Improving the Representation of Climate Risks in Long-Term Electricity Systems Planning: A Critical Review

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Abstract

Electricity systems face substantial and growing climate risks which are escalating due to electrification, renewable energy intermittency, population changes, and the intensifying impacts of climate change such as extreme temperatures and weather-induced infrastructure damage. This critical review investigates climate risks to the electricity sector and scrutinizes the methodologies used to represent climate risk in long-term electricity system planning studies. We find that many studies rely on weather data and socio-economic scenarios that are inadequate to fully characterize climate risks to present and future electricity systems. We advocate for more holistic assessments that incorporate comprehensive weather data, acknowledge dynamic multi-sector interactions, and employ adaptive and robust methodologies.

Keywords: Climate Risk, Electricity Systems, Climate Change

1 Introduction

The impacts of recent weather extremes worldwide highlight the vulnerability of electricity systems to severe weather. This is particularly true when extreme temperatures cause spikes in heating or cooling demand while disrupting power supply, resulting in challenges to meet peak loads on electricity systems. In 2022, for example, heatwaves in India and Pakistan caused unprecedented spikes in electricity demand that exceeded supply (Jain and Jain, 2022). Similarly, during a severe freeze in Texas in February 2021, record-breaking demand for heating coincided with supply failures, leaving millions without power (Doss-Gollin et al, 2021). Severe weather also affects energy supply by limiting thermal and renewable generation and damaging transmission and distribution infrastructure. For example, power shortfalls that exacerbated the impacts of the 2021 Texas freeze were caused by failures throughout the electricity supply chain, especially in natural gas fuel supply and power plant operations (Busby et al, 2021). From the perspective of human health, the vulnerability of electricity systems to tropical cyclones (TCs) (Shahid, 2012; Kwasinski et al, 2019) and severe weather (Do et al, 2023) is a particularly critical challenge because electricity is often most needed during severe weather. For example, it is estimated that a concurrent blackout and heatwave event could kill 1% of the population of Phoenix, AZ (Stone et al, 2023).

Factors beyond extreme weather also contribute to growing climate risks for electricity systems. For example, population growth, electrification, and economic development are driving increases in electricity demand (International Energy Agency, 2022). At the same time, the increasing penetration of intermittent renewable generation, motivated in part by commitment to mitigating global climate change (Meinshausen et al, 2022), is changing the electricity system's vulnerability to weather risks. Studies that examine the influence of climate change on existing infrastructure find that while overall changes in electricity demand may be modest, peak demand will see a significant increase due to climate change effects (Auffhammer et al, 2017; Romitti and Sue Wing, 2022; Amonkar et al, 2023).

In light of these evolving risks, the primary objective of this paper is to critically review the methods used to incorporate climate risk into long-term energy systems planning. In this paper, we focus on a key question: are these methods sufficient to accurately assess and robustly manage climate risks? Previous reviews have addressed parts of this literature, including methods for data compression and slicing (Plaga and Bertsch, 2023); wind resources in a changing climate (Jung and Schindler, 2022); community resilience (Koliou et al, 2020); and climate change impacts on energy demand and generation potential (Yalew et al, 2020; Schaeffer et al, 2012; Clarke et al, 2022). Our contribution is to apply a multisector, climate risk perspective with a particular emphasis on comparing best practices identified in the field of climate risk management to identify research gaps and opportunities for the electricity sector. We structure the paper as follows. In section 2, we review vulnerabilities of electricity systems to extreme weather, considering impacts on demand, supply, and transmission and distribution. In section 3, we consider how these vulnerabilities may be affected by evolving risks, summarizing the expected effects of climate change on extreme weather, how these effects have been projected to affect electricity systems, and how technological and social change will affect overall climate risk. In section 4, we summarize how climate risks are represented in long-term electricity planning models and analyses, which we contrast in section 5 with the state of the art to identify three focus areas for improvement. We conclude in section 6 with a brief summary.

2 Vulnerabilities of Electricity Systems to Extreme Weather

We begin by identifying vulnerabilities of electricity systems to extreme weather. In the context of energy systems, vulnerability refers to the susceptibility of the system to suffer damage or disruption due to external factors, such as weather events. Vulnerability is related to reliability, resilience, and robustness. Reliability, as defined in power systems, is the probability of a normal operation of the electrical grid at a given time, ensuring a continuous supply of energy by measuring the frequency, duration, and scale of supply interruptions. Resilience is the ability to limit the extent, severity, and duration of system degradation following an extreme event. Robustness, on the other hand, is the inherent ability of the electricity system to endure a set of disturbances and maintain functionality, performing well over a wide range of plausible futures. Understanding how weather affects these aspects is critical to safeguarding electricity systems.

2.1 Weather Impacts on Electricity Demand

Temperature is the primary weather variable that influences energy demand, although other variables like humidity also matter (Maia-Silva et al, 2020). A deep literature characterizes the temperature-electricity demand relationship using a variety of statistical methods (Henley and Peirson, 1997; Moral-Carcedo and Vicéns-Otero, 2005). For example, analysis of different studies modeling electricity demand in Texas using a polynomial fit (Lee and Dessler, 2022), a binning method (Shaffer et al, 2022), and a tree-based machine learning approach (Alipour et al, 2019) find that these approaches yield similar estimates under normal operating conditions, yet diverge substantially under extreme conditions for which impacts are especially great.

2.2 Weather Impacts on Electricity Generation

Extreme weather and normal weather fluctuations affect all forms of electricity generation.

For example, the output of solar photovoltaic panels is primarily dependent on the amount of sunlight they receive and the ambient air temperature (Bett and Thornton, 2016; Craig et al, 2020; Jerez et al, 2015). Wind power is highly sensitive to variations in wind speed: wind power scales cubically with wind speed, but turbines also have a minimum wind speed required to start generating power ("cut-in"), a speed at which peak mechanical output is reached, and a speed at which turbines must be shut down for safety ("cut-out") (Bett and Thornton, 2016). Furthermore, local topography, turbine design, and wake effects can significantly impact wind generation (Lundquist et al, 2019).

Hydropower generation is dependent on water availability, and drought conditions can limit power production by reducing water levels and increasing evaporation rates. Additionally, during hot or dry conditions, water availability may be further limited due to increased demand from urban and agricultural sectors (van Vliet et al, 2016, 2012; Kern et al, 2020; Su et al, 2020).

Thermal power plants, including coal, natural gas, and nuclear plants, rely on air and water for cooling. The efficiency of these plants decreases with rising temperatures (Loew et al, 2020; International Energy Agency, 2022). Hot weather can lead to reductions in thermal power generation, and this issue is compounded by droughts which limit the availability of cooling water (Coffel and Mankin, 2020; Liu et al, 2017; van Vliet et al, 2012).

Climate variability at multiple spatial and temporal scales can also stress electricity systems, even if the conditions are not extreme at a particular moment. For example, in northern Europe, periods of low wind and sunlight, termed "dunkelflaute", can persist for weeks and are linked to persistent or quasi-stationary weather patterns called blocks (Otero et al, 2022; Li et al, 2021). Similar patterns have been observed in other regions including Western North America, Australia, and Japan (Boston et al, 2022; Ohba et al, 2023; Brown et al, 2021). A range of other climate oscillations that drive weather risks at subseasonal to multidecadal time scales are documented in the climate literature (Ghil and Lucarini, 2020; Doss-Gollin et al, 2019). For example, the North Atlantic Oscillation is an important driver of supply and demand fluctuations in Europe, especially from late winter to early spring (Ely et al, 2013; Jerez and Trigo, 2013; Neubacher et al, 2021).

2.3 Weather Impacts on Electricity Transmission and Distribution

Extreme weather poses significant challenges to the transmission and distribution of electricity, making it a critical factor in climate risk assessment. Flooding can threaten electrical systems by inundating substations and underground cables, causing temporary outages or long-term damage (Clarke et al, 2022). High temperatures can reduce electric transmission capacity by affecting the thermal properties of transmission lines (Bartos et al, 2016). Snow and ice can accumulate on overhead power lines, straining them beyond their mechanical limits and leading to collapses and cascading outages (Feng et al, 2015; Yaji et al, 2014; Croce et al, 2018; Clarke et al, 2022). Wildfires are particularly hazardous to electrical systems in arid regions, as they can damage power lines and other infrastructure (Dian et al, 2019; Clarke et al, 2022). Finally, severe storms, such as TCs, can inflict extensive damage on transmission and distribution infrastructure, primarily through fallen trees and broken transmission lines. These impacts can be devastating, leading to prolonged outages and requiring substantial resources for restoration (Ranasinghe et al, 2021; Committee on Enhancing the Resilience of the Nation's Electric Power Transmission and Distribution System et al, 2017).

3 Evolving Climate Risks to Electricity Systems

Evolving climate risks to electricity systems stem from the interplay of climate changes, technological evolutions, and societal shifts. Notably, while climate change directly poses hazards to electricity supply and demand, technological and social alterations can modify how different weather conditions impact these systems.

3.1 Climate Change Impacts on Extreme Weather

Before examining evolving climate risks to electricity systems, we summarize consensus science on anticipated changes in weather patterns that are directly relevant to electricity systems.

Many forms of hazardous weather are expected to increase in frequency and intensity as the climate warms. For example, there is an expectation for an increase in frequency, intensity, and amount of heavy precipitation events as well as agricultural and ecological droughts in many regions (Seneviratne et al, 2021). While the sensitivity of TC frequency to warming remains uncertain (Knutson et al, 2020; Sobel et al, 2021), increases in global average TC rain rates of about 12% for a 2 °C global warming (relative to pre-industrial) are projected, consistent with the Clausius–Clapeyron scaling of saturation-specific humidity (Knutson et al, 2020), and peak rainfall rates are likely to increase faster than this for some regions (Seneviratne et al, 2021). Moreover, global maximum TC surface wind speeds are projected to increase by about 5% at 2 °C (Knutson et al, 2020). Considering projected sea level rise (Kopp et al, 2017) and TC dynamics, risk from coastal storm surge is projected to increase substantially (Gori et al, 2022). Similarly, Convective Available Potential Energy, which describes the potential of the atmosphere to generate heavy rainfall and thunderstorms, is projected to increase in the tropics and subtropics, as is precipitation from convective storms (Seneviratne et al, 2021). Climate change is also likely to make wildfires more frequent and severe worldwide, with particular increases at high latitudes and in some mountainous regions (Flannigan et al, 2013; Clarke et al, 2022).

Changes in average and extreme temperatures are also expected. One important point is that warming over land will exceed global average increases in temperature (Lee et al, 2021). Climate change also affects the diurnal and seasonal cycles: warmer and more frequent hot days and nights over most land areas are expected, with mid-latitude, semi-arid regions and the South American Monsoon region experiencing the most significant increases (Seneviratne et al, 2021). Additionally, in most subtropical and mid-latitude land regions, except some parts of Asia, models predict more pronounced warming during summer than winter, resulting in an amplified seasonal cycle (Santer et al, 2018; Donohoe and Battisti, 2013).

The effect of climate change on persistent weather regimes remains an area of active research. In the mid-latitudes, weather regimes are influenced by storm tracks, which are in turn affected by competing processes with uncertain net results (Shaw et al, 2016). There is a projection for an increase in the size of atmospheric blocks, particularly during summers in the Northern Hemisphere (Nabizadeh et al, 2019), but robust trends have only been identified in observations for some regions and seasons (Gulev et al, 2021). Physical mechanisms such as quasi-resonant amplification have been linked with climate extremes (Petoukhov et al, 2016; Kornhuber et al, 2019; Trenberth and Fasullo, 2012), bolstering evidence that global warming increases the persistence of summer weather (Pfleiderer et al, 2019), but the magnitude and extent of these changes remain uncertain.

3.2 Climate Change Impacts on Electricity Systems

3.2.1 Electricity Demand

A critical driver of changes in electricity consumption patterns is increased temperature, particularly due to the use of electrical heating and cooling systems. For example, researchers combined an empirical relationship between high temperatures and electricity demand for California with projections of future temperature, holding technology and population constant, and found that electricity demand and deficits could surge (Miller et al, 2008). Similarly, a comparison of 1996-2005 weather data in Texas with downscaled projections under RCP 8.5 for 2041-2050 revealed that under this high-emissions scenario, net demand could increase by up to 6% and thermal deratings during peak hours could increase by 40% (Craig et al, 2020). A retrospective and temperature-based analysis observed consistent increases in summer average and peak cooling demand across the continental United States (Amonkar et al, 2023). While warmer winters reduce total electricity demand during winters, researchers found that the likelihood and severity of extreme cold temperatures in the mid-latitudes, which are particularly consequential for electricity systems, are unlikely to decrease for several decades (Doss-Gollin et al, 2021; Cohen et al, 2020).

3.2.2 Electricity Supply

Climate change affects electricity generation in various ways, specific to particular regions and technologies.

Climate change is not expected to substantially impact global solar insolation (Clarke et al, 2022). While regional variations in dimming and brightening driven by changes in cloud cover, aerosols, and water vapor are possible, these are not likely to significantly lower the global potential of solar energy. Wind power is more susceptible to the influences of climate change, and numerous studies have modeled wind production for different regions and climate scenarios. Most studies find overall reductions to be modest; for example, a regional climate model assessment of wind resources in Europe finds reductions of $< 5\%$ at $2\,^{\circ}\mathrm{C}$ of global warming for all countries considered (Tobin et al, 2018), in line with other studies (Bonanno et al, 2023; Hahmann et al, 2022), though in specific regions some studies find larger impacts plausible (Wohland, 2022; Gonzalez et al, 2019).

Hydropower presents unique challenges and considerations. Generally, increased precipitation is expected to increase water availability and, consequently, hydropower production. However increased precipitation intensity can affect dam structures and power production by increasing debris accumulation and vegetation growth (Clarke et al, 2022). Changes in the risk of interannual droughts, however, pose significant risks to hydropower systems in some regions (Clarke et al, 2022)

Thermal power generation is also affected by climate change, particularly due to its dependence on water resources for cooling. In general, significant decreases in available thermal power plant capacity due to climate change are projected (van Vliet et al, 2016; Yalew et al, 2020). Several options to mitigate the impacts of reduced cooling water availability, increased water temperature, and lower flows have been suggested, including switching from freshwater to seawater or air cooling, replacing once-through cooling systems with recirculation systems, and increasing the efficiency of power plants (Dodman et al, 2022).

Finally, it is critical to consider the uncertainties and complexities associated with these projections. For instance, when examining least-cost options for the hydropower-dominated Ecuadorian power system up to 2050, the uncertainty between different Earth system models (ESMs) ("model uncertainty") was found to surpass the uncertainty between different climate scenarios ("scenario uncertainty") (Carvajal et al, 2019), consistent with other studies (*e.g.*, Dittes et al, 2018; Lafferty and Sriver, 2023). Uncertainties in renewable energy potential and demand could trigger a significant performance gap and drop in power supply reliability due to future climate variations and extreme weather events (Perera et al, 2020). This emphasizes the need to adopt bottom-up risk assessment and management approaches to more effectively address the complexities and uncertainties in the energy sector.

3.3 Technological and Social Factors Contributing to Climate Risks for Electricity Systems

Energy system transformation is essential for climate change mitigation, but investments in the energy and electricity sectors respond to a wide range of concerns including economic development, energy access, energy justice, energy security, air pollution, land use, and energy cost (Clarke et al, 2022; International Energy Agency, 2022). To understand climate risks to future electricity systems, it is critical to assess interactions between different social and technological pathways and climate change.

Despite efficiency gains, electricity consumption is projected to increase in most regions due to population growth and economic development (DeAngelo et al, 2021). In places ranging from Texas to West and Central Africa, this can increase the sensitivity of electricity demand to temperature (Shaffer et al, 2022; Kondi-Akara et al, 2023).

The integration of electricity into new sectors, including road transport, heating, industrial processes, and electrolytic hydrogen production, is anticipated to alter load curves and has the potential to make electricity demand more variable (International Energy Agency, 2022). The electrification of heating is particularly significant. Currently, a large proportion of energy used for home heating is sourced from natural gas or oil, but a shift to electric heating is considered critical for the energy transition. Electric heat pumps are far more efficient than traditional electric furnaces overall, but their energy use increases more sharply as temperatures decline. One study accounting for temperature-dependent energy demand, local building stocks and heating technologies, population, and other socio-economic factors to calculate electricity demand in the United States finds that even with the most energy-efficient heat pumps, electrification of heating would cause wintertime peaks to be 70% higher than current summertime peaks overall, and more than twice as high in 23 states (Waite and Modi, 2020).

A particular challenge is that in many regions, the interannual variability of peak heating demand (*i.e.*, winter temperature extremes) is substantially larger than peak cooling demands (*i.e.*, summer temperature extremes). As electrification of building heating continues, grids must prepare for rare and variable winter peaks rather than for frequent and more predictable summer peaks (Amonkar et al, 2023; Doss-Gollin et al, 2021).

Over the past decade, technological advances such as the falling costs of solar panels and lithium-ion batteries have transformed the energy sector (Hausfather and Peters, 2020). While future technological advances are deeply uncertain (Walker et al, 2013; Mathy et al, 2016), understanding the impact of plausible technological pathways on climate risks to electricity systems is critical. For example, demand-side response schemes, including smart appliances and electric vehicles, can provide flexibility, while energy storage technologies can act as both demand and generation sources and can provide a variety of ancillary grid services (Sepulveda et al, 2021).

4 Representation of Climate Risks in Long-Term Planning Studies

Given the significance of evolving climate risk to electricity systems, it is crucial to scrutinize how these risks are incorporated into the long-term electricity systems planning literature. In this section, we review several influential studies that focus on long-term energy planning with the objective of achieving a net-zero or clean electricity future. While this review is not exhaustive, these studies are broadly representative of the field.

The Princeton "Net-Zero America" study (Larson et al, 2021) investigates the least-cost energy mix necessary for reaching net-zero emissions by utilizing the EnergyPATHWAYS and RIO models. The National Renewable Electricity Laboratory (NREL) "Examining Supply-Side Options to Achieve 100% Clean Electricity by 2035" (Denholm et al, 2022) focuses on identifying the energy mix and requisite grid modifications to realize 100% clean electricity by 2035, employing the ReEDS model. The International Energy Agency's "World Energy Outlook 2022" (International Energy Agency, 2022) offers a critical analysis of trends in energy demand and supply and the associated implications for energy security, environmental protection, and economic development. The Decarb America "Pathways to Net-Zero Emissions" study (Walter et al, 2021) concentrates on evaluating the trade-offs between different strategies aimed at net-zero emissions, and gauging the economic opportunities that emerge from a clean energy economy. Finally, we consider two academic papers (Shaner et al, 2018; Tong et al, 2021) that employ a more simplified model to study the feasibility of achieving high renewable energy penetration and analyzes the implications for storage and overbuilding.

Many studies use only a few years of weather data to assess climate risks, and only some impacts of weather on electricity systems are typically represented. For example, (Larson et al, 2021) samples electricity operations using 41 days from the 2011 weather year. The Pathways to Net-Zero Emissions study (Walter et al, 2021) uses heating and cooling degree days from 2000 and 2017 to model electricity demand. The NREL study (Denholm et al, 2022) incorporates a more extensive dataset, with timeslice profiles based on the weather year of 2012 and hourly profiles from seven years (2007-2013). The two academic studies considered (Shaner et al, 2018; Tong et al, 2021) utilize a broader dataset, consisting of 36 and 39 years, respectively, of hourly reanalysis data. Finally, the World Energy Outlook 2022 (International Energy Agency, 2022) models electricity demand and supply without relying explicitly on weather. None of these data sources considers climate change impacts, and the short data lengths used may not be sufficient for capturing the full range of weather variability (Doss-Gollin et al, 2019).

With respect to non-weather variables, a majority of the studies explore only a handful of technological, social, and policy futures (Denholm et al, 2022; The Nature Conservancy, 2023; Walter et al, 2021; International Energy Agency, 2022). The Princeton study (Larson et al, 2021) explores 55 scenarios representing deviations from the baseline scenario, providing some characterization of uncertainties, though this "one at a time" sensitivity analysis limits the conclusions that can robustly be drawn (Pianosi et al, 2016; Srikrishnan et al, 2022b; Saltelli et al, 2008). (Shaner et al, 2018) and (Tong et al, 2021) analyze a broad range of values for the carbon intensity of electricity. Generally, there is a need for more comprehensive scenario analyses to address the intricacies and uncertainties inherent in long-term energy planning.

5 Research Gaps and Opportunities

Accurately characterizing and quantifying climate risks to electricity systems requires not only drawing many samples from the distribution of possible weather but also considering the interaction with other pertinent factors that drive demand and vulnerability. In this section, we draw from literatures on climate risk management, including but not limited to electricity systems, to identify areas to strengthen the assessment of climate risks to electricity systems.

5.1 Representing Weather Extremes and Variability

Forecasting energy demand and generation in electricity systems necessitates high-resolution weather data, such as temperature, insolation, wind speed, and streamflow. However, acquiring such data is challenging, and while ESMs offer valuable insights, they face fundamental limitations in (i) simulating small-scale hazards (Stephens et al, 2010; Muller et al, 2011), (ii) representing some dynamical processes (Espinoza et al, 2018; Smith et al, 2020; Kravtsov, 2017; Greene and Robertson, 2017; Feng et al, 2019), and (iii) exploring the full range of climate emissions forcings (Srikrishnan et al, 2022a). At the same time, relying solely on observational data for risk assessment might not be indicative of future scenarios given the non-stationarity induced by climate change (Milly et al, 2008; Doss-Gollin et al, 2019) and sampling bias from using short observational records (Doss-Gollin and Keller, 2023; Jain and Lall, 2001; Dowling et al, 2020; Collins et al, 2018).

Downscaling methods aim to tackle the scale mismatch between coarse climate data and the site-specific information needed for energy planning. A challenge is that the statistical relationship between inputs (*e.g.*, reanalysis fields) and outputs (*e.g.*, site-scale weather variables) may not hold, either because the future inputs are different (*e.g.*, if climate model outputs are used as input) or because climate change can alter the statistical relationship (Lanzante et al, 2018; Ehret et al, 2012). Advanced techniques like generative computer vision show promise, but they require extensive training data and share the fundamental assumptions of classical downscaling methods (Harder et al, 2022; Price and Rasp, 2022).

Bootstrap methods can be used to extend historical data to create scenarios conducive to risk management (Lall and Sharma, 1996; Rajagopalan and Lall, 1999; Amonkar et al, 2022). These methods have the advantage of reduced dependence on parametric statistical assumptions but are still constrained by the extent of historical data and the challenge of accounting for climate change-induced nonstationarity. Stochastic weather generators that combine bootstrap-like methods, physical models, nonparametric statistics, and parametric statistics have been used to generate synthetic meteorological sequences that capture the properties of the observed variables (Papalexiou et al, 2023; Steinschneider and Brown, 2013; Gupta et al, 2023; Bracken et al, 2014). These models often outperform model chains that rely on downscaled and bias-corrected climate variables (Merz et al, 2014), but these approaches require significant customization for each location and application.

Managing the complexity and computational demands of high-resolution datasets and simulations in energy system optimization is another challenge. Data compression techniques like time-slice compression address this by strategically selecting and simulating representative time intervals from the dataset instead of the entire timeline (Plaga and Bertsch, 2023). For instance, (Larson et al, 2021) selects 41 days per year, equivalent to 984 hours, to sample electricity operations, significantly reducing computational costs. However, this approach has limitations, especially when dealing with stocks, like batteries and hydropower, where decisions made at one point can have nonlinear effects on future options.

5.2 Representing Multi-Sector Dynamics

Assessing climate risk in multisector systems necessitates a comprehensive approach that represents the complex interplay between climate and socioeconomic variables. Such assessments need to dynamically and endogenously account for interactions across sectors, rather than treating them as isolated boundary conditions or external factors (Srikrishnan et al, 2022b). Understanding the interconnected nature of these interactions and transparently communicating modeling choices are crucial for accurately representing societal systems on varying spatio-temporal scales (Srikrishnan et al, 2022b). For example, a study expanded the five Shared Socioeconomic Pathways by analyzing over 30,000 scenarios from an integrated assessment model and found that many of the most significant scenarios arose from interactions between different parameters (Lamontagne et al, 2018). Another study coupled an Earth system model, a global hydrologic model, and an economic surplus loss metric and concluded that impactful scenarios often arise from combinations of standard scenarios (Dolan et al, 2021). Further, a study combined a damage model, flood frequency model, and economic model to evaluate the optimal elevation of the house under uncertainty and found that the flood probability distribution and the discount rate drive the outcomes (Zarekarizi et al, 2020). These studies collectively underscore the imperative for integrated modeling and comprehensive scenario analysis in assessing climate risk in multi-sector systems.

In the energy sector, certain models have made strides in capturing these risks. For example, the impact of climate risk on human health through power plant emissions was examined using a 500-year synthetic weather ensemble, highlighting the highest damages during hot, dry years when hydropower availability dwindled and electricity demand surged, and implementing a tax on power plant operations based on their contribution to exposure led to a significant reduction in damage (Zeighami et al, 2023). Similarly, a coupled water-energy model for the Laotian-Thai grid was developed with a focus on the Mekong River basin, investigating the risk posed by prolonged droughts on hydropower production, electricity costs, and carbon dioxide emissions (Chowdhury et al, 2021). Climate risks have also been represented as correlated hydrometeorological processes that influence both supply and demand in electricity markets throughout the western United States (Su et al, 2020).

Increasing simulation lengths and ensemble sizes by several orders of magnitude to credibly assess climate risks poses a significant computational challenge. To address this computational bottleneck, many studies have explored the use of emulators, idealized models, hierarchical models, and surrogate models to model and mitigate climate risks in infrastructure systems (Gómez et al, 2013; Zhou et al, 2023; Kazadi et al, 2022; da Silva et al, 2020; Wong et al, 2017; Kopp et al, 2017).

5.3 Adaptive and Robust Adaptation Pathways

The unique challenges in assessing and managing climate risks call for the integration of multidisciplinary insights, the incorporation of ethical values into decision-making, and the rigorous characterization and quantification of uncertainties and their impacts on metrics relevant to stakeholders (Keller et al, 2021; Srikrishnan et al, 2022b). Bottom-up methodologies are particularly illuminating in this context. Eschewing the traditional "predict-then-plan" approach, these methodologies embrace a comprehensive exploration of plausible scenarios, assessing potential system responses before evaluating the likelihood of each scenario. Exploratory modeling, for example, improves understanding of potential system behaviors, facilitates hypothesis formulation, and helps focus attention on scenarios that merit in-depth analysis (Bankes, 1993). Methods like decision scaling and robust decision making also emphasize exploring interactions between different decisions and possible futures to identify robust plans (Brown et al, 2012; Steinschneider et al, 2015; Taner et al, 2019; Lempert, 2019; Kasprzyk et al, 2013). Moreover, recognizing infrastructure planning as a dynamic, sequential problem, methodologies such as Real Options Analysis, Reinforcement Learning, and Direct Policy Search highlight the importance of adaptability and flexibility for efficacious, robust long-term planning (Gupta and Rosenhead, 1968; de Neufville and Smet, 2019; Erfani et al, 2018; Hino and Hall, 2017; Quinn et al, 2017; Schmidhuber, 2001; Sutton and Barto, 2018).

While these approaches are less common in long-term electricity planning systems, they are valuable for identifying decisions that meet multiple objectives, such as minimizing cost, improving resilience, decarbonizing, and protecting nature, under deep uncertainty. Several promising approaches may support these goals. One such approach is optimizing explicitly for robustness. Alternatively, employing subjective probabilities over possible futures allows exploration of low-probability scenarios without biasing final results (Doss-Gollin and Keller, 2023). Third, where robustness is not considered in the optimization step, stress-testing plausible alternatives can be an insightful exploratory step. These methods, when employed judiciously, pave the way for long-term electricity planning that adeptly addresses the complexities and uncertainties of climate risks, fostering the development of resilient and adaptive electricity systems.

6 Summary

This paper critically examines the multifaceted dimensions of climate risk assessment and management, with a particular emphasis on electricity systems. Climate change poses significant risks to electricity systems, with its direct and cascading effects causing severe consequences. Additionally, emerging technologies are transforming energy demand and load profiles, potentially adding additional stress to the grid. It is evident that climate risks are already impacting electricity systems and the stresses are likely to escalate in the future due to the changing climate patterns and technology trends.

The studies considered represent climate risks using short weather records and a small number of technological and economic scenarios, which limits the extent to which climate risks to the modeled electricity systems can be quantified. There is thus a pressing need to improve the representation of extreme weather events and long-term climate change, embrace multisector dynamics, and critically evaluate uncertainties in long-term electricity systems planning studies. This will require adopting integrated modeling, broadening scenario analyses beyond standardized scenarios, developing use-tailored weather generators, and employing adaptive and robust methodologies that account for system dynamics and uncertainties.

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