal (parent) variable(s)	5-year model		8-year model	
		r squared	Accuracy	r squared	Accuracy
INSTALLED	$DEMAND_{QC}$, INVESTMENT, PRICE	0.76	-	0.96	-
INTERTIE	INVESTMENT, INSTALLED	-	0.70	-	0.89
EXPORTS	PRICE, INSTALLED, INTERTIE	0.78	-	0.92	-
INVESTMENT	EXPORTS	-	0.76	-	0.96
PRICE	$DEMAND_{US}$	0.60	-	0.76	-

Table 4: Summary of the results when conditioning on parents for the unsupported links presented in Figure 2. Variables are transformed following footnotes in Table 2.

Response	Causal (parent) variable	Conditional independence results
INSTALLED	INTERTIE	Conditionally independent
INTERTIE	$DEMAND_{US}$	Conditionally independent
INTERTIE	PRICE	Conditionally independent
INVESTMENT	$DEMAND_{QC}$	Potential missing link
PRICE	$DEMAND_{QC}$	Conditionally independent

AIC and BIC models broadly agree with the results presented here. In AIC and BIC models, 5-year formulations were more detailed, likely because fewer observations were discarded in the creation of 5-year-lagged variables than 8-year-lagged variables. In the BIC models, Hypothesis 1 was supported, but the direction of effect was negative. Model structures generated using the AIC and BIC criteria are available in SI Figures S3 (AIC) and S4 (BIC). These figures demonstrate how stricter criteria, such as AIC or BIC, limit the model's ability to identify edges that can be discovered using our data.

For all methods evaluated here, we explored the use of longer lag periods to account for longer average lead times between project sanction and development (e.g., up to 15 years). However, these models returned only fragmentary network structures, likely due to the significant amounts of data that must be discarded to calculate the first averaging period (see Section 2.3). All code for these (and other) averaging periods is available via GitHub.

Figure 3 shows the signs of the fitted relations, indicating that most variables are positively influenced by their causal predictors. Supplemental figures characterizing the direction of effect of the different relations are included in the SI. SI Figure S5 shows that installed generation capacity increases if any of its predictors increase. SI Figure S6 shows that intertie capacity is positively impacted by increases in installed generation capacity and investment levels. SI Figure S7 shows that price difference is positively impacted by increases of average demand in the NE USA. By contrast, investments are negatively influenced by total exports in the previous time step, which in turn is negatively influenced by installed capacity (thus leading to an indirect positive relation between installed capacity and subsequent investments) as shown in SI Figure S8. SI Figure S9 shows that the relation between intertie capacity and total exports is ambiguous, being positive or negative depending on the values of the other predictors of total exports: installed generation capacity and price difference.

3.2. Temporal evolution of the generation-transmission system

Our analysis suggests that there is no direct association between increased intertie capacity and increased generation capacity (Hypothesis 1). There is an indirect link through exports and investment, meaning that increased exports facilitated by increased intertie capacity allows investments in both generation and transmission infrastructure. Therefore, intertie capacity appears to play at most an indirect, ancillary role in decisions around generation expansion.

Instead, this analysis reveals that investments in installed capacity are driven by a combination of domestic demand and price signals in the form of a difference between electricity prices in the northeastern United States and Quebec (Hypothesis 2). These price signals also drive export decisions over existing infrastructure. The significant reserve capacity of Hydro-Québec (up to 177 TWh) allows for selective exports at times of relative greater prices in the U.S (Hydro-Québec, 2020).

While intertie capacity does not directly drive installed generation capacity, our analysis reveals that installed generation may partially drive intertie capacity. This may correspond to Hydro-Québec's seeking markets for excess supply; hydropower projects are likely to be overdesigned in order to guarantee the ability to meet local demand and to supply existing contracts, potentially posing a choice between non-revenue spills and pursuit of export opportunities. We do not find evidence that intertie capacity is the direct consequence of price signals (Hypothesis 3) or U.S. demand (Hypothesis 4). However, it may be a second-order consequence of these variables via the role of price signals on installed capacity.

As described earlier, the premise that increased transborder transmission capacity stimulates increased generation in Quebec has been used to argue for increased scope of assessments/statements under NEPA (Birchard, 2017) and to attribute greenhouse gas emissions from reservoirs to proposed transmission projects (New York State Energy Research and Development Authority, 2021). This premise has also adversely affected support for such projects among environmental stakeholders whose support is important for achieving decarbonization of the electrical sector (Webster, 2022). Overall, this analysis supports a contrary view, i.e., that new transborder transmission projects should be considered independently from the suite of environmental and health impacts associated with reservoir construction.

Historically, electricity exports from Quebec have been overwhelmingly settled on the short-term spot market (i.e., between 86–91% every year since 2001), which are the market behaviors captured by the causal model developed here. By contrast, several recently proposed projects tie long-term power purchase agreements to purpose-built infrastructure (*Appeal of Northern Pass Transmission, LLC & a.*, 2019; BloombergNEF, 2023; Maine Department of Environmental Protection, 2021). It is possible that power commitments via these long-term contracts will stimulate reservoir development in a way that we do not observe with historic export patterns, for example, by creating commitments that cannot be satisfied without new generation. In recent work, we described model and data gaps that make such situations difficult to identify and identified this as a priority area for model development given its importance in debates over environmental and social impacts (Calder et al., 2024).

Theoretically, capacity expansion models can simulate how individual transmission projects affect the overall economics of new generation projects (and vice-versa) but in practice there are no publicly available models with project-scale resolution. Because Hydro-Québec does not publish reservoir levels, capacity factors, or other key statistics on the generation fleet, impacts of new long-term power purchase agreements on build-out of generation or on exports to other markets are currently speculative (Calder et al., 2022, 2024). Overall, this analysis suggests that the new transmission infrastructure is not driving build-out of hydroelectric generation in Canada per se, but that a shift to long-term power purchase agreements may introduce pressures on electrical supply that are not currently easily modeled.

3.3. Strengths and limitations of causal inference methodologies for analysis of other socially mediated systems

This analysis suggests that formal causal inference methodologies may be used to understand evolving sociotechnical systems more broadly, for example, to scope environmental impact, life cycle, and cost-benefit analysis by building consensus on the range of relevant second-order effects. Because sociotechnical systems in general feature complex feedbacks, plausible narrative claims can be advanced for many alternative causal interpretations across a wide range of settings including the energy system (studied here), urban housing supply and affordability (Li, 2021), and investments in resource conservation and protection of environmental resources (Owens et al., 2022). We posited earlier that formal causal inference methodologies could help resolve debates around and build consensus over the most parsimonious causal structures to overlay on complex systems where "everything is connected".

We have demonstrated several modeling and interpretation approaches that may facilitate the use of Bayesian network analysis in other contexts. This includes the consideration of multiple BN algorithms, models and the interpretation of evidentiary support for hypothesized relationships on the basis of (1) agreement across models for a given hypothesized relationship and (2) whether it manifests as part of a causal structure with a plausible mechanistic interpretation. We have endeavored to describe evidence in support of potential causal relationships on the basis of a holistic analysis that considers multiple modeling choices and alternative causal structures, accepting that certain subjective choices may have significant effects on certain conclusions.

In certain cases, conclusions about features of the causal network may be robust to a wide variety of modeling choices. This was illustrated in this case study by our conclusion that hydroelectric generation in Canada is not the outcome of increased transborder intertie capacity, despite a plausible narrative claim advanced by expert stakeholders. In that case, our conclusions are robust to all possible models considered and thus seem robust enough to dismiss this assertion. For example, we failed to find evidence for this assertion across model formulations that varied in averaging/lag periods assumed and BN algorithm retained.

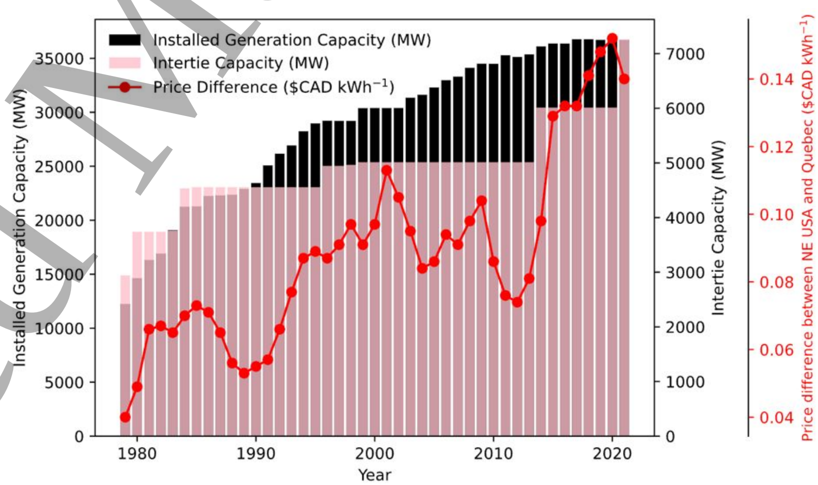

Figure 4: Time series of installed generation capacity and intertie capacity, and of retail electricity price differences between Quebec and New York and New England (average) 1979-2021.

Conversely, our analysis suggests that these modeling choices can affect network structure in ways that could change the interpretation of causal dynamics in other settings. For example, our analysis based on the BIC criterion returns subtly different network structures when 5-year lag/averaging periods are considered vs. 8-year periods (SI Figure S10). In this analysis, data availability and the objective of ruling out asserted links suggested the BIC criterion was not well-suited. As in other types of quantitative modeling, professional judgment is required to exercise subjective decisions to interpret potentially contradictory results across model formulations.

The data available to parameterize a model clearly influence model predictions, and data are usually fragmentary and incomplete. In the setting of BNs, this may manifest as an unobserved counterfactual, creating uncertainties around a causal relationship between two nodes. For example, in the period 1979-2021, the price difference between Quebec and New York/New England was always positive (Figure 4), even while the magnitude of this difference varied. This limits the range of conditions over which the model may be valid. The shapes of the distributions of available data furthermore required extensive transformation to respect the assumptions of Bayesian analysis as summarized in Table 2 and described in Section 2.2. These transformations, though necessary to respect the assumptions of Bayesian analysis, result in a loss of information that increase uncertainties in any model returned.

In the setting of the renewable energy transition, such unobserved counterfactuals may also manifest as changes to the relative value of different energy sources such as the increased value of hydropower in a heavily decarbonized system (Miller et al., 2022). For a given model structure (e.g., Figure 2), such changes may increase probability of hydropower construction all else being equal. As described in Section 3.2, changes to the structure of underlying power purchase agreements can also change the relationship between variables represented in any causal model; however, such changes could be captured with the introduction of a new node.

BN analysis is subject to the same limitations as any graphical modeling strategy, and the use of these tools to describe evolving sociotechnical and socioenvironmental systems presents several inherent challenges. In particular, such systems have no inherent temporal beginning or end, feature multiple feedbacks across temporal and spatial scales, are characterized by evidence generated by a range of methodological traditions, and feature “mechanisms” that can be articulated at arbitrary levels of detail (Calder et al., 2020). Conceptual models for such systems thus necessarily reflect the judgments and specific decision context of the people who create these conceptual models.

As we have demonstrated here, these challenges can be compounded by the application of quantitative analysis, which necessarily embeds decisions made by modelers. This includes approaches to transforming and normalizing data and the selection of models, but also subjective elements of interpretation, for example, the description of results that conflict across model implementations with different BN learning algorithms. These are likely to be compounded by disagreements over the precise meaning of “reasonably foreseeable” and “reasonably close” in the application of NEPA and other institutional features that govern the interpretation of quantitative information, but that is outside the scope of this analysis.

3.4. Applications to life cycle and cost-benefit analysis

This analysis has demonstrated evaluated the utility of causal inference methodologies for structuring debates around the scope of environmental impact assessment, which frequently reflect disagreements over the causal relationship between variables mediated by social systems. We note that analogous debates also complicate cost-benefit and life-cycle analysis, with subjective judgments of the range of effects to attribute to an intervention, process, or technology often driving the outcome (Dubois-Iorgulescu et al., 2018). In the setting of Canadian hydropower in northeast U.S. energy transitions, this has manifested as disagreements over the valuation of GHG emissions from reservoirs (the “Scope 2” emissions of intertie projects in the terminology of the Greenhouse Gas Protocol) (Calder et al., 2020; Sotos, 2015).

In general, “attributional” assessment of impacts (Ekvall, 2019), whereby a fraction of the life cycle emissions of existing reservoirs is assigned to energy imported over new electrical interties, is common, even among prospective cost-benefit analyses (New York State Energy Research and Development Authority, 2021). We have previously argued that this has the effect of underestimating net benefits from incremental expansion in transmission when these projects have no causal connection to new reservoir development (Calder et al., 2022). Indeed, a “consequentialist” perspective, whereby alternative interventions are compared in terms of the impacts causally connected to each candidate intervention, is better suited to decision support but rarely used in energy systems analysis due in part to difficulties in causal analysis (Curran et al., 2005). Thus, causal inference methodologies such as those proposed here may promote the uptake of the consequentialist frame of reference in energy systems decision analysis.

4. Ethics declaration

The authors declare no competing interests.

5. Data and computer code availability statement

Data and computer code are available via GitHub. For the latest updates, visit this project’s GitHub page.

6. Manuscript preprint

The preliminary draft of this manuscript and supplemental documents were made available online via Engineering Archive preprint server on May 3, 2024.

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

8. Acknowledgements

The authors acknowledge U.S. Environmental Protection Agency (grant number RD840558 awarded to R.S.D.C.) for sponsoring this project. The authors thank Richard B. Howarth (Dartmouth College), Sam Evans-Brown (Clean Energy New Hampshire), and the anonymous reviewers for their comments and suggestions.

9. Literature Cited

Andersen, A. D., & Geels, F. W. (2023). Multi-system dynamics and the speed of net-zero transitions: Identifying causal processes related to technologies, actors, and institutions.

Energy Research & Social Science, *102*, 103178. https://doi.org/10.1016/j.erss.2023.103178

Ansar, A., Flyvbjerg, B., Budzier, A., & Lunn, D. (2014). Should we build more large dams? The actual costs of hydropower megaproject development. *Energy Policy*, *69*, 43–56. https://doi.org/10.1016/j.enpol.2013.10.069

Appalachian Mountain Club. (2018, September 27). The Next Northern Pass? AMC Intervenes on NECEC. *Appalachian Mountain Club (AMC)*. https://www.outdoors.org/resources/amc-outdoors/conservation-and-climate/the-next-northern-pass-amc-intervenes-on-necec/

Appeal of Northern Pass Transmission, LLC & a., No. No. 2018-0468 (Supreme Court of New Hampshire July 19, 2019). https://law.justia.com/cases/new-hampshire/supreme-court/2019/2018-0468.html

Arif, S., & MacNeil, M. A. (2022). Utilizing causal diagrams across quasi-experimental approaches. *Ecosphere*, *13*(4), e4009. https://doi.org/10.1002/ecs2.4009

Ba, A., Caron, J., & Pineau, P.-O. (2024). More transmission or more storage? Decarbonization in the context of hydro-rich Northeastern North America. *The Electricity Journal*, *37*(2), 107375. https://doi.org/10.1016/j.tej.2024.107375

Batel, S. (2020). Research on the social acceptance of renewable energy technologies: Past, present and future. *Energy Research & Social Science*, *68*, 101544. https://doi.org/10.1016/j.erss.2020.101544

Beuzen, T., Marshall, L., & Splinter, K. D. (2018). A comparison of methods for discretizing continuous variables in Bayesian Networks. *Environmental Modelling & Software*, *108*, 61–66. https://doi.org/10.1016/j.envsoft.2018.07.007

Birchard, M. (2017, January 31). *Supplemental Comments of CLF on DEIS and SDEIS, Northern Pass Transmission LLC, Presidential Permit Application, OE Docket No. PP-371*. Conservation Law Foundation.

Bistline, J., Brown, M., Domeshek, M., Marcy, C., Roy, N., Blanford, G., Burtraw, D., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Mayfield, E., McFarland, J., … Zhao, A. (2024). Power sector impacts of the Inflation Reduction Act of 2022. *Environmental Research Letters*, *19*(1), 014013. https://doi.org/10.1088/1748-9326/ad0d3b

BloombergNEF. (2023, April 20). Hydro-Québec's $6 Billion New York Line on Track for 2026 Start. *BloombergNEF*. https://about.bnef.com/blog/hydro-quebecs-6-billion-new-york-line-on-track-for-2026-start/

Border Power Plant Working Group v. Department of Energy, No. 02-CV-513-IEG (US District Court for the Southern District of California May 2, 2003). https://law.justia.com/cases/federal/district-courts/FSupp2/260/997/2578803/

Börjesson Rivera, M., Håkansson, C., Svenfelt, Å., & Finnveden, G. (2014). Including second order effects in environmental assessments of ICT. *Environmental Modelling & Software*, *56*, 105–115. https://doi.org/10.1016/j.envsoft.2014.02.005

Bouffard, F., Debia, S., Dhaliwal, N., & Pineau, P.-O. (2018). A Decarbonized Northeast Electricity Sector: The Value of Regional Integration. *Northeast Electricity Modelling Project Montreal, QC, Canada*. https://energie.hec.ca/wp-content/uploads/2018/06/ScopingStudy_NortheastHydroModelling_13june2018.pdf

Calder, R. S. D., Borsuk, M. E., & Robinson, C. (2020). Analysis of environmental and economic impacts of hydropower imports for New York City through 2050. *Duke University*, *NI R 20-12*. https://nicholasinstitute.duke.edu/publications/analysis-environmental-and-economic-impacts-hydropower-imports-new-york-city-through

Calder, R. S. D., Dimanchev, E., Cohen, S., & McManamay, R. A. (2024). Decision support for United States—Canada energy integration is impaired by fragmentary environmental and electricity system modeling capacity. *Environmental Research: Infrastructure and Sustainability*, *4*(3), 033002. https://doi.org/10.1088/2634-4505/ad763e

Calder, R. S. D., Robinson, C. S., & Borsuk, M. E. (2022). Total Social Costs and Benefits of Long-Distance Hydropower Transmission. *Environmental Science & Technology*, *56*(24), 17510–17522. https://doi.org/10.1021/acs.est.2c06221

Calder, R. S. D., Schartup, A. T., Li, M., Valberg, A. P., Balcom, P. H., & Sunderland, E. M. (2016). Future Impacts of Hydroelectric Power Development on Methylmercury Exposures of Canadian Indigenous Communities. *Environmental Science & Technology*, *50*(23), 13115–13122. https://doi.org/10.1021/acs.est.6b04447

Canada Energy Regulator. (2024a). *CER – Provincial and Territorial Energy Profiles – Quebec*. https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/provincial-territorial-energy-profiles/provincial-territorial-energy-profiles-quebec.html

Canada Energy Regulator. (2024b). *Electricity – Imports and Exports—Open Government Portal* [Dataset]. https://open.canada.ca/data/en/dataset/5c358f51-bc8c-4565-854d-9d2e35e6b178

Castro Pérez, J. E., & Flores, D. (2023). The effect of retail price regulation on the wholesale price of electricity. *Energy Policy*, *173*, 113408. https://doi.org/10.1016/j.enpol.2022.113408

Cederlöf, G., & Hornborg, A. (2021). System boundaries as epistemological and ethnographic problems: Assessing energy technology and socio-environmental impact. *Journal of Political Ecology*, *28*(1), Article 1. https://doi.org/10.2458/jpe.2303

Cheng, J., Greiner, R., Kelly, J., Bell, D., & Liu, W. (2002). Learning Bayesian networks from data: An information-theory based approach. *Artificial Intelligence*, *137*(1–2), 43–90. https://doi.org/10.1016/S0004-3702(02)00191-1

Colburn, J. E. (2016). The Risk in Discretion: Substantive NEPA's Significance. *Columbia Journal of Environmental Law*, *41*(1), Article 1. https://doi.org/10.7916/cjel.v41i1.3569

Council on Environmental Quality. (2020). *Update to the Regulations Implementing the Procedural Provisions of the National Environmental Policy Act* (No. CEQ-2019-0003; pp. 43304-43376 (73 pages)).

https://www.federalregister.gov/documents/2020/07/16/2020-15179/update-to-the-regulations-implementing-the-procedural-provisions-of-the-national-environmental

Council on Environmental Quality. (2021). *National Environmental Policy Act Implementing Regulations Revisions* (No. CEQ-2021-0002; pp. 55757-55769 (13 pages)). https://www.federalregister.gov/documents/2021/10/07/2021-21867/national-environmental-policy-act-implementing-regulations-revisions

Curran, M. A., Mann, M., & Norris, G. (2005). The international workshop on electricity data for life cycle inventories. *Journal of Cleaner Production*, *13*(8), 853–862. https://doi.org/10.1016/j.jclepro.2002.03.001

Dafnomilis, I., den Elzen, M., & van Vuuren, D. (2024). Paris targets within reach by aligning, broadening and strengthening net-zero pledges. *Communications Earth & Environment*, *5*(1), 1–10. https://doi.org/10.1038/s43247-023-01184-8

Dalton, J. (2024, March 7). National Grid no longer pursuing the Twin States Clean Energy Link. *Power Advisory LLC*. https://www.poweradvisoryllc.com/reports/national-grid-no-longer-pursuing-the-twin-states-clean-energy-link

Das, R. (2024). *Politics of Regulation: The Role of Environmental Impact Assessments in Shaping India's Socio-Political Landscape* (SSRN Scholarly Paper No. 4848337). https://doi.org/10.2139/ssrn.4848337

Dimanchev, E. G., Hodge, J. L., & Parsons, J. E. (2021). The role of hydropower reservoirs in deep decarbonization policy. *Energy Policy*, *155*, 112369. https://doi.org/10.1016/j.enpol.2021.112369

Ding, J., & Rebai, A. (2010). *Probabilistic Inferences in Bayesian Networks*. Sciyo. https://doi.org/10.5772/258

Dubois-Iorgulescu, A.-M., Saraiva, A. K. E. B., Valle, R., & Rodrigues, L. M. (2018). How to define the system in social life cycle assessments? A critical review of the state of the art and identification of needed developments. *The International Journal of Life Cycle Assessment*, *23*(3), 507–518. https://doi.org/10.1007/s11367-016-1181-y

Dutta, N., Noble, B., Poelzer, G., & Hanna, K. (2021). From Project Impacts to Strategic Decisions: Recurring Issues and Concerns in Wind Energy Environmental Assessments. *Environmental Management*, *68*(4), 591–603. https://doi.org/10.1007/s00267-021-01518-2

Eisenson, M., Elkin, J., Singh, H., & Schaffir, N. (2024). *Opposition to Renewable Energy Facilities in the United States: June 2024 Edition*.

Ekvall, T. (2019). *Attributional and consequential life cycle assessment*. IntechOpen. https://books.google.com/books?hl=en&lr=&id=yJj8DwAAQBAJ&oi=fnd&pg=PA41&ots=4uGARjVEYk&sig=P4ejPx2879tGDB0_XvpTUx97NQE

Federal Reserve Board. (2023, March 20). *US-Canada Dollar Exchange Rate*. https://www.federalreserve.gov/datadownload/Download.aspx?rel=H10&series=2e3510c

7c810ec01030aa1e14c9f361b&filetype=spreadsheetml&label=include&layout=seriescolumn&from=01/01/1971&to=12/31/2022

Fell, R., MacGregor, P., Stapledon, D., & Bell, G. (2005). *Geotechnical Engineering of Dams*. CRC Press. https://www.routledge.com/Geotechnical-Engineering-of-Dams/Fell-MacGregor-Stapledon-Bell-Foster/p/book/9781138749344

Forest Society. (n.d.). *The Northern Pass*. Retrieved May 3, 2024, from https://www.forestsociety.org/advocacy-issue/northern-pass

Gaus, R., Ejderyan, O., Grêt-Regamey, A., Leach, W. D., & Buchecker, M. (2023). How previous experiences shape actors' current perspectives in integrated natural resource management. *People and Nature*, *5*(6), 2048–2060. https://doi.org/10.1002/pan3.10541

Geels, F. W. (2005). Processes and patterns in transitions and system innovations: Refining the co-evolutionary multi-level perspective. *Technological Forecasting and Social Change*, *72*(6), 681–696. https://doi.org/10.1016/j.techfore.2004.08.014

Geels, F. W., Berkhout, F., & van Vuuren, D. P. (2016). Bridging analytical approaches for low-carbon transitions. *Nature Climate Change*, *6*(6), 576–583. https://doi.org/10.1038/nclimate2980

Geels, F. W., Sovacool, B., Schwanen, T., & Sorrell, S. (2017). The socio-technical dynamics of low-carbon transitions. *Joule*, *1*(3), 463–479. https://doi.org/10.1016/j.joule.2017.09.018

Glasson, J., & Therivel, R. (2013). *Introduction To Environmental Impact Assessment* (4th ed.). Routledge. https://doi.org/10.4324/9781315881218

Government of Newfoundland and Labrador. (2012). *Sanction of the Muskrat Falls Development*. Commission of Inquiry Respecting the Muskrat Falls Project. https://www.muskratfallsinquiry.ca/files/P-00067.pdf

Gronendyke, K. (2018, January 25). *Baker-Polito Administration Announces Selection of Project to Bring Clean Energy to the Commonwealth*. Commonwealth of Massachusetts, Executive Office of Energy and Environmental Affairs. https://archives.lib.state.ma.us/handle/2452/755982

Gutman, R., Marchenko, P. P., & Dunlop, R. D. (1979). Analytical Development of Loadability Characteristics for EHV and UHV Transmission Lines. *IEEE Transactions on Power Apparatus and Systems*, *PAS-98*(2), 606–617. https://doi.org/10.1109/TPAS.1979.319410

Hall, R., Topham, E., & João, E. (2022). Environmental Impact Assessment for the decommissioning of offshore wind farms. *Renewable and Sustainable Energy Reviews*, *165*, 112580. https://doi.org/10.1016/j.rser.2022.112580

Hernan, M. A., & Robins, J. M. (2023). *Causal Inference: What If*. CRC Press. https://www.hsph.harvard.edu/miguel-hernan/wp-content/uploads/sites/1268/2023/10/hernanrobins_WhatIf_30sep23.pdf

Herza, J., Ashley, M., & Thorp, J. (2018, September 28). *Factor of safety? Do we use it correctly?* https://www.researchgate.net/publication/327920961_Factor_of_Safety-Do_we_use_it_correctly

Hess, D. J., & Sovacool, B. K. (2020). *Sociotechnical Matters: Reviewing and Integrating Science and Technology Studies with Energy Social Science* (SSRN Scholarly Paper No. 3540100). https://papers.ssrn.com/abstract=3540100

Huang, M.-T., & Zhai, P.-M. (2021). Achieving Paris Agreement temperature goals requires carbon neutrality by middle century with far-reaching transitions in the whole society. *Advances in Climate Change Research*, *12*(2), 281–286. https://doi.org/10.1016/j.accre.2021.03.004

Hydro-Québec. (2018–2023). *Annual report—Rapport annuel*. Hydro-Québec. https://www.hydroquebec.com/about/financial-results/annual-report.html

Hydro-Québec. (2020). *Cue Card 2019—2020*. Hydro-Québec. https://www.hydroquebec.com/data/documents-donnees/pdf/2020G106A_Info-carte_301-acc.pdf

Hydro-Québec. (2022a). *Annual report 2022—Rapport annuel 2022* (p. 91). Hydro-Québec. https://www.hydroquebec.com/about/financial-results/annual-report.html

Hydro-Québec. (2022b). *Comparison of Electricity Prices in Major North American Cities*. Hydro-Québec. https://www.hydroquebec.com/data/documents-donnees/pdf/comparison-electricity-prices.pdf

Independent Electricity System Operator. (n.d.). *Annual Imports and Exports Between Quebec and Ontario*. Retrieved April 7, 2024, from https://www.ieso.ca/en/Power-Data/Supply-Overview/Imports-and-Exports

Kern, F., & Rogge, K. S. (2016). The pace of governed energy transitions: Agency, international dynamics and the global Paris agreement accelerating decarbonisation processes? *Energy Research & Social Science*, *22*, 13–17. https://doi.org/10.1016/j.erss.2016.08.016

Khemlani, S. S., Barbey, A. K., & Johnson-Laird, P. N. (2014). Causal reasoning with mental models. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00849

Köhler, J., Geels, F. W., Kern, F., Markard, J., Onsongo, E., Wieczorek, A., Alkemade, F., Avelino, F., Bergek, A., Boons, F., Fünfschilling, L., Hess, D., Holtz, G., Hyysalo, S., Jenkins, K., Kivimaa, P., Martiskainen, M., McMeekin, A., Mühlemeier, M. S., … Wells, P. (2019). An agenda for sustainability transitions research: State of the art and future directions. *Environmental Innovation and Societal Transitions*, *31*, 1–32. https://doi.org/10.1016/j.eist.2019.01.004

Kolkman, M. J., Veen, A. van der, & Geurts, P. A. T. M. (2007). Controversies in water management: Frames and mental models. *Environmental Impact Assessment Review*, *27*(7), 685–706. https://doi.org/10.1016/j.eiar.2007.05.005

Larsen, S. V., Hansen, A. M., & Nielsen, H. N. (2018). The role of EIA and weak assessments of social impacts in conflicts over implementation of renewable energy policies. *Energy Policy*, *115*(C), 43–53. https://doi.org/10.1016/j.enpol.2018.01.002

Li, X. (2021). Do new housing units in your backyard raise your rents? *Journal of Economic Geography*, *22*(6), 1309–1352. https://doi.org/10.1093/jeg/lbab034

Lovering, J., Swain, M., Blomqvist, L., & Hernandez, R. R. (2022). Land-use intensity of electricity production and tomorrow's energy landscape. *PLOS ONE*, *17*(7), e0270155. https://doi.org/10.1371/journal.pone.0270155

Maine Department of Environmental Protection. (2021, November 23). *Central Maine Power Co. & NECEC Transmission, LLC, License Suspension Proceeding, Decision and Order 12*. State of Maine Department of Environmental Protection. https://www.maine.gov/dep/ftp/projects/necec/SuspensionProceeding/2021-11-23Final%20Order%20Revised.pdf

Miller, N., Simonelli, J., & Stark, G. (2022). *The Future Role of Hydropower in the Northeastern United States: May 2020-May 2022*. https://doi.org/10.2172/1864718

Moore, F. C., Lacasse, K., Mach, K. J., Shin, Y. A., Gross, L. J., & Beckage, B. (2022). Determinants of emissions pathways in the coupled climate-social system. *Nature*, *603*(7899), 103–111. https://doi.org/10.1038/s41586-022-04423-8

Morgan, R. K. (2012). Environmental impact assessment: The state of the art. *Impact Assessment and Project Appraisal*, *30*(1), 5–14. https://doi.org/10.1080/14615517.2012.661557

National Academies of Sciences, Engineering, and Medicine. (2021). *Accelerating Decarbonization of the U.S. Energy System*. National Academies Press. https://doi.org/10.17226/25932

Natural Resources Council of Maine. (2018, May 1). *CMP Corridor Proposal: A Bad Deal for Maine*. https://www.nrcm.org/programs/climate/proposed-cmp-transmission-line-bad-deal-maine/

NECEC Transmission LLC et al. v. Bureau of Parks and Lands et Al., No. BCD-21-416 (Maine Business and Consumer Court April 27, 2022). https://www.courts.maine.gov/news/necec/index.html

Needham, C. J., Bradford, J. R., Bulpitt, A. J., & Westhead, D. R. (2007). A Primer on Learning in Bayesian Networks for Computational Biology. *PLOS Computational Biology*, *3*(8), e129. https://doi.org/10.1371/journal.pcbi.0030129

New York State Energy Research and Development Authority. (2021). *Appendix C – Cost analysis. Petition regarding agreements for procurement of Tier 4 renewable energy certificates* (No. Case 15-E-0302). NYSERDA. https://documents.dps.ny.gov/public/MatterManagement/CaseMaster.aspx?Mattercaseno=15-E-0302

Nilsson, A. E., Avango, D., & Rosqvist, G. (2021). Social-ecological-technological systems consequences of mining: An analytical framework for more holistic impact assessments. *The Extractive Industries and Society*, *8*(4), 101011. https://doi.org/10.1016/j.exis.2021.101011

Nogueira, A. R., Pugnana, A., Ruggieri, S., Pedreschi, D., & Gama, J. (2022). Methods and tools for causal discovery and causal inference. *WIREs Data Mining and Knowledge Discovery*, *12*(2), e1449. https://doi.org/10.1002/widm.1449

Olofsson, K. L., Selvakumar, P. P., Peach, K., Leon-Corwin, M., Stormer, S. A., Gupta, K., Carlson, N., & Sibley, M. (2023). Effective stakeholder engagement in environmental problem-solving though group model building: An Oklahoma case study. *Environmental Challenges*, *13*, 100755. https://doi.org/10.1016/j.envc.2023.100755

Owens, K., Carmody, E., Grafton, Q., O'Donnell, E., Wheeler, S., Godden, L., Allen, R., Lyster, R., Steduto, P., Jiang, Q., Kingsford, R., & Quiggin, J. (2022). Delivering global water security: Embedding water justice as a response to increased irrigation efficiency. *WIREs Water*, *9*(6), e1608. https://doi.org/10.1002/wat2.1608

Paul, W. L. (2011). A causal modelling approach to spatial and temporal confounding in environmental impact studies. *Environmetrics*, *22*(5), 626–638. https://doi.org/10.1002/env.1111

Pearl, J. (1995). Causal diagrams for empirical research. *Biometrika*, *82*(4), 669–688. https://doi.org/10.2307/2337329

Pearl, J. (2000). *Causality: Models, reasoning, and inference* (2nd ed.). Cambridge University Press, New York, second edition, reprint 2009. https://doi.org/10.1017/CBO9780511803161

Peggy Kurtz, Laura Burkhardt, & Gale Pisha. (2018). *Canadian Hydropower—Wrong Direction for the Future*. Sierra Club. https://www.sierraclub.org/atlantic/blog/2018/05/canadian-hydropower-wrong-direction-future

Pohl, J., Hilty, L. M., & Finkbeiner, M. (2019). How LCA contributes to the environmental assessment of higher order effects of ICT application: A review of different approaches. *Journal of Cleaner Production*, *219*, 698–712. https://doi.org/10.1016/j.jclepro.2019.02.018

Righetti, N. (2022). *Chapter 12 VAR | Time Series Analysis With R*. https://nicolarighetti.github.io/Time-Series-Analysis-With-R/var.html

Ripley, B., & Venables, W. N. (2003). *Modern Applied Statistics with S (MASS library)* (Version 7.3-60) [R]. http://www.stats.ox.ac.uk/pub/MASS4/

Riverkeeper. (n.d.). *Champlain Hudson Power Express*. Riverkeeper. Retrieved May 3, 2024, from https://www.riverkeeper.org/campaigns/river-ecology/champlain-hudson-power-express/

Rodríguez-Sarasty, J. A., Debia, S., & Pineau, P.-O. (2021). Deep decarbonization in Northeastern North America: The value of electricity market integration and hydropower. *Energy Policy*, *152*, 112210. https://doi.org/10.1016/j.enpol.2021.112210

Rosenberg, D. M., Berkes, F., Bodaly, R. A., Hecky, R. E., Kelly, C. A., & Rudd, J. W. (1997). Large-scale impacts of hydroelectric development. *Environmental Reviews*, *5*(1), 27–54. https://doi.org/10.1139/a97-001

Sabin Center for Climate Change Law. (2024). *U.S. Climate Change Litigation*. Columbia Law School; Arnold & Porter. http://climatecasechart.com/us-climate-change-litigation/

Scutari, M., & Denis, J.-B. (2021). *Bayesian Networks: With Examples in R* (2nd edition). Routledge. https://www.routledge.com/Bayesian-Networks-With-Examples-in-R/Scutari-Denis/p/book/9780429347436

Scutari, M., Silander, T., & Ness, R. (2023). *Bayesian Network Structure Learning, Parameter Learning and Inference* (Version [4.8.3]) [R]. https://www.bnlearn.com/

Snyder, J. (2018, April 19). "Without exports, our profits are in trouble": Hydro-Quebec plugs into U.S. markets for growth. *Financial Post*. https://financialpost.com/commodities/energy/without-exports-our-profits-are-in-trouble-hydro-quebec-plugs-into-u-s-markets-for-growth

Sotos, M. E. (2015). *GHG Protocol Scope 2 Guidance*. https://www.wri.org/research/ghg-protocol-scope-2-guidance

Sovacool, B. K. (2009). Rejecting renewables: The socio-technical impediments to renewable electricity in the United States. *Energy Policy*, *37*(11), 4500–4513. https://doi.org/10.1016/j.enpol.2009.05.073

Sovacool, B. K., Ryan, S. E., Stern, P. C., Janda, K., Rochlin, G., Spreng, D., Pasqualetti, M. J., Wilhite, H., & Lutzenhiser, L. (2015). Integrating social science in energy research. *Energy Research & Social Science*, *6*, 95–99. https://doi.org/10.1016/j.erss.2014.12.005

Sovacool, B. K., Turnheim, B., Hook, A., Brock, A., & Martiskainen, M. (2021). Dispossessed by decarbonisation: Reducing vulnerability, injustice, and inequality in the lived experience of low-carbon pathways. *World Development*, *137*(C). https://ideas.repec.org//a/eee/wdevel/v137y2021ics0305750x20302436.html

Spirtes, P., Glymour, C., & Scheines, R. (2001). *Causation, Prediction, and Search*. The MIT Press. https://doi.org/10.7551/mitpress/1754.001.0001

Stedinger, J. R., Sule, B. F., & Loucks, D. P. (1984). Stochastic dynamic programming models for reservoir operation optimization. *Water Resources Research*, *20*(11), 1499–1505. https://doi.org/10.1029/WR020i011p01499

Stokes, L. C., Franzblau, E., Lovering, J. R., & Miljanich, C. (2023). Prevalence and predictors of wind energy opposition in North America. *Proceedings of the National Academy of Sciences*, *120*(40), e2302313120. https://doi.org/10.1073/pnas.2302313120

Su, C., Andrew, A., Karagas, M. R., & Borsuk, M. E. (2013). Using Bayesian networks to discover relations between genes, environment, and disease. *BioData Mining*, *6*(1), 6. https://doi.org/10.1186/1756-0381-6-6

Tsamardinos, I., Brown, L. E., & Aliferis, C. F. (2006). The max-min hill-climbing Bayesian network structure learning algorithm. *Machine Learning*, *65*(1), 31–78. https://doi.org/10.1007/s10994-006-6889-7

United Nations. (2024). *Net Zero Coalition*. United Nations; United Nations. https://www.un.org/en/climatechange/net-zero-coalition

U.S. Department of Energy. (1979–2021). *Archived Presidential Permits, Grid Deployment Office*. https://www.energy.gov/gdo/archived-presidential-permits

U.S. Department of Energy. (2016). *Hydropower Vision Report, Water Power Technologies Office*. Water Power Technologies Office. https://www.energy.gov/eere/water/articles/hydropower-vision-report-full-report

U.S. Department of Energy. (2017). *Record of Decision for Issuing a Presidential Permit to Northern Pass Transmission LLC for the Northern Pass Transmission Line Project, Office of Electricity Delivery and Energy Reliability* (No. OE Docket No 371; pp. 55595-55599 (5 pages)). https://www.federalregister.gov/documents/2017/11/22/2017-25254/record-of-decision-for-issuing-a-presidential-permit-to-northern-pass-transmission-llc-for-the

U.S. Energy Information Administration. (2022, October 6). *EIA-861 Annual Electric Power Industry Report*. https://www.eia.gov/electricity/data/state/

van de Grift, E., & Cuppen, E. (2022). Beyond the public in controversies: A systematic review on social opposition and renewable energy actors. *Energy Research & Social Science*, *91*, 102749. https://doi.org/10.1016/j.erss.2022.102749

van Soest, H. L., den Elzen, M. G. J., & van Vuuren, D. P. (2021). Net-zero emission targets for major emitting countries consistent with the Paris Agreement. *Nature Communications*, *12*(1), 2140. https://doi.org/10.1038/s41467-021-22294-x

Warner, S., & Coppinger, R. (1999). *Hydroelectric power development at James Bay: Establishing a frame of reference. In: J.F. Hornig, ed. Social and Environmental Impacts of the James Bay Hydroelectric Project. Hornig*. McGill-Queens University Press.

https://www.mqup.ca/social-and-environmental-impacts-of-the-james-bay-hydroelectric-project-products-9780773518377.php

Webster, R. (2022, February 7). *Comments of Riverkeeper Regarding Proposed Tier 4 Contract Award to the Champlain Hudson Power Express Project*. Riverkeeper. https://www.riverkeeper.org/wp-content/uploads/2022/02/2022.02.07-RvK-CHPE-Tier-4-comments.pdf

Weise, E., & Bhat, S. (2024, February 6). Across America, clean energy plants are being banned faster than they're being built. *USA TODAY*. https://www.usatoday.com/story/news/investigations/2024/02/04/us-counties-ban-renewable-energy-plants/71841063007/

Zarzavilla, M., Quintero, A., Abellán, M. A., Serrano, F. L., Austin, M. C., & Tejedor-Flores, N. (2022). Comparison of Environmental Impact Assessment Methods in the Assembly and Operation of Photovoltaic Power Plants: A Systematic Review in the Castilla—La Mancha Region. *Energies*, *15*(5), 1926. https://doi.org/10.3390/en15051926