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The importance of spatial resolution in large-scale, long-term planning models

Louisa Serpe *, Wesley Cole, Brian Sergi, Maxwell Brown, Vincent Carag, Akash Karmakar

Grid Planning and Analysis Center National Renewable Energy Laboratory Golden, Colorado, United States

HIGHLIGHTS

- A county-resolution capacity expansion model for the contiguous United States is presented.
- Scenarios covering the Texas and Western Interconnections are compared at different spatial resolutions.
- Spatial resolution has an impact on model results, particularly for land-based wind and transmission.
- The tradeoffs between high spatial resolution, accuracy, and computational burden are discussed.

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ABSTRACT

Capacity expansion models are important tools for examining the evolution of the electric power sector. Embedded in these tools are many modeling choices with consequential impacts on computational burden and associated analysis. In this study, the spatial resolution of the national-scale Regional Energy Deployment System (ReEDS) model is adjusted to understand the implications of higher-fidelity modeling on energy system projections and model solve times. The default ReEDS regions capture the contiguous United States in 134 balancing areas, while the regions in the higher resolution version are defined by more than 3000 U.S. counties. Using both resolutions, a case study is conducted in the United States for the Texas Interconnection (ERCOT) and the Western Interconnection (WI) to explore how differences in spatial resolution impact model projections and to inform appropriate applications of high spatial resolution in a large-scale capacity expansion model. In both interconnections, the higher spatial resolution model achieves a lower-cost solution, attributed to the more detailed representation of variable renewable resources and transmission. Shifts in land-based wind capacity between the balancing-area-level model and the county-level model are more prominent than the changes in solar, in part because of the heterogeneity of wind resource across the United States and the stronger dependency of wind on transmission. Furthermore, at higher spatial resolution there is a locational shift in the installed capacity toward regions characterized by resource profiles that are better aligned to contribute to resource adequacy. Beyond the nuances in the results, running the high-fidelity ReEDS model introduces a significant computational burden, with an order of magnitude increase in the number of model regions leading to at least an order of magnitude increase in the runtime. Spatial flexibility can offer users and developers the opportunity to perform high-fidelity analysis, however the benefits of high-resolution modeling must be weighed against the availability of the necessary data and the scope of the research question.

1. Introduction

Long-term strategic energy planning has been an established field for many decades. As the industry has evolved, hundreds of modeling tools have emerged to play an important role in forecasting future energy systems and formulating policies [1,2]. In recent years, the burgeoning need to address climate impacts and ensure reliability has led to global efforts to improve energy system optimization models, particularly in the electricity sector. The paradigm of relying on higher shares of renewable resources has challenged established methods based on large-scale centralized electricity generation, particularly with respect to spatial and temporal detail [3]. Several studies have reviewed the trade-

* Corresponding author.
E-mail address: louisa.serpe@nrel.gov (L. Serpe).

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offs associated with manipulating modeling resolution levers across multidecade capacity expansion models [4–6]. Typically, these tools solve for the least-cost portfolio of generation, storage, and transmission; however, the regions represented in these models span a range of spatial resolutions and geographic areas, at times leading to conflicting trends that result from changes in spatial resolution. In [7], the authors compare four national-scale capacity expansion models of the U. S. electricity sector, noting the methods used to construct various spatial resolutions within each model can lead to opposing results, even when the geographic scope remains constant. Despite the difficulty in identifying consistent trends associated with spatial resolution across models, some congruency exists: Spatial resolution has a meaningful impact on the location of variable renewable deployment, transmission system congestion and expansion, system costs, and computational burden.

Enhancing the spatial resolution of long-term electricity system models creates several challenges. The electricity system is large and complex, imposing limitations in geographic scope to remain computationally tractable. Furthermore, input data with sufficient spatial detail are often unavailable. Nevertheless, the transition away from electricity systems with centralized, conventional, dispatchable generation that can be represented using heuristics to systems exposed to weather-driven variability necessitates a different modeling approach [8]. Recent literature has indicated a high spatial resolution is required to accurately capture regional variability—particularly regarding resource availability and electricity demand—and to ascertain the deployment of new grid infrastructure. Numerous studies spanning many countries and various spatial aggregations exist [5,9–15]; however, defining best practices for establishing appropriate spatial detail remains elusive. The two prominent levers related to spatial fidelity are extent and resolution. Spatial extent describes the geographic coverage of the model (e.g., continental, national, regional) whereas spatial resolution describes the handling of supply- and demand-side resources included in the model (e.g., represents resources through aggregation or as individual sites) [6]. For high-resolution representation in single-sector energy system optimization models, prior work has identified the principal administrative division of a country (such as states, provinces, or autonomous communities) as a generally tractable level of detail across models [4].

Although decisions about the most suitable representation must be made on a case-by-case basis, multiple studies using an assortment of energy system modeling tools cohesively suggest finer spatial resolution offers significant added value for regions with heterogenous renewable potential [4,5,16] because local weather conditions drive wind and solar availability. In models that are partitioned using relatively large zones—entire countries, for example—the climate within individual model regions can vary substantially. In these coarser resolution models, the attractiveness of higher-quality resources can be diluted when they are aggregated with lower-quality resources within the same region and vice versa. In [16], the authors aggregate renewable resources across the contiguous United States at three increasingly coarse resolutions and observe changing the spatial resolution leads to differences in the relative competitiveness of renewable technologies and can result in suboptimal capacity investments. A similar analysis in Europe found high renewable resource resolution allows the optimal solution to concentrate wind and solar capacity at sites with better capacity factors, reducing system costs compared to a low-resolution version of the model [5]. Changing resolution can also lead to a dramatic shift in the dominant resource. For instance, a study conducted in the United Kingdom compares single- and multiregion models and notes wind energy is less competitive in the coarser model because the high-potential coastal resources present at greater resolution are not explicitly available [17].

In addition to the underlying renewable resource representation, the resolution of the transmission network is a meaningful lever in energy system modeling. Higher granularity of the transmission system enables analysis of critical bottlenecks and helps ascertain optimal routing of new infrastructure to align with high-potential renewable sites. One study using the TIMES–Brazil model evaluates the deployment of renewable resources under scenarios with increasingly detailed transmission representation and concludes the fidelity of the network significantly affects capacity build and electricity prices across the country [18]. In [5], the authors extricate the effect of spatial resolution on the renewable resources and the network by considering various clustering methods for generation and transmission. They conclude higher network resolution can drive up total system costs because grid bottlenecks limit access to renewable sites with higher capacity factors in favor of assets closer to load centers. However, complementary work using the same modeling framework suggests—particularly for continental-scale systems such as Europe—grid expansion can serve as a cost-effective alternative to localized storage capacity when cooperation between balancing areas exists [19].

Another spatially dependent model parameter that plays an influential role in results is electricity demand. Traditionally, bottom-up models consider spatially aggregated regions for which annual load profiles can generally be obtained on a national level as well as from transmission system operators. For instance, in Germany, electricity demand data are available at 15-min resolution for each control area by a central electricity market platform hosted by the German regulatory authority [20]. Across Europe, the European Network of Transmission System Operators for electricity (ENTSO-E) publishes a breadth of energy-system-related time series data via the Transparency platform [21]. In the United States, hourly load data can be sourced directly from the websites of the regional transmission organization (RTO) or independent system operators (ISO). For regions serviced by utilities, the Federal Energy Regulatory Commission (FERC) publishes hourly load data via form 714 [22]. Despite this availability, the hourly demand data typically lack spatial flexibility and must therefore be disaggregated to be used as an input in a spatially resolved model. A common technique to obtain localized profiles from aggregated load data is to perform a heuristic allocation based on gross domestic product (GDP) and population [23] to obtain static disaggregation factors. In [24], the authors suggest dynamic regionalization factors are necessary to more accurately replicate actual systems. A more sophisticated approach to electricity demand disaggregation is introduced in [25] where the authors use a regional partial decomposition to identify processes and appliances with a high impact on the shape of the load profile. This work relies on the bottom-up load forecasting and adjustment tool developed by Fraunhofer ISI [26], which consists of individual modules representing different sectors of energy demand. The National Renewable Energy Laboratory (NREL) similarly endeavors to create regionalized county-level demand profiles using bottom-up models across all major economic sectors [27]. Another project in Europe has led to the development of an open-source disaggregation tool specifically for energy-system-related data [28]. This Python package takes as inputs natural gas and electricity demand data at the national level, categorized by sector (private households, commerce and trade, industry), and disaggregates to the subnational level using a combination of sector-relevant metrics. For instance, the residential demand disaggregation depends on subnational GDP, population, number and size of households, income per capita, and building stock heating mechanism (natural gas or electric). In contrast to these models that attempt to construct demand profiles as inputs to the energy system optimization, some research attempts to extract regional data ex post. Tracing emissions flows through the grid allows pollution associated with generation, exchanges, and consumption to be quantified and geographically allocated to inform regional patterns [29].

Ultimately, data availability is a primary challenge in increasing the spatial resolution of energy system optimization models [30]. The information sourced and the methods used to disaggregate the data can bias the results; therefore, higher resolution should not be conflated with higher accuracy. Nevertheless, the aggregation of spatially dependent parameters in coarser region optimization models can lead to refutable results from the perspective of demand-side, supply-side, and socio-political issues [4], demonstrating the relevance of spatial detail. Furthermore, the solutions offered by lower-spatial-resolution capacity expansion models may result in an infeasible system when fed into a higher detailed representation [31]. Of course, a significant disadvantage of higher spatial resolution is the inevitable computational burden that arises from solving a larger model. Although runtime ultimately depends on the machine specifications, in some cases high-resolution, national-scale models may only be executed using a high-performance computing environment.

Outside of the technical significance of spatial resolution in energy system modeling, socio-political considerations are also motivating the need for higher-fidelity analysis. Research in energy system transformation has expanded in recent years to encapsulate multiple dimensions of sustainability [32]. Various indicators (e.g., levelized cost of energy, life cycle emissions, capacity factor, job creation, land use) can be used in multicriteria decision analysis to assess the sustainability of energy systems [33,34]; however, more generally these measures can be categorized as social, economic, environmental, or technical. Although each dimension is often addressed at the national level, there is a need to understand how the opportunities and challenges of transitioning toward a clean energy future are distributed subnationally. Higher-resolution analysis can be particularly meaningful in the field of energy justice, where emerging research is exposing inequitable consequences for vulnerable populations [35]. For instance, in [36] the authors link national decarbonization scenarios for the U.S. electricity sector to the regional distribution of air pollution to evaluate the exposure of different racial/ethnic groups across the country, concluding decarbonization policies that are guided by national-scale capacity expansion modeling fall short of environmental justice and equity goals. High geographic granularity is also called out in [37] where the authors use a county-specific metric to investigate the efficacy of the U.S. Inflation Reduction Act in supporting communities affected by the shift away from fossil fuels. The energy transition could also provide many positive benefits across the country. Power-sector job growth is likely in almost all states, promoting changes in workforce dynamics such as increased gender diversity [38]. Another aspect of the energy transition that motivates high-spatial-resolution modeling is land use. Many siting ordinances for wind and solar deployment are defined at the county level, necessitating high-fidelity representation to capture restrictions [39]. Furthermore, competing land-use interests create obstacles for building transmission lines [40], and more granular modeling can help avoid overstating transmission expansion potential.

In conjunction, the technical challenges of modeling variable renewable energy combined with the complexity of capturing multiple dimensions of sustainability warrant the implementation of higher-fidelity modeling and analysis in the energy sector. Moreover, executing a capacity expansion model at multiple resolutions and comparing the results can provide valuable insight into the unintended consequences of model simplifications incurred from using a coarser spatial resolution. Uncovering these effects can help analysts and decision makers better interpret model results and better understand trade-offs when selecting the spatial resolution for a given study. In addition to highlighting the impacts of spatial resolution, this work introduces an open source, high-fidelity capacity expansion model that captures the U. S. electricity sector in greater detail than previously available.

2. Methods

In this section, the capacity expansion model used for this study is presented. Next, the disaggregation methods used to obtain high-resolution data are discussed, followed by an overview of the scenarios considered in the analysis.

2.1. Model description

The Regional Energy Deployment System (ReEDS) is a linear least-cost deterministic model that optimizes generation, storage, and transmission capacity investment for the contiguous United States given assumptions concerning electricity demand, technology costs, policies, and other key electricity sector characteristics. In this section, a brief introduction to the model is provided along with details outlining differences in modeling choices between the default ReEDS spatial resolution and the U.S. county resolution. The ReEDS model is described in detail in a separate publication [41]; however, pertinent details for the discussion of this work are included here. The analysis in this work is conducted using ReEDS version 2024.3.0 (available at https://github.com/NREL/ReEDS-2.0).

ReEDS determines the minimum capital and operational costs for the U.S. electricity sector subject to system constraints. The total system costs captured in the objective function include the overnight capital costs of each generation, storage, and transmission technology scaled by a financial multiplier (which accounts for regional factors, construction financing costs, cost of capital, and tax incentives), the fixed operations and maintenance costs of each technology, any policy costs (e.g., alternative compliance payments), growth penalties, and the dispatch costs. This objective is subject to energy balance constraints within each modeled region, transmission constraints, planning reserve constraints, operating reserve constraints, technology-specific operational constraints, resource constraints, policy constraints, and emissions constraints. ReEDS is a myopic model, solving sequentially for existing conditions without foresight.

2.1.1. Spatial resolution

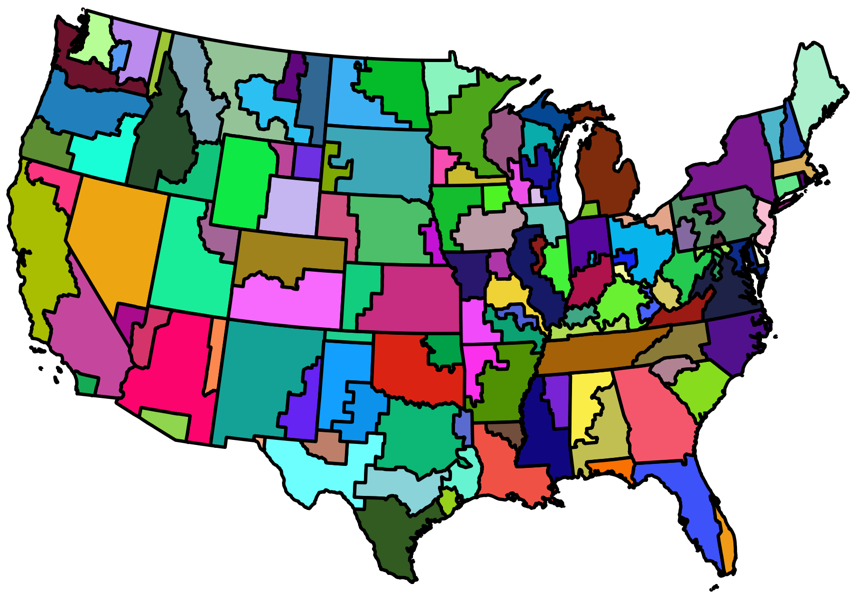
Until the development of the county version of ReEDS (first available as 2024.0.0), the spatial hierarchy in the model has been relatively static and inflexible. Fig. 1 shows both the default spatial resolution in ReEDS—which captures the contiguous United States in 134 balancing areas—and the county resolution, which contains 3109 U.S. counties. The default model balancing areas are not intended to accurately represent actual balancing authority areas; however, the ReEDS balancing area boundaries generally align with state lines, interconnection borders, and RTO service territories. Most analysis performed using ReEDS consists of national-scale studies; however, there is a growing need to examine smaller subsets of the U.S. electricity system in greater detail [42–44]. The spatial flexibility required for higher-fidelity analysis is added to ReEDS by building a county resolution version of the model. U.S. counties were chosen because many datasets are available at the county resolution. At both resolutions, the model regions—balancing area or county—represent model zones within which electricity supply and demand are balanced. In addition, the regions at both fidelities can be aggregated so state borders and division across the three asynchronous interconnections are still respected.

Table 1 summarizes the number of regions at each resolution for the Western Interconnection, the Eastern Interconnection, and the Electricity Reliability Council of Texas (ERCOT) interconnection.

2.1.2. Network topology

The transmission network in ReEDS is a synthetic network developed from nodal data assembled as part of the North American Renewable Integration Study (NARIS) [45]. This dataset relies on nodal transmission models developed for the Eastern, Western, and ERCOT interconnections under the guidance of the North American Reliability Corporation (NERC) and includes ~56,000 buses, ~94,000 transmission lines, and ~ 37,000 transformers. Capacity expansion models, such as ReEDS, typically use zonal representation to remain tractable, forgoing the modeling of individual generation, consumption, or transmission assets and instead grouping them into zones that are treated as copper plates. In [46], the authors propose a method for estimating the interface transfer limits between zones from nodal transmission data using a direct current (DC) power flow approximation. In this approach, two independent optimizations.

GW = gigawatt.



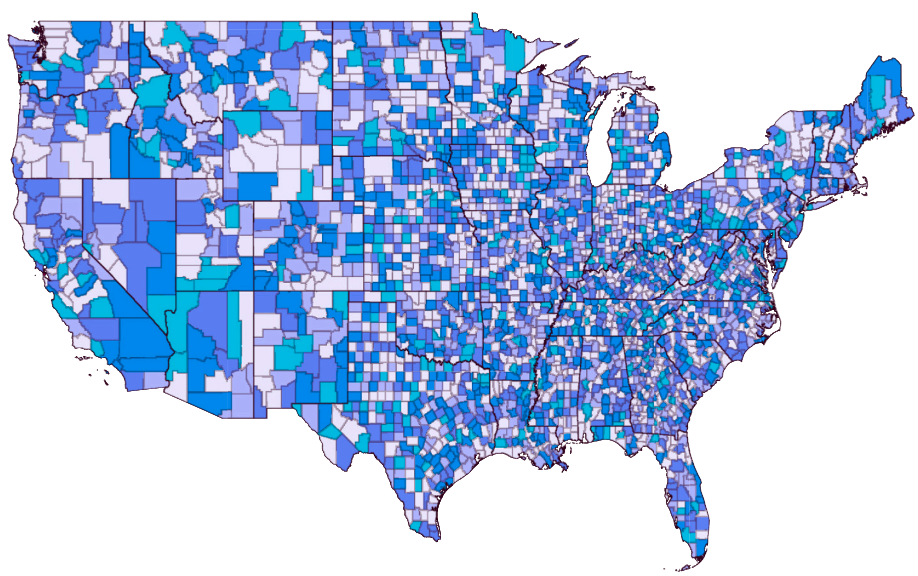


Fig. 1. Maps of the ReEDS model regions at the default balancing area resolution (top) and county resolution (bottom) for the contiguous United States.

Table 1
Summary of Model Regions for Balancing Area and County Resolution in Each Interconnection.

Interconnection	Number of Balancing Areas	Number of Counties
ERCOT (Texas)	7	192
Western	35	403
Eastern	92	2514

are performed to maximize the sum of flows in the forward direction on the transmission lines crossing the interface and to minimize the sum of flows in the reverse direction crossing the interface.

This method for deriving interface transfer limits is used to create the transmission networks in both the default balancing area resolution of ReEDS and the county-level representation. At the balancing area resolution, the optimization is run within each U.S. interconnection separately because they operate nearly independently as a result of limited transfer capacity [47]. Because of the relative density of the eastern interconnection, subsets of the network—defined by a distance threshold from the interface in question—are solved iteratively to reduce the complexity of the optimization [46]. Taking a subset of each interconnection is also explored to simulate the county-level transmission network; however, the metric to determine the size of the subset network is based on number of interface crossings rather than distance. In [48], a subnetwork size of six interface crossings is established as an appropriate basis for determining the transfer capacity limits in the county resolution model. Although both county and balancing area networks are derived from the NARIS data, they are fundamentally different because of their geographic resolution. Fig. 2 shows the transmission networks in ReEDS at the two spatial resolutions.

2.1.3. Resource adequacy

Resource adequacy is the ability of supply-side and demand-side resources to meet demand [49]. In ReEDS, resource adequacy is ensured in every model year by requiring the system to have sufficient firm capacity to meet the peak forecasted demand plus the planning

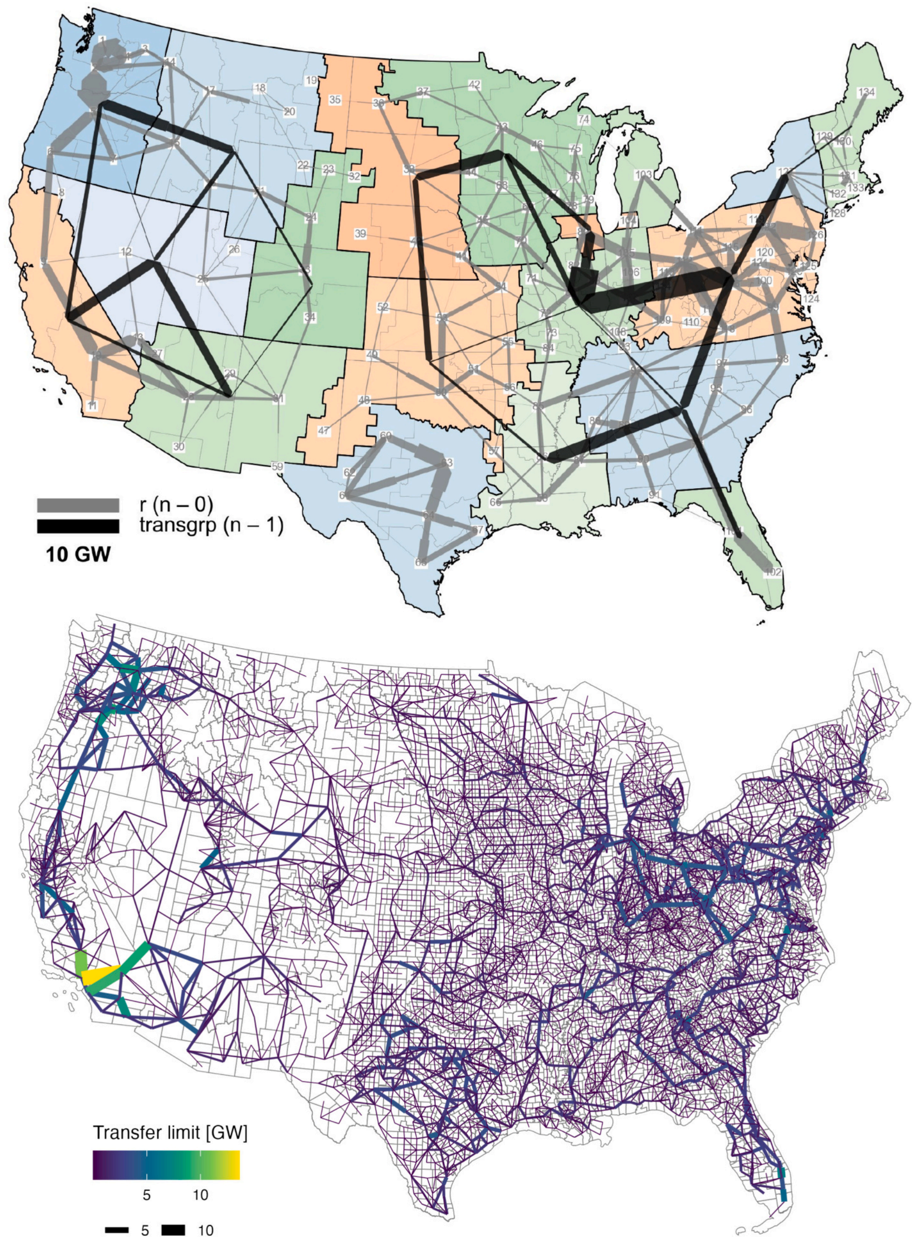


Fig. 2. Maps of the ReEDS transmission networks at the balancing area (top) and county (bottom) resolutions.

reserve margins suggested by NERC. The model can ensure resource adequacy in one of two ways: a capacity-credit-based approach or a stress period formulation. Because the scenarios included in this work use only the capacity-credit-based approach, only this method is described; however, the stress period formulation is described in a separate publication [50].

In the capacity-credit-based approach, each technology is evaluated based on its ability to contribute to serving load during highest net load hours. Conventional, dispatchable generation is assigned a capacity credit value of 1 to reflect the fact that 100 % of its nameplate capacity is counted toward the planning reserve requirement. For variable renewable energy (VRE), the capacity credit is determined in a module that runs between solve years and calculates the technology-specific capacity credit using the highest net load hours [51]. This approach assumes the highest net load hours are also the hours with the highest loss of load probability. ReEDS identifies these hours using 7 years of 8760 load and net (residual) load duration curves (LDCs). The LDC is created by sorting the total load in each model region from hours of highest load to lowest. The net LDC is created by taking the VRE capacity deployed in ReEDS and evaluating its time-synchronous contribution over the 7 years of weather data. The capacity credit (a proxy for effective load carrying capacity) is estimated as the difference in the LDC and net LDC during the top 20 h of the hot (meteorological summer) and cold (meteorological winter) seasons. Each technology in each region is assigned a fractional annual capacity credit that reflects the contribution toward meeting the regional peak load and additional NERC planning reserve margin.

2.2. Regionalization of input data

2.2.1. Available county data

High spatial resolution data exist for some ReEDS model inputs, including wind and solar resource potential, existing and planned generator information, and the transmission network. The renewable resource availability is obtained using NREL's Renewable Energy Potential (reV) model [52]. The reV model relies on the National Solar

Radiation Database [53] and the Wind Integration National Dataset Toolkit [54] open-access datasets to build 7 years of hourly capacity factors for more than 50,000 potential photovoltaic (PV) and wind sites in the United States. In addition to the high temporal resolution, reV includes high spatial detail to characterize land costs and availability. Across the contiguous United States, there are many regions with technical, environmental, or regulatory considerations that prohibit or restrict the deployment of solar and wind technologies. The reV model captures these land exclusions and applies siting ordinances that establish limitations for the deployment of wind and solar projects [55]. For instance, some U.S. counties have enforced setbacks from various infrastructure or restrictions on noise, which can impact siting opportunities [39]. In conjunction with the land availability, reV accounts for several costs associated with renewable deployment. These include land use costs, investments required to reinforce the bulk transmission network to avoid congestions because of new installed capacity, and the interconnection costs (spur line) to connect the renewable plant to the existing grid infrastructure. In the case of the county resolution supply curves, the bulk network reinforcement costs are not included because the more granular transmission network at county resolution can explicitly capture transmission investment decisions. Ultimately, the resource availability and costs from reV are compiled into supply curves that reflect the quantity and capital cost of renewable resources. Fig. 3 shows an example set of supply curves for all classes of land-based wind in the southernmost ERCOT ReEDS balancing area. The reV model generates site-level supply curves for each technology class in ReEDS using an 11.5-km (km) grid across the contiguous United States. The curves from the individual sites are assigned and aggregated to their respective ReEDS balancing area or county to produce a single representative curve for each technology class and model region. Land-based wind and utility-scale PV (UPV) technologies are grouped into resource classes based on capacity factor, with higher classes corresponding to higher capacity factors. Land-based wind can be assigned to classes 1–10 and UPV to classes 1–5.

MW = megawatt.

In addition to renewable resource potential, the existing and proposed generation plant data exist at a high resolution. The initial generation fleet in ReEDS is taken from the National Electricity Modeling System (NEMS) [56] and the Energy Information Administration's form 860 M [57]. It consists of existing plants, expected builds, and announced retirements. The dataset includes each plant's latitudes and longitudes, allowing each unit to be assigned to the appropriate balancing area or county. Technology costs and performance assumptions for new generators are taken from the 2023 Annual Technology Baseline [58], with moderate cost assumptions used across the scenarios in this study. ReEDS incorporates a wide range of generation and storage technologies including land-based wind, offshore wind, utility-scale PV, rooftop PV, concentrating solar power, geothermal, hydropower, pumped hydropower storage, batteries (with durations of 2–10 h), traditional large-scale nuclear, nuclear small modular reactors (SMRs), coal (with and without carbon capture), natural gas combined cycle (with and without carbon capture), natural gas combustion turbines, biopower (with and without carbon capture), landfill gas, and hydrogen combustion turbines.

2.2.2. *Disaggregation methods*

All remaining inputs to ReEDS exist at their default resolution—typically the 134 balancing area resolution. To solve the model at the county resolution, these datasets must be downscaled using one of the following approaches: uniform, geographic size, existing hydropower capacity, and transmission line size. The input data and their disaggregation techniques are summarized in Table A3 and explained briefly in the following. Uniform disaggregation assigns the balancing area value to all counties within that balancing area. The regional technology financial multipliers are an example of data treated with this approach. Population-based disaggregation uses population-based weighting to spread the balancing area value across all counties within a balancing area. The hourly load data are one example dataset downscaled in this way. Although some studies in the literature suggest regionalizing demand data using a weighted share of population and GDP [23,24] to better capture regions with large industrial demand, these data tend to be correlated at a resolution as detailed as U.S. county level. Fig. A3 shows the strong correlation between county population [59] and GDP [60] for available 2022 data. Still, population and GDP are not perfectly correlated, and further analysis is needed to evaluate whether one or both metrics better represents regionalized demand

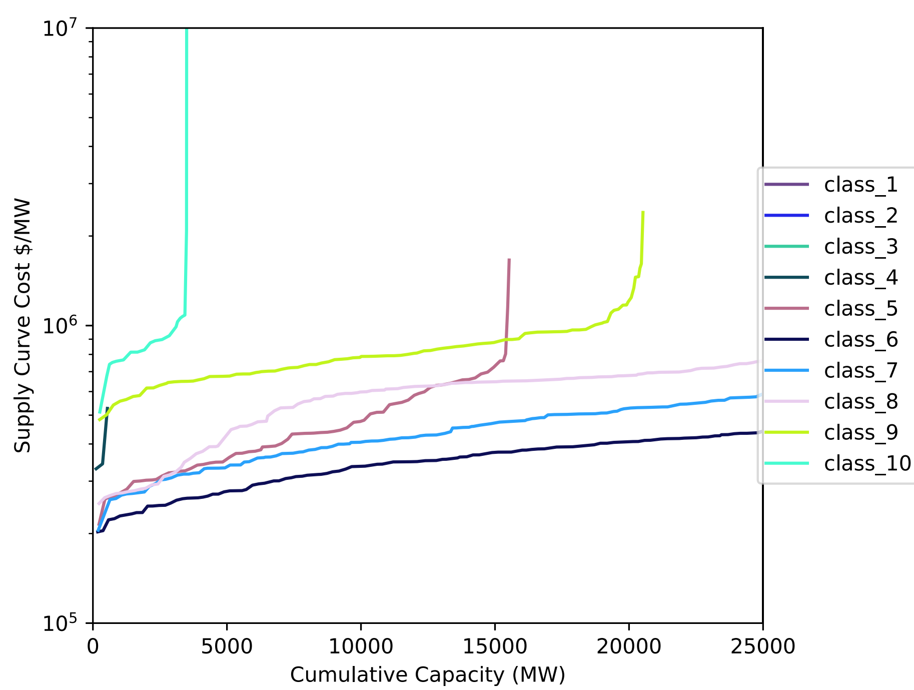


Fig. 3. Example supply curves by class for land-based wind resources in southernmost ERCOT ReEDS balancing area.

data. The scenarios analyzed in the remainder of this work use the population-based approach; however, a more detailed investigation is included in A.1 Load Disaggregation.

Geographic size disaggregation is similar to the population method, but the fraction assigned to each county is determined based on the geographic area of each county relative to the entire balancing area. Examples of data subject to geographic disaggregation include geothermal supply curves and inputs associated with water availability. Some hydropower datasets have their own unique disaggregation method. This procedure assigns multipliers to each county based on the amount of existing hydropower capacity in the county, as reported in the NEMS database, relative to the total hydropower capacity in the balancing area. Finally, Canadian imports and exports are disaggregated based on transmission line size for lines that cross the U.S.-Canada boundary. This approach creates fractional multipliers that represent the ratio of transmission capacity between a U.S. county and a Canadian balancing area relative to the cumulative transmission capacity between the United States and Canada for all counties within the ReEDS balancing area. This method assumes imports and exports from and to Canada are split based on transmission line size. Further details concerning the disaggregation methods selected for various model inputs are included in A.2 Disaggregation Summary.

2.3. Scenarios

This section describes the scenarios used in this work. Table 2 summarizes the eight scenarios considered. The scenarios are described in more detail in Sections 2.3.1 and 2.3.2.

2.3.1. Scenario assumptions

For each scenario, the temporal horizon extends until 2050, with model solve years occurring every 3 years starting in 2020. The scenarios analyzed fall into one of two policy-related categories: business as usual (BAU) and decarbonization (Decarb). In the BAU scenarios, technology cost and performance assumptions align with moderate trajectories from the 2023 Annual Technology Baseline [58]. The load projections are taken from Evolved Energy Research and include impacts of the Inflation Reduction Act, which reflect relatively moderate impacts because of economywide decarbonization and incentives for demand-side management technologies. The BAU scenarios also capture current policies as of April 2024. The Decarb scenarios apply the same assumptions but enforce a 100 % reduction in carbon dioxide emissions by 2035. The assumptions under these two categories align with the corresponding cases in NREL's Standard Scenarios report [61].

2.3.2. Scenario regions

The BAU and Decarb scenarios are evaluated at two spatial resolutions and for two isolated regions encompassing the interconnection managed by ERCOT and the Western Interconnection (WI). Fig. 4 presents maps of both regions at the two resolutions considered: the default ReEDS model balancing area and U.S. county. For ERCOT, the balancing area resolution contains 7 modeled regions whereas the county representation contains 192. The WI spans a larger geographic area with more heterogeneity than ERCOT. At the balancing area resolution, WI consists of 35 model regions; at the county resolution, it contains 403.

Table 2
Summary of Scenarios.

ERCOT and WI Scenarios	
Balancing Area BAU	Business as usual scenario at balancing area resolution
County BAU	Business as usual scenario at county resolution
Balancing Area Decarb	Decarbonization scenario at balancing area resolution
County Decarb	Decarbonization scenario at county resolution

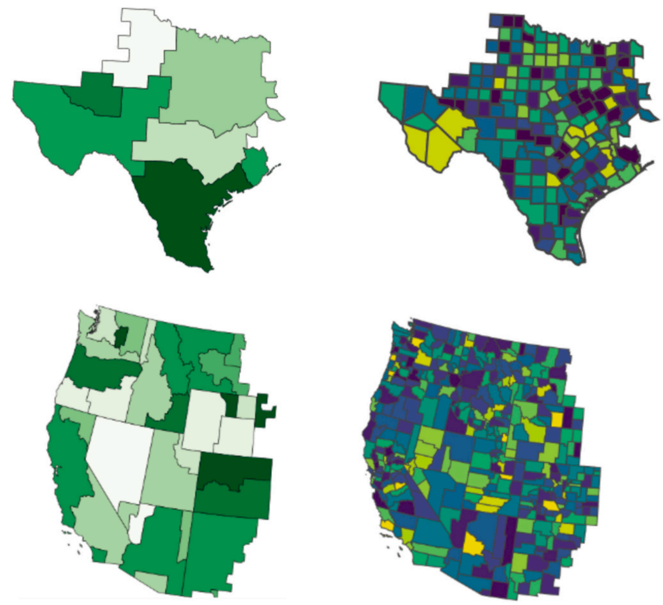


Fig. 4. Maps illustrating ERCOT (top) and WI (bottom) at balancing area (left) and county (right) resolutions.

3. Results

In this section, we evaluate the implications of spatial resolution in ReEDS across the ERCOT and Western Interconnections. For each region, the BAU and Decarb scenarios are considered. The results focus on the amount and location of installed capacity, the differences in resource adequacy contributions, the use of renewable resources based on transmission connectivity, and the overall effects on system cost and model runtime.

3.1. Installed capacity

Fig. 5 shows the total installed capacity in 2050 across the BAU and Decarb scenarios at both resolutions for ERCOT and WI. In the ERCOT BAU scenarios, the installed land-based wind capacity is 37 % greater in the county level relative to the balancing area resolution. This increase is accompanied by a 26 % decrease in UPV and a combined 34 % decrease in natural gas combined cycle (gas-CC) and natural gas combustion turbine (gas-CT) capacity. For the ERCOT Decarb scenarios, land-based wind capacity increases by 20 % at the county resolution relative to the balancing area case, whereas the UPV capacity is 30 % less than what is observed in the balancing area results. Under the enforced decarbonization scenarios, the combined gas-CC and gas-CT capacity is replaced by hydrogen CT (H2-CT) capacity. The relative 2050 installed.

Gas-CT = gas combustion turbine; Gas-CC: gas combined cycle = Gas-CC-CCS: gas combined cycle with carbon capture and storage; Gas-CC-CCS Upgrade = gas combined cycle upgraded to gas combined cycle with carbon capture and storage; H2-CT = Hydrogen; H2-CT-upgrade = gas-combustion turbine upgraded to hydrogen.

capacity of these H2-CT technologies in the county- level solution is 16 % less than the balancing area case. These differences are discussed further in the following paragraphs.

In the WI BAU scenarios, the county solution has a 67 % decrease in offshore wind compared with the balancing area case but a 49 % increase in land-based wind and a 28 % increase in UPV. In the balancing area BAU scenario, new gas-CC with carbon capture and storage (CCS) is built, whereas in the county BAU solution the fossil plants do not use CCS. In the BAU county solution, renewable sources contribute a greater share toward systemwide energy needs, avoiding the need for carbon sequestration technologies that are employed in the balancing area

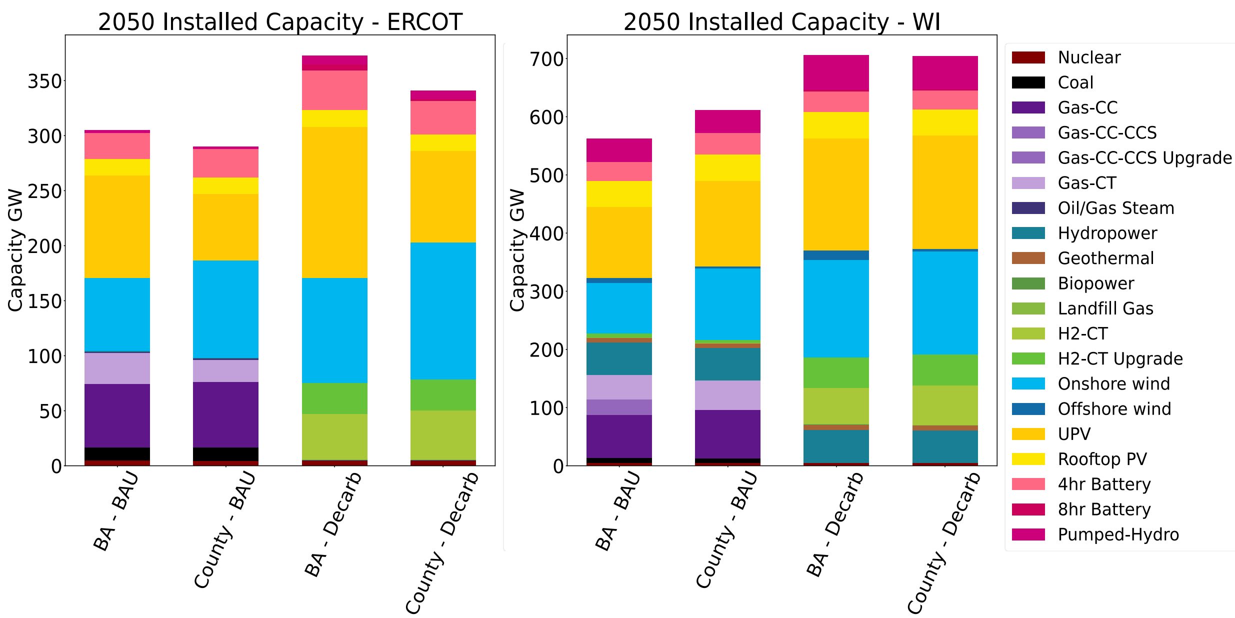


Fig. 5. 2050 installed capacity by technology.

scenario. In the WI Decarb scenarios, land-based wind increases by 3.5 % in the county solution relative to the balancing area, whereas installed UPV decreases by 18 % and offshore wind decreases by 79 %. Under decarbonization, the natural gas capacity present in the BAU scenario is replaced by H2-CT, either as new builds or upgraded from existing gas-CT. Across ERCOT and WI, the county-level resolution results in more

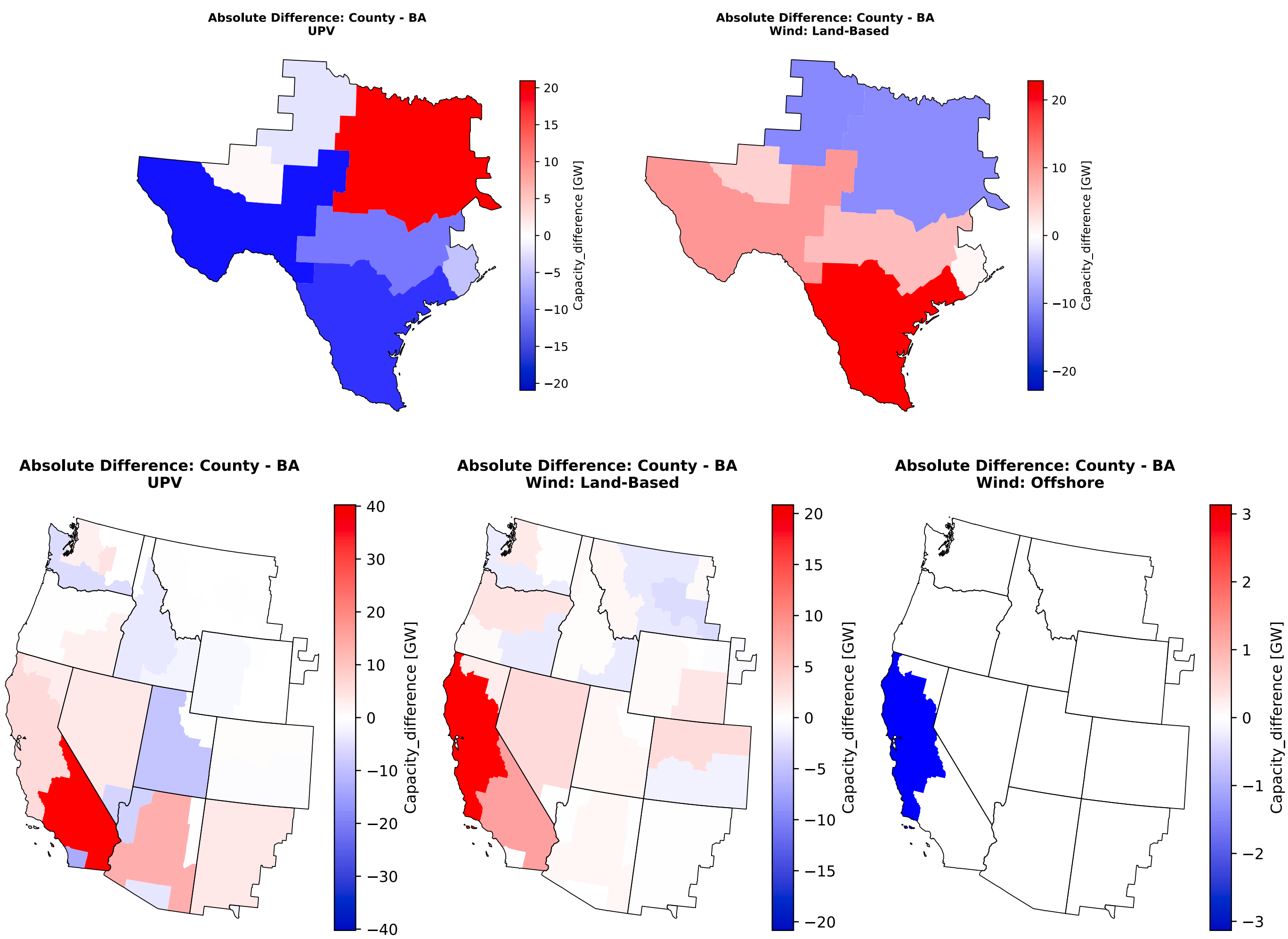


Fig. 6. Absolute difference in installed capacity in the county solution relative to the balancing area (BA) for the ERCOT (top) and WI (bottom) BAU scenarios.

land-based wind, less offshore wind, and similar amounts of conventional, dispatchable capacity.

In addition to differences in the total installed capacities, the results at the two spatial resolutions indicate prominent locational shifts in where the model builds the wind and solar capacity. Fig. 6 shows the absolute difference in installed capacity in the county solution relative to the balancing area. In ERCOT, the county solution shifts much of the installed land-based wind capacity from the northern to the southern regions. Part of the impetus for this change is the underlying resource supply curves. Regardless of the spatial resolution, each model region—either county or balancing area—is assigned one unique supply curve per resource class. In the case of land-based wind, ReEDS groups individual sites into 1 of 10 resource classes based on capacity factor [41]. Therefore, at the balancing area resolution there are 70 unique profiles

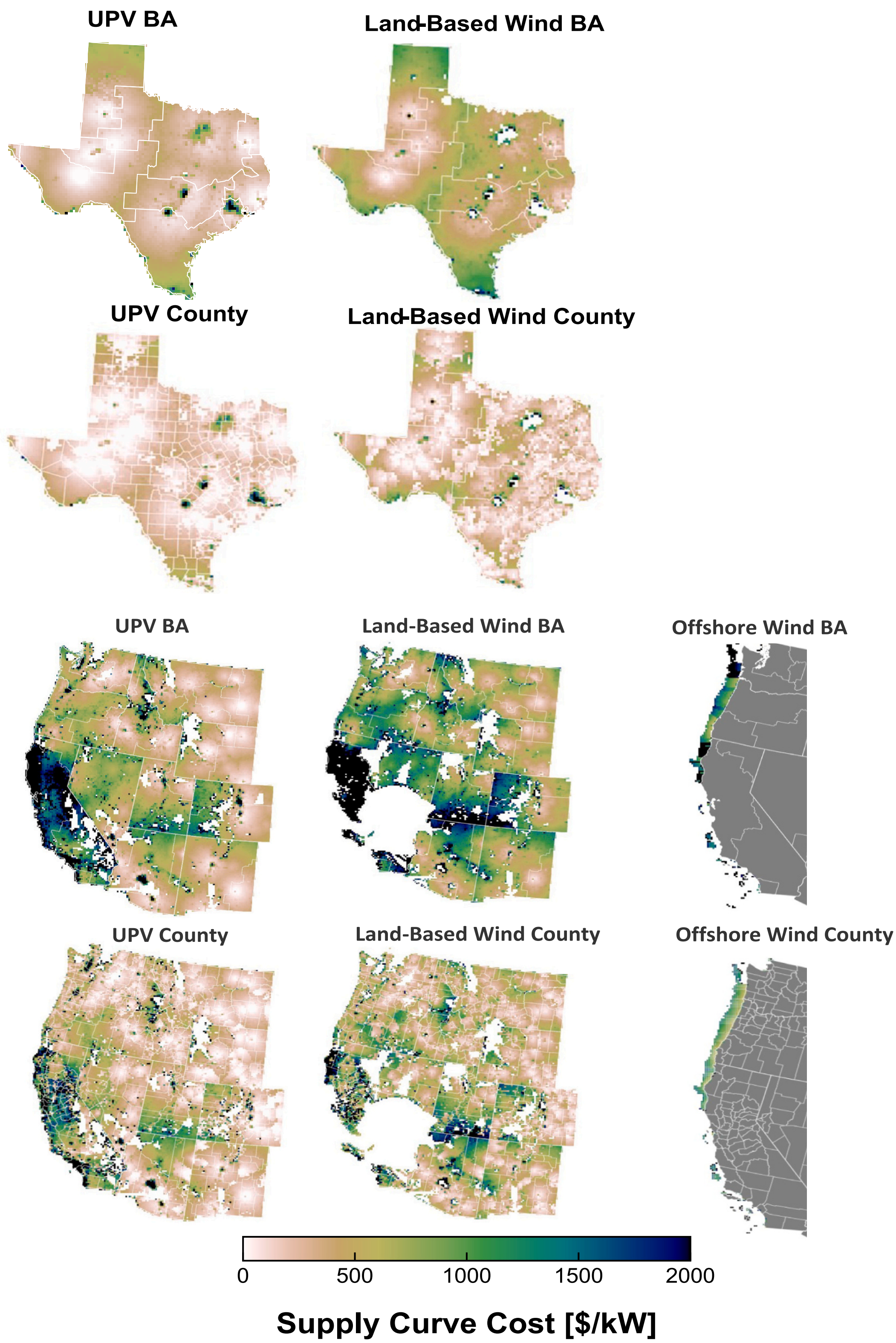


Fig. 7. ERCOT and WI supply curve costs at the balancing area (BA) and county resolution for UPV, land-based wind, and offshore wind.

for wind across ERCOT (10 profiles per region x 7 regions), whereas at the county resolution there are 10 × 192 regions = 1920 profiles. The additional detail in the county resolution allows the model to identify higher-value resources in areas for which the potential is diluted at lower resolution. Furthermore, the granularity of the transmission representation can alter the accessibility of high-potential resources. In the county-level resolution, the network reinforcement costs are excluded from the resource supply curve costs because the transmission investment decisions between counties are explicitly represented in the model.

The impact of the supply curves is exemplified in the southernmost model region. The installed wind capacity in this model balancing area in 2050 amounts to 31 gigawatts (GW) in the BAU county-level solution and 15 GW in the BAU balancing area solution. A closer look at the county-level results, shown in Fig. A6, reveals most of this capacity lies along the coast and along the border with Mexico, a region that is less attractive in the balancing area resolution because of the network reinforcement costs required to transfer the capacity to the nearest network node located at the balancing area's load center in the north (at San Antonio, Texas). This is further illustrated in Fig. 7 where the supply curve costs across ERCOT are plotted for the balancing area and county resolution resource data. Embedded in the total supply curve costs at both.

resolutions are the land-use costs and the spur-line costs. However, the cost component that drives the greatest differences between the curves is the network reinforcement cost that is included in the balancing area resolution but not in the county. The interconnection costs comprise the spur-line costs, which represent short-distance transmission connecting new wind and solar capacity to a point of interconnection on the existing transmission system, and the bulk network reinforcement costs, which are heuristically determined by tracing a path from the point of interconnection to the largest load center in the region. The spur-line and network reinforcement costs vary drastically by region and magnitude, ranging from \$0–2000/kW. Because the higher fidelity of the county-level transmission network allows the model to capture intrazonal transmission investment decisions, the network reinforcement costs are not included in the county resolution supply curves. In other words, the county-level resolution allows local loads to be served by in-county or nearby generation without requiring the full network reinforcement assumed in the balancing-area-level resolution.

In WI, the supply curve costs also play an influential role, particularly in California.

where the interconnection costs for wind and solar are high. Fig. 7 shows the supply curve costs across California in the county representation have greater availability of lower-cost areas across all three resources compared to the balancing area supply curves, making these technologies more attractive at the higher resolution and leading to greater installed capacity in the region. Another noteworthy difference in California's capacity portfolio between the balancing area and county solutions is the shift away from offshore wind at the higher resolution. The county BAU model installs 40 % less offshore wind capacity, in part because the supply curve cost for land-based wind is comparatively lower in the higher-resolution model. At the balancing area resolution, both offshore and land-based wind have similarly high costs (\$1500–2000/kW) in northern California; however, at the county resolution, land-based wind is more abundantly available at lower cost than offshore wind.

Beyond California, the differences in supply curve costs are less dramatic but persist and contribute to differences in the resulting installed capacity. Both land-based wind and UPV capacity increase in the county solution relative to the balancing area scenario. Several factors play a role in the locational shifts (Fig. 6) between the spatial resolutions. The partitioning of some states at the balancing area resolution dilutes the attractiveness of some renewable resources, particularly for heterogenous regions. For instance, at the balancing area resolution, Colorado is divided north to south; however, the land-based wind resource is better split east to west, along the natural barrier created by the Rocky Mountains. Fig. A7 shows in the county BAU solution, all the land-based wind capacity is installed in the eastern part of the state, where the capacity factor.

for wind is higher. Furthermore, Colorado has a relatively large, concentrated load near the center of the state (Denver and nearby parts of the Front Range), which forces resources on the outskirts of the state to incur additional network reinforcement costs—creating a barrier for land-based wind capacity at the balancing area resolution.

3.2. Firm capacity

In addition to the supply curve cost, resource adequacy requirements can play a role in determining where renewable capacity is deployed. As described in Section 2.1.3 Resource Adequacy, we use a capacity credit method in ReEDS to quantify the contribution of a particular technology toward meeting system resource adequacy needs. Fig. 8 shows the installed firm capacity in 2050 for ERCOT and WI. In ERCOT, land-based wind contributes a 45 % and 43 % greater share in the county solution relative to the balancing area solution for the BAU and Decarb scenarios, respectively. It is difficult to disentangle the increased resource adequacy contribution from land-based wind with the overall increase in installed wind capacity in the county-level scenarios; a sensitivity analysis is presented in A.7 Sensitivity Analysis, highlighting the challenge of linking differences between the balancing area and county resolutions results to specific changes in the underlying models. Nevertheless, the alignment of the land-based wind in the southern regions (Fig. 6) coincides with areas characterized by higher capacity credit values as shown in Fig. A4, indicating resource adequacy as a contributing driver for the locational shifts between the two spatial resolutions. The locational shifts in WI are less prominent because of the heterogeneity of wind resources in the western United States; the contribution of land-based wind.

increases by 38 % and 8 % in the BAU and Decarb scenarios, respectively. In [62], the authors evaluate capacity credit for land-based wind in the western United States, demonstrating land-based wind exhibits both a high capacity credit and a high capacity factor in the eastern plains of Montana, Wyoming, Colorado, and New Mexico, shown in Fig. A5. In comparing the installed capacity of land-based wind in these states between the spatial resolutions (Fig. 6), northern Colorado and southeastern Wyoming exhibit increases at the county resolution, with substantial capacity built in regions characterized by higher capacity credit and capacity factor values (Fig. A7).

3.3. Curtailment

As described in Section 2.1.2 Network Topology, the transmission networks in the balancing area and county resolution models are fundamentally different. One of the impacts of the difference in network resolutions is that congestion can be better captured in the higher-resolution scenarios. For example, Fig. 9 shows the curtailment in ERCOT and the California Independent System Operator (CAISO) during historic years at the balancing area and county resolutions compared with the historically reported curtailment in these RTOs. The balancing area resolution underestimates curtailment because ReEDS forces the model to build sufficient intrazonal transmission to ensure all installed wind and solar can be delivered to load centers. Because the county resolution model does not enforce this, congestion-driven curtailment from insufficient local transmission can be better captured.

3.4. Transmission

Fig. 10 shows the cumulative transmission additions from 2020 through 2050 and the average power flow in 2050 for the BAU ERCOT scenario at both spatial resolutions. The county-level solution installs 44 % more alternating current (AC) transmission capacity (as measured in

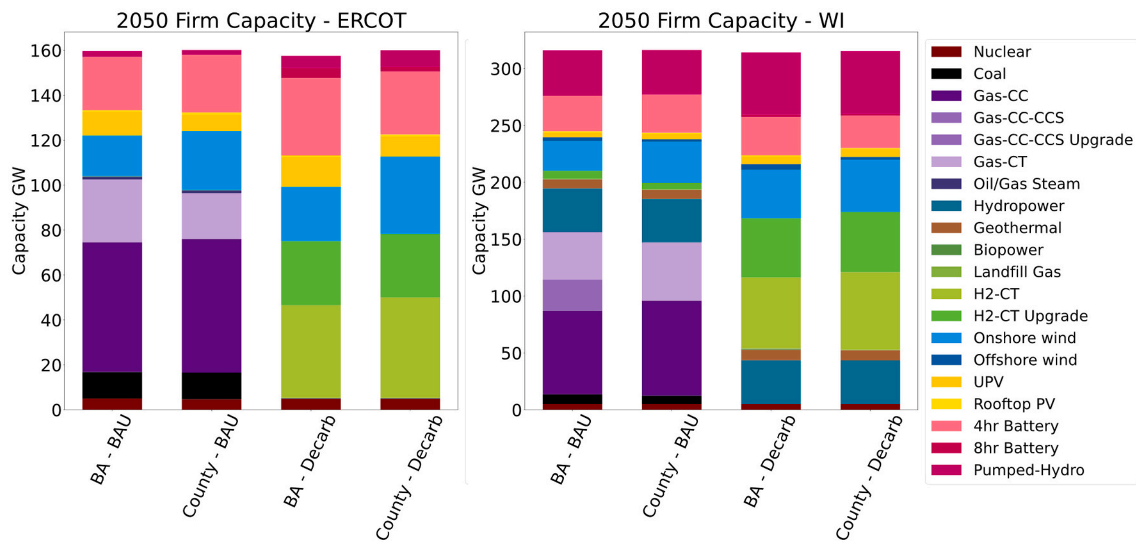


Fig. 8. 2050 firm capacity by technology.

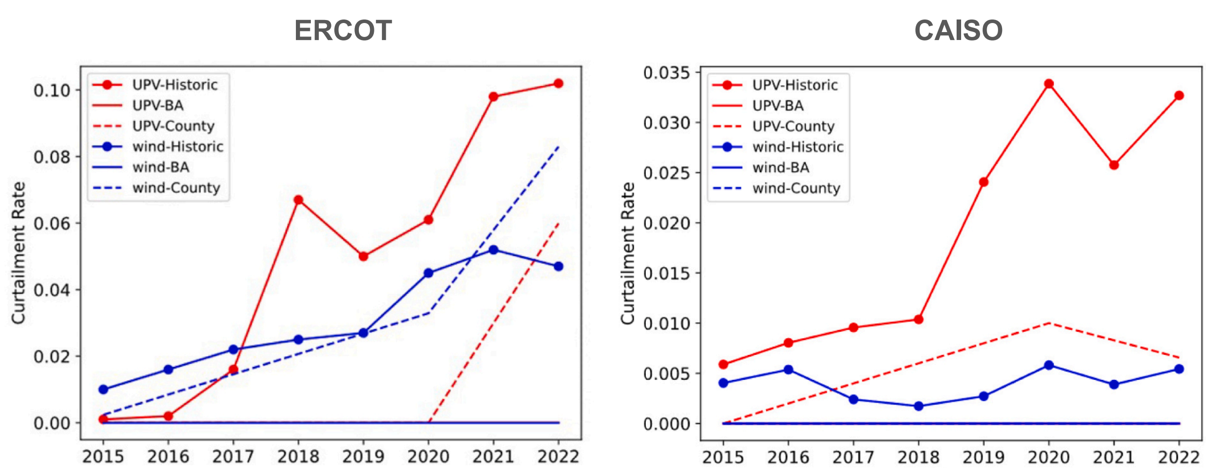


Fig. 9. Reported curtailment in historic years with curtailment reported by ReEDS at the balancing area and county resolutions. Note at the balancing area resolution, no curtailment is reported for either UPV or wind in both ERCOT and CAISO.

GW-miles) than the balancing area counterpart. The differences in transmission line location between the balancing area and county resolution networks coincide with regions that exhibit greater differences in installed land-based wind capacity. For instance, in the county scenario the southernmost model region has substantial transmission additions to deliver wind to the load center (Houston, Texas) in the smaller neighboring region to the east as indicated by the average power flow in Fig. 10. In the higher-resolution network, shorter, more distributed lines are built to enable resource sharing between the regions. These shorter transmission lines can be interpreted as locations where extra line capacity, through whatever means, is especially valuable. The transmission capacity broken out by transmission type is show in Fig. A8. The impact of the explicit county-to-county transmission expansion can also be seen in Fig. A9, which shows the county network exhibits lower transmission losses than the balancing area network.

In WI, the county solution installs 24 % more AC transmission capacity than the balancing area solution in the BAU scenario. The largest transmission addition in the county model, shown in Fig. 11, connects southern Arizona with southern California, with the average power flow indicating California is primarily importing energy. A closer look at southern California reveals this model region has 50 % less gas -CT, gas-CC and gas-CC-CCS capacity installed in the county solution relative to the balancing area solution (Fig. A10), compensated for by increases in land-based wind and UPV capacity in southern California and surrounding regions. The trade-off between localized generation capacity and transmission capacity is exemplified in this region, where at higher spatial resolution the amount of generation capacity decreases while the amount of transmission capacity increases compared to the coarser model.

3.5. Total system costs and runtime

Finally, the impacts of spatial resolution on comprehensive system results are considered. Fig. 12 shows the net present value of bulk power system costs broken out into individual components. The county-level scenarios have lower total system costs than their balancing area counterparts across both the BAU and Decarb cases, with more substantial differences in the Decarb cases amounting to a 2 % and 6 % decrease in ERCOT and WI, respectively. Generally, the lower costs in the county solutions can be attributed to higher-potential and lower-cost resources being more accessible and driving differences in installed capacity (Fig. 5). Regarding computational impacts, Table 3 summarizes the runtime at each spatial resolution for the BAU and

Decarb scenarios. The runs were completed on a virtual machine

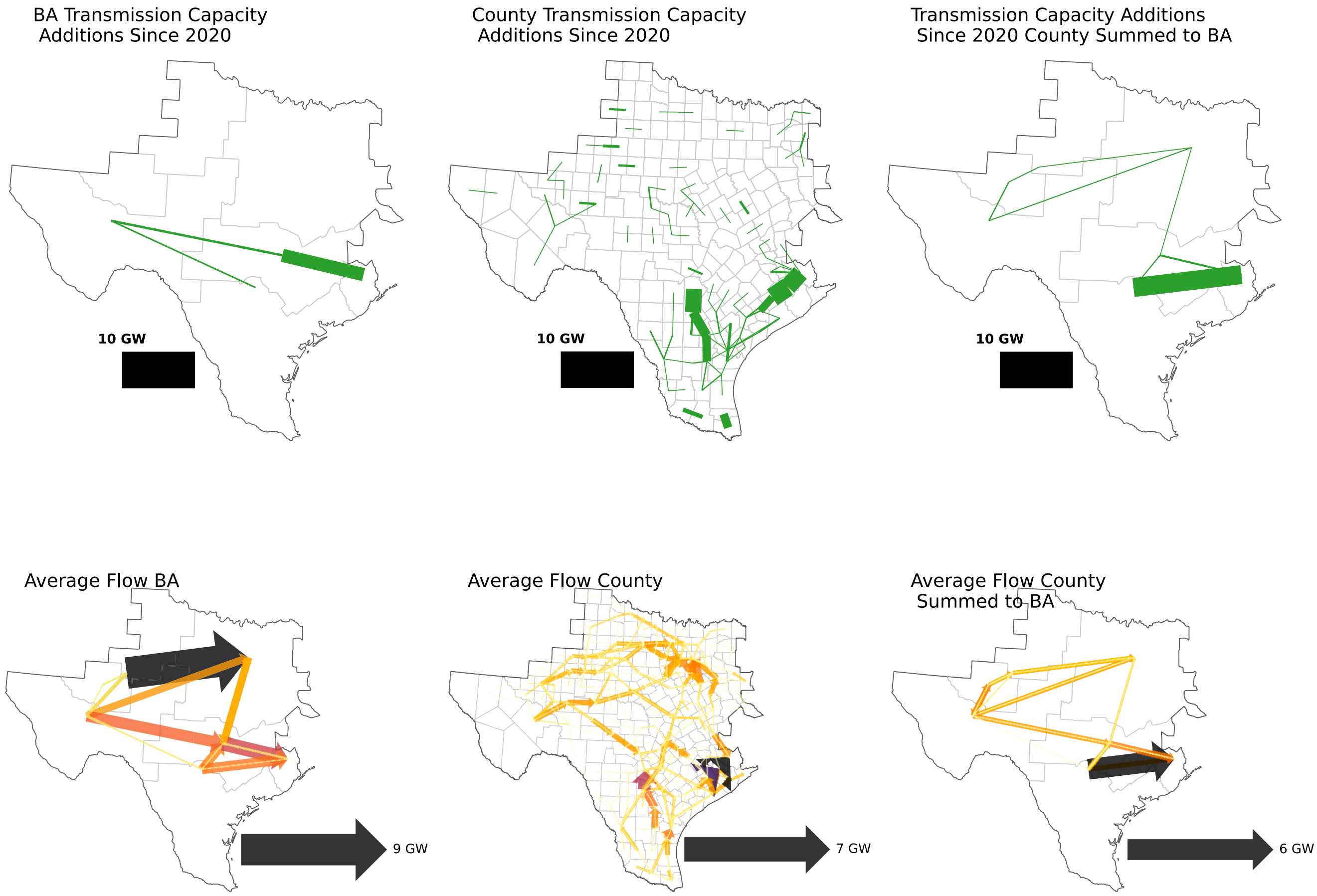


Fig. 10. ERCOT new transmission capacity from 2020 to 2050 (top) and average power flow in 2050 (bottom).

with 500 GB of RAM. At the county resolution, WI contains approximately twice as many model regions as ERCOT and takes more than 20 times as long to solve. Although not presented in this work, scenarios of the eastern interconnection have been challenging to solve and often require other model simplifications (such as turning off operating reserves) to get the model to solve in less than 48 h. As summarized in Table 1, the eastern interconnection contains approximately 80 % of all counties in the contiguous United States—substantially scaling up the size of the model compared to ERCOT and WI. Similarly, national-scale scenarios at county-level resolution are intractable unless the model formulation (e.g., reducing the number of eligible technologies; reducing the number of representative days) is dramatically simplified.

PTC = production tax credit; ITC = investment tax credit; O&M = operations and maintenance; WECC = Western Electricity Coordinating Council, CO2 T&S Capex = CO2 transportation and storage.

BA = balancing area.

4. Conclusions

Spatial resolution is a consequential lever in long-term energy system modeling. Higher-resolution models provide an opportunity to investigate custom, user-defined focus areas and can enhance the granularity of model results, especially regarding the transmission system, resource siting, resource quality, and distribution of costs. This work describes the development of a high-fidelity capacity expansion model for the contiguous United States and showcases results for several scenarios that demonstrate the impact of spatial resolution on model projections. The information needed to build high-fidelity models is often unavailable at the desired resolution and must therefore be created using disaggregation techniques. The methods chosen could bias the results, meaning higher resolution should not automatically be conflated with higher accuracy. Nevertheless, for variable renewable energy, higher spatial resolution does lead to a better representation of the heterogeneity of resource quality—especially as the geographic scope of the study expands to include areas with varying terrain and weather patterns.

4.1. *Key findings*

To identify consistencies in the implications of spatial resolution on the results, the same suite of scenarios is analyzed for ERCOT and for WI. To this end, both interconnections are evaluated under BAU and Decarb pathways. The results indicate the county-level representation offers a lower-cost solution relative to the balancing area representation in both the BAU and Decarb cases. Furthermore, the county resolution Decarb scenarios in ERCOT and WI both have less installed generation capacity but more transmission capacity in 2050 than the balancing area counterparts. These results can be attributed to the fidelity of the UPV and wind resource and the transmission costs associated with accessing the renewable sites. The detail in the county-level UPV, wind, and transmission input data allows higher-capacity-factor sites to be economically accessible to the system. This is captured in ERCOT with the shift in land-based wind capacity to the southern regions at the county resolution. It is also captured in WI with greater amounts of UPV and land-based wind capacity in the county solution aligning with regions associated with lower supply curve costs relative to the balancing area representation.

In addition to resource quality, accessibility, and cost, the resource adequacy assessment performed in ReEDS also contributes to the locational shift in installed capacity. In both the WI and ERCOT county resolution scenarios, land-based wind capacity is placed more prominently in areas where the capacity credit values are higher. Correspondingly, land-based wind amounts to a greater share of installed firm

Fig. 11. WI installed transmission capacity since 2020 (top) and average power flow in 2050 (bottom).

capacity in the county scenarios, alleviating the need for some gas capacity. The granularity of both the renewable resources and the transmission network enables better asset identification and utilization across the system. In contrast, the balancing area resolution results tend to clump renewable capacity closer together and closer to load centers. This comes as a consequence of characterizing renewable resources at a coarser resolution, reducing the attractiveness and therefore the incentive for the model to invest in transmission to reach for a more distributed selection of resources. Partitioning regions to align with natural boundaries, such as mountain ranges, could help mitigate the dilution of resources in coarser resolution models by creating zones with a more homogenous spread of renewable quality. However, natural barriers and important administrative divisions are not always in alignment. The last significant distinction between the two spatial resolutions is model solve time. An order of magnitude increase in the number of model regions leads to at least an order of magnitude increase in runtime.

4.2. *Efficacy of high spatial resolution modeling*

Generally, the results across ERCOT and WI indicate higher spatial resolution modeling leads to more opportunistic allocation of resources, more transmission capacity to enable resource sharing between regions, and an augmented valuation of resource adequacy contribution. The county solution offers more granular reporting at a substantial computational expense; therefore, the value added depends on the research question. In [63], the authors provide a framework to help researchers evaluate an appropriate spatial resolution, noting the motivation for higher spatial detail should act as the driving deciding factor. For certain studies, the availability of spatially resolved results can alleviate the need to perform post-processing to obtain pertinent information. For instance, in the field of energy justice, regionalized emissions can help quantify the air pollution disparities across racial/ethnic groups [36]. Furthermore, higher spatial detail allows modelers to implement region-specific policy constraints. For example, siting ordinances across the United States are often created at the county level and can have a meaningful impact on land availability for renewable deployment [39]. Including these ordinances as constraints in the higher-fidelity representation ensures the model results are feasible. Ultimately, the county-level representation offers the capability for users to consider spatially dependent data and constraints that are overlooked or simplified at coarser resolutions.

Comparing the balancing area and county resolution results

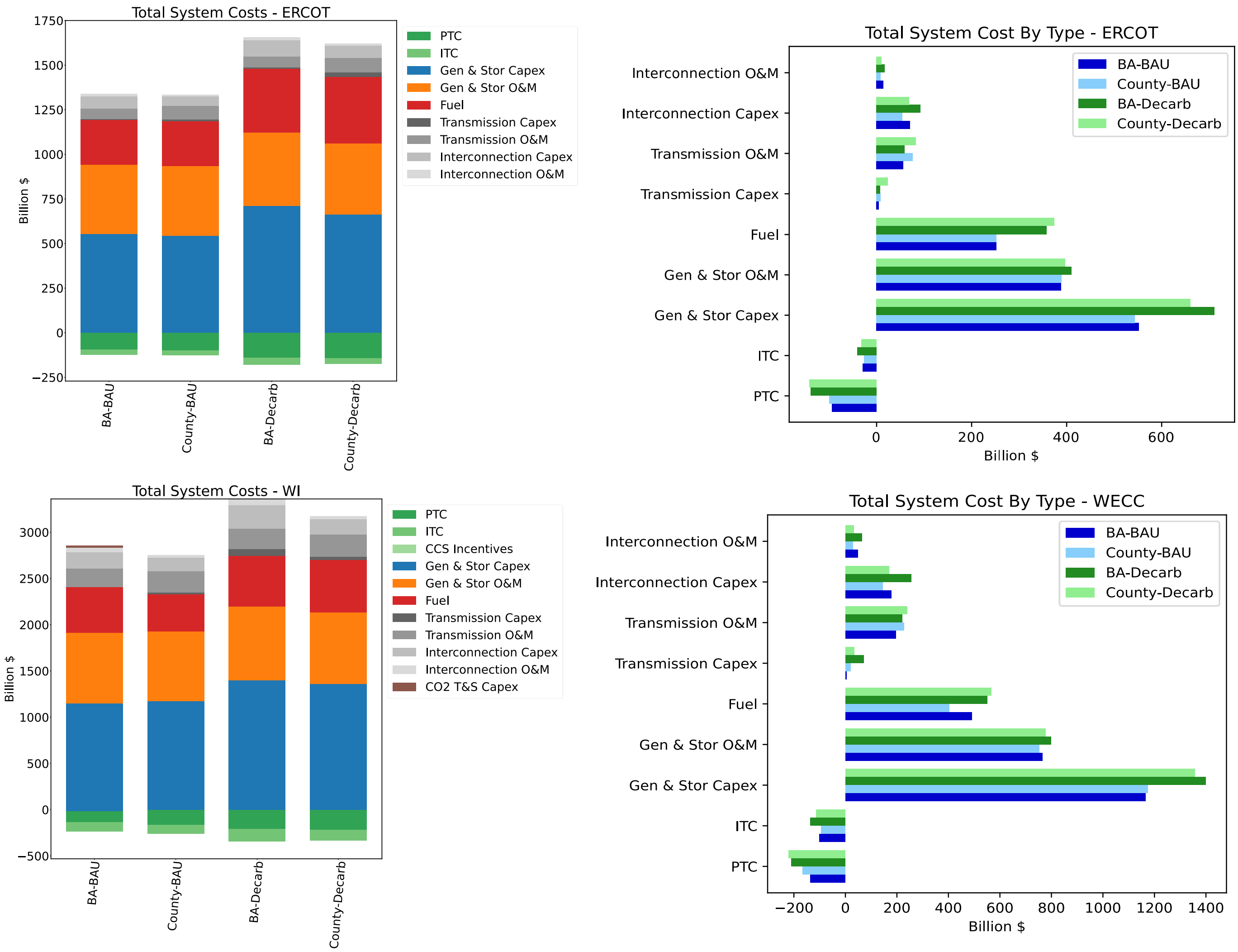


Fig. 12. Net present value of total bulk power system costs broken out by type for ERCOT (top) and WI (bottom).

Table 3
Summary of Runtime Across ERCOT and WI Scenarios.

	ERCOT Scenarios				WI Scenarios			
	BA BAU	*County BAU*	*BA Decarb*	*County Decarb*	*BA BAU*	*County BAU*	*BA Decarb*	*County Decarb*
Runtime (hours)	0.06	0.67	0.06	0.61	0.44	14.94	0.47	14.92

identifies areas for improvements in ReEDS at both resolutions. The high-resolution model is less suitable for studies that span multiple interconnections, where runtime and memory usage arise as the primary barriers. In addition, at the county resolution, the availability of spatially resolved input data remains a challenge; further work should investigate the effects of the selected disaggregation techniques, particularly for electricity demand. Regarding intrazonal transmission representation, the county-resolution model excludes transmission reinforcement costs in place of explicit county-to-county investment decisions. The heuristic approach to develop this cost for the balancing area resolution supply curves could be applied to the counties for comparison. Finally, burgeoning interest in high-fidelity modeling coupled with computational challenges associated with solving large geographic scopes has motivated the consideration of a mixed-resolution representation in ReEDS (A.8 Mixed Resolution Capability). With this capability, focus areas could be modeled at the county resolution while retaining the interactions with the surrounding regions modeled at the balancing area resolution. Future analysis should compare the implementation and results of the mixed resolution model against the balancing area and county resolution models to validate its performance and inform potential modeling changes across all spatial resolutions.

In summary, the implications of adjusting the spatial resolution in an applied capacity expansion model are discussed in this work to both validate and improve upon the resulting projections. Enhanced granularity in long-term planning provides many advantages, especially as the energy transition unfolds to impact individual communities across the county. Spatial flexibility can offer users and developers the opportunity to implement localized policies and examine their subsequent implications on a subnational level. However, the benefits of high-resolution modeling must be weighed against the availability of the necessary data and the scope of the research question.

CRediT authorship contribution statement

Louisa Serpe: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Wesley Cole:** Writing – review & editing, Software, Project administration, Methodology, Funding acquisition, Conceptualization. **Brian Sergi:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Maxwell Brown:** Writing – review & editing, Software, Conceptualization. **Vincent Carag:** Software, Methodology, Data curation. **Akash Karmakar:** Software, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Appendix

A.1. Load Disaggregation

Another possibility for evaluating the population-based load disaggregation method is to consider just the U.S. counties that constitute a NERC balancing authority, for which the U.S. Energy Information Administration (EIA) publishes hourly demand data [64]. Within this subset of counties, the comparison between the county-level demand used in ReEDS and the balancing authority demand is imperfect as illustrated in the following examples. Fig. A1 shows the comparison between the load data used in the county version of ReEDS for Grant County in Washington to the EIA load data published for the Public Utility District of Grant County in 2016. The EIA demand is consistently higher than the demand represented in ReEDS; however, this could be attributed to the service territory of the utility spilling into neighboring counties and therefore serving load outside of Grant County. Another consideration is the year selected. ReEDS uses weather data for 2007–2013; however, the data available from the EIA start in 2015. Finally, Grant County hosts several large data centers [65] that contribute to the local GDP; however, a comparison of the population and GDP shares indicates the purely population-based approach results in the higher demand allocation and therefore including a combined population and GDP weighting would not lead to a demand profile that better aligns with the EIA data. This may not hold true in all U.S. counties, and a multilinear regression analysis is included next to better quantify population and GDP as predictors for demand.

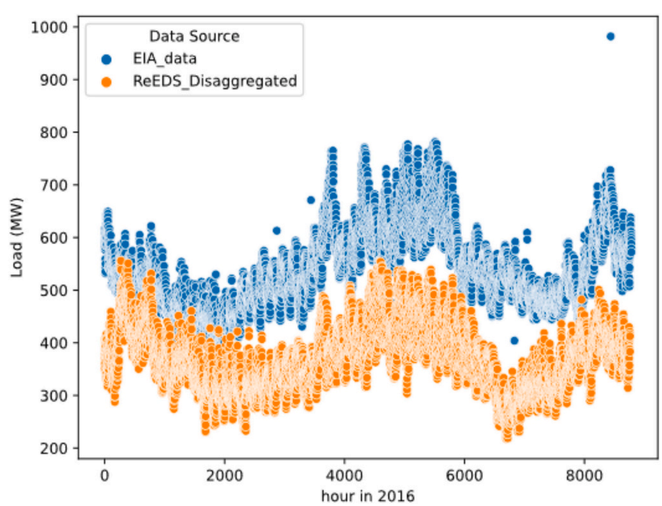

Fig. A1. Comparison of ReEDS population-based load vs. EIA hourly load for the Public Utility District No. 2 of Grant County in 2016.

Another balancing authority that seemingly covers a single county is the Los Angeles Department of Water and Power. Fig. A2 shows the EIA demand data in 2023 for the territory served by the L.A. municipality utility compared to the disaggregated load assigned to L.A. County in ReEDS. The disparate profiles result in part because the service area of the utility only covers a portion of Los Angeles County as well as an isolated region in eastern California. The population-weighted demand assigned to L.A. county in the ReEDS model encompasses the entire jurisdiction and is therefore attributed a greater demand than the EIA balancing authority. Ultimately, the misalignment of real system boundaries and administrative borders complicates the comparison of high spatial resolution data. Future demand-side work in ReEDS will incorporate county-level load profiles constructed with sectoral-specific energy modeling [27]. The bottom-up approach to generating demand curves in each county will serve as an easier benchmark to compare the population-based disaggregated data against.

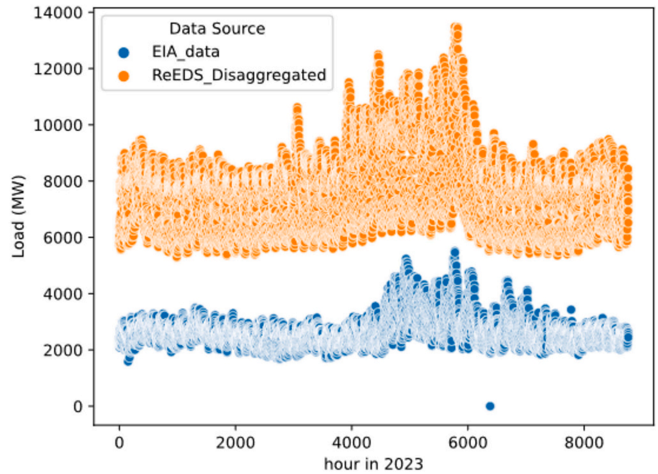

Fig. A2. Comparison of ReEDS population-based load vs. EIA hourly load for the Los Angeles Department of Water and Power in 2023.

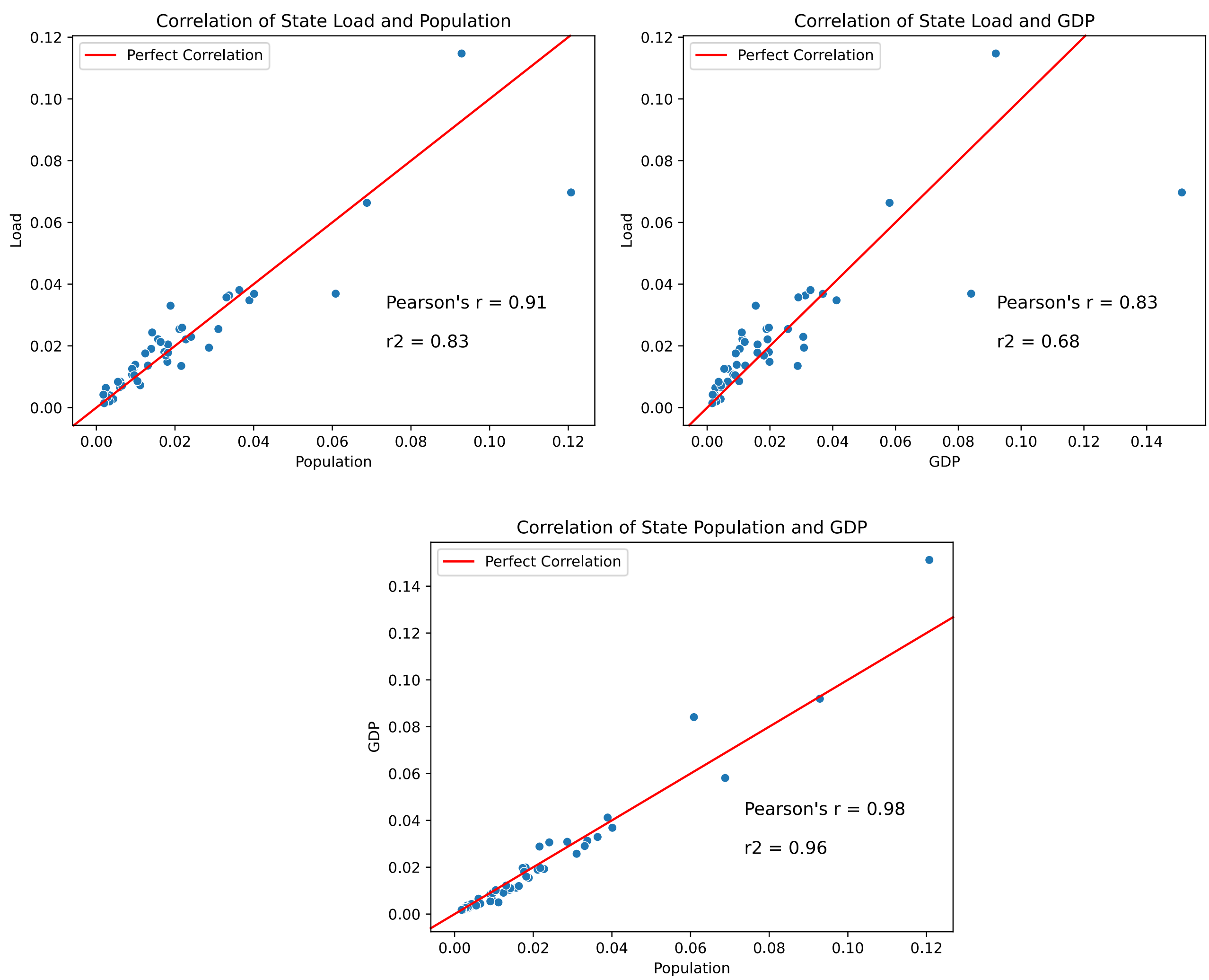

Fig. A3. Correlation of state-level load, GDP, and population.

Even though it is challenging to validate the county-level load data used in ReEDS against real system data, it is still possible to perform a statistical analysis to determine if multiple independent variables can better predict demand. First, GDP and population are evaluated independently as shown in Fig. A3. State-level demand profiles are used as the highest resolution data representing the ground truth. Population has a higher coefficient of determination (0.83) than GDP (0.68), indicating population performs better as an indicator for demand. However, the results of the multilinear regression summarized in Table A1 and Table A2 show a combination of population and GDP performs the best of all three. At 95 % confidence level, a p-value less than 0.05 indicates the independent variable is statistically significant. Both GDP and population meet this criterion. Based on the coefficients assigned to each independent variable, an increase in population will increase the mean load whereas an increase in GDP will decrease the mean load. The negative correlation between GDP and electricity demand is counterintuitive; however, a closer look at the outliers in the correlation of state load and GDP reveals California and New York have the greatest disparity between the two measures. Within each of these states, the counties affiliated with the highest GDP are Manhattan and Los Angeles, neither of which has economies driven largely by energy-intensive operations. If California and New York are excluded from the multilinear regression analysis, the coefficient for normalized GDP remains negative (−0.36614); however, the *p*-value (0.16) indicates it is no longer a statistically significant independent variable. Although removing outliers is not a reliable approach, it does highlight some regions disproportionately skew the regression. Ultimately, further work is needed to evaluate the best path forward regarding demand disaggregation, and results from scenarios that incorporate GDP and population as regionalization factors should be compared to the purely population-based approach.

Table A1
Multilinear Regression Statistics for GDP and Population Analysis.

Regression Statistics	
Multiple R	0.959823
R Square	0.92126
Adjusted R Square	0.91776
Standard Error	0.005821
Observations	48

Table A2
Multilinear Regression Statistics for GDP and Population Analysis.

	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95 %*	*Upper 95 %*
Intercept	0.000456	0.001242	0.367338	0.715089	-0.002046	0.002959
normalized_gdp	−1.13255	0.1532	−7.39261	2.68E-09	-1.441107	−0.823987
normalized_pop	2.087342	0.178798	11.67431	3.28E-15	1.727225	2.447460

A.2. Disaggregation Summary

Table A3 summarizes the disaggregation techniques used for various input file types. The disaggregation technique used for each file in the model repository is listed in runfiles.csv. The ReEDS model is available at https://github.com/NREL/ReEDS-2.0. This work was completed using version 2024.3.0.

Table A3
Summary of Disaggregation Methods Used Based on File Type.

File Category	Disaggregation Method
Canadian imports/exports	Transmission line capacity
Load/demand-side technologies	Population
Water supply	Geographic size
Regional capital cost multipliers	Uniform
Hydrogen demand	Geographic size
Hydro upgrade availability	Existing hydro capacity
Existing SMR capacity	Population
Transmission capital cost multiplier	Uniform
Seasonal adjustments to hydro availability	Uniform
Forced retirements	Uniform
Available hydrogen storage technologies	Uniform
Hydro capacity factors	Uniform
Carbon storage	Uniform

A.3. Capacity Credit Evaluation

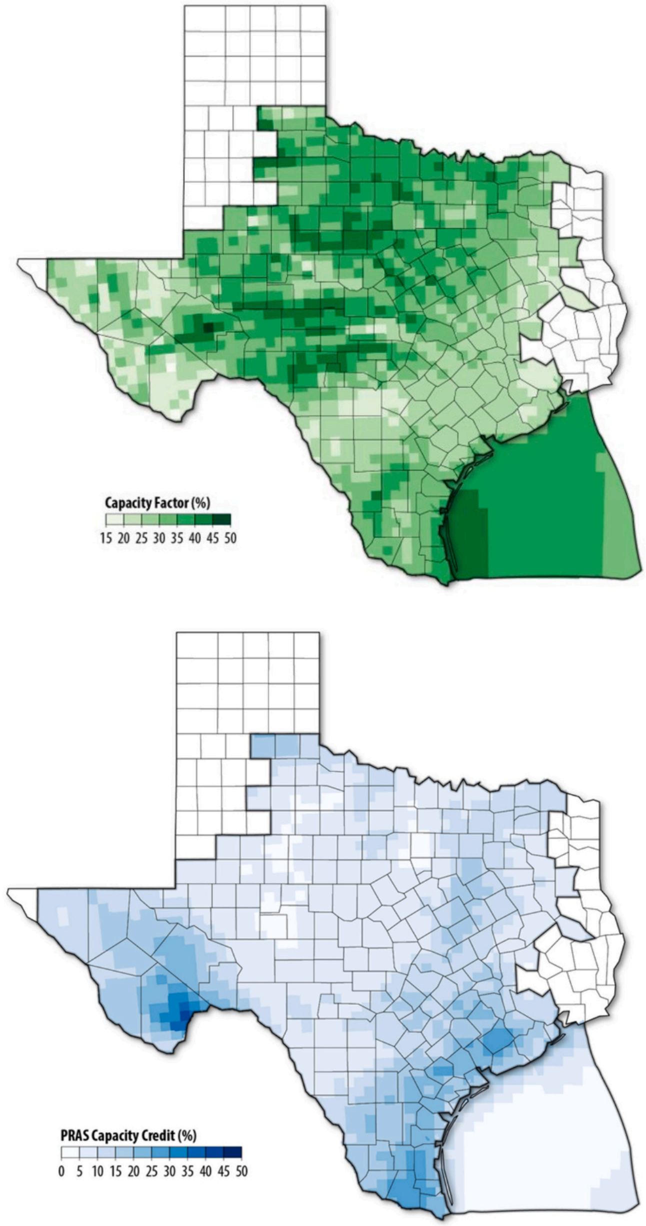

Fig. A4. Map of the capacity factor (top) and capacity credit (bottom) values across ERCOT [66].

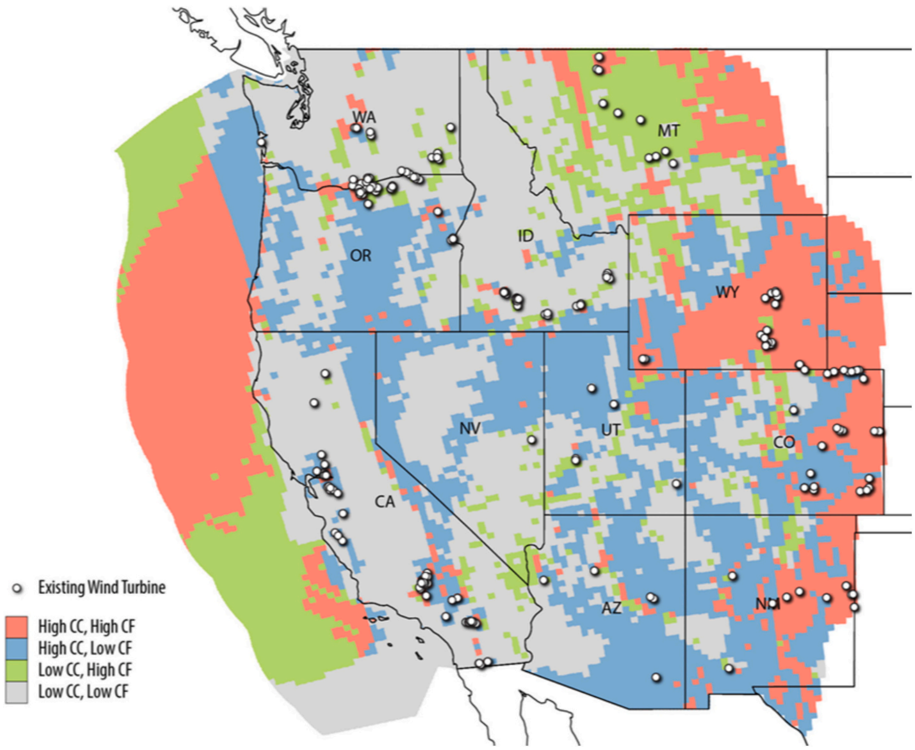

Fig. A5. Land-based wind capacity credit values across the Western Interconnection [62].

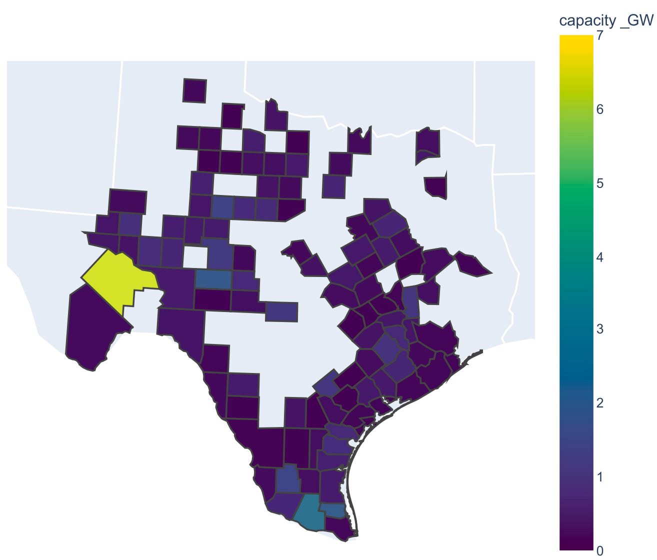

Fig. A6. County-level capacity for land-based wind in the ERCOT BAU scenario.

A.4. County-Level Capacity

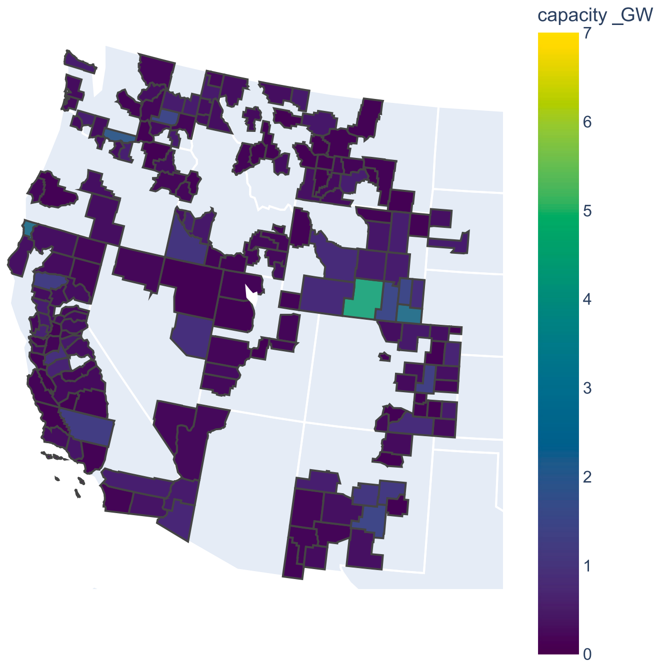

Fig. A7. County-level capacity for land-based wind in the WI BAU scenario.

A.5. Transmission

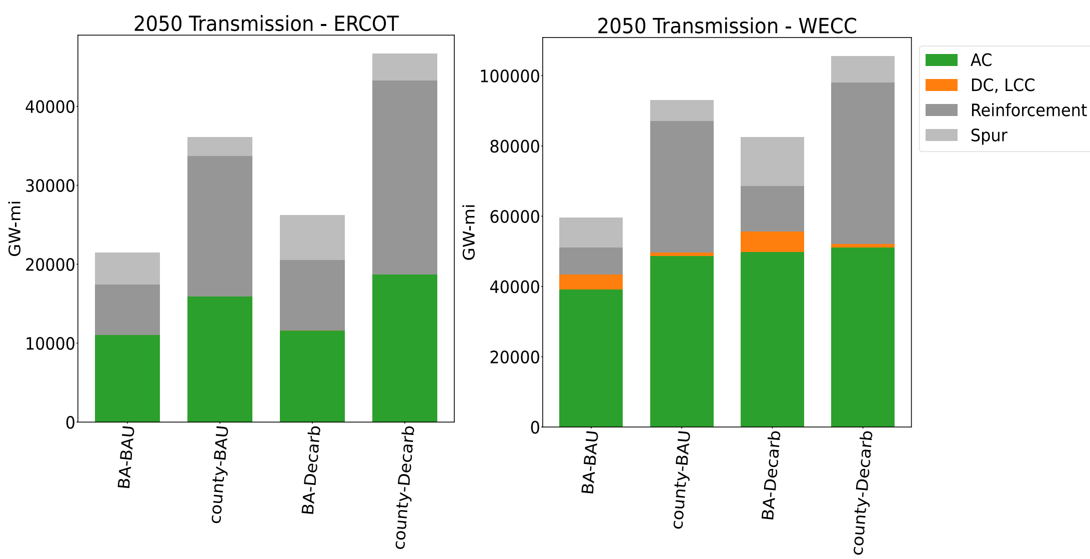

Fig. A8. Installed Transmission in 2050.

A.6. Installed Capacity

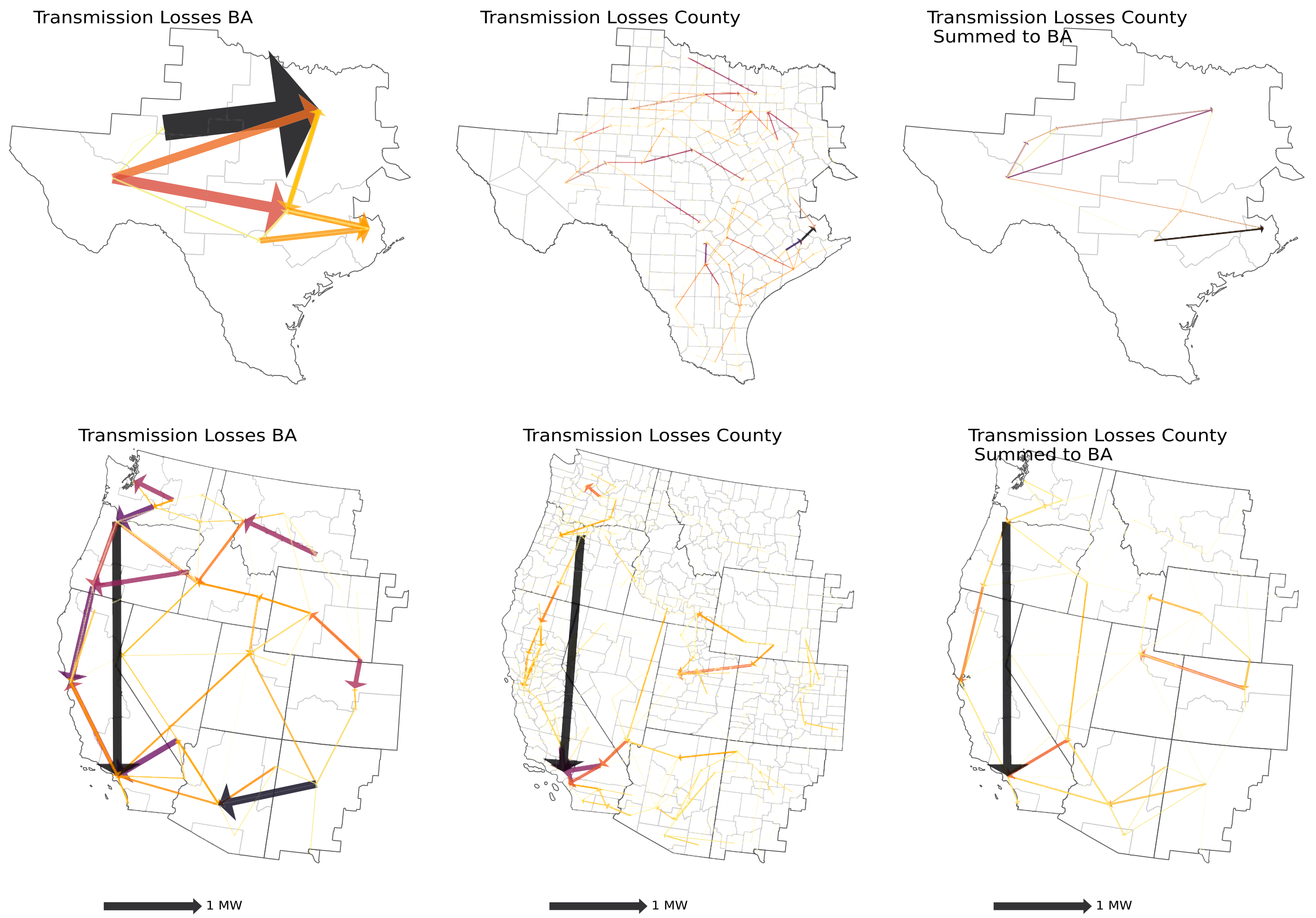

Fig. A9. Transmission losses in ERCOT (top) and WI (bottom) in 2050.

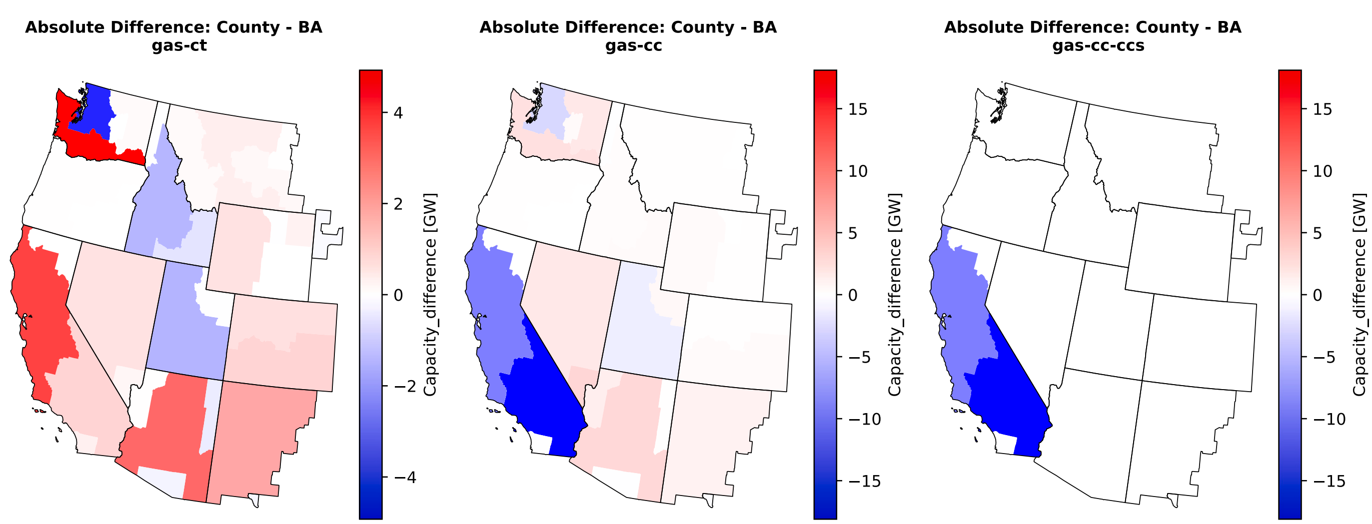

Fig. A10. Absolute difference in 2050 installed capacity in the county solution relative to the balancing area for gas technologies.

A.7. Sensitivity Analysis

Beyond the two policy-dependent categories (BAU and Decarb), additional sensitivity scenarios are analyzed to aid in understanding the implications of spatial resolution in ReEDS. With the sensitivity cases, modeling differences are systematically eliminated to determine the drivers for regional variance. First transmission congestion and costs are removed to create a copperplate representation of ERCOT (Sensitivity Scenario 1). This is achieved by removing the network reinforcement costs from the balancing area-level resource supply curves and increasing the initial AC transmission capacity of both networks, effectively rendering them as copper plates (uniform locational marginal price across ERCOT). To minimize differences between the balancing area and county resolution models several other transmission-related parameters are manipulated. First, the transmission losses are set to 0 for AC and DC lines. Next the hurdle rate (cost penalty) for transferring power between model regions is set to 0 (by default ReEDS includes a < $0.1/MWh hurdle rate to reduce model degeneracy). Finally, the fixed operational and maintenance costs of transmission lines are set to 0. In the subsequent sensitivity case (Sensitivity Scenario 2) the same resource availability is assigned to both resolutions of the model by assigning the balancing area supply curves to the appropriate U.S. counties. This overwrites the county-level supply curves and ensures that the supply curve representation is equivalent between the county and balancing area versions of the model. Finally, any deviations which arise because of the representative day selection and the resource adequacy evaluation are eliminated by forcing ReEDS to select identical user-defined time slices across both resolutions (Sensitivity Scenario 3). Ultimately, the sequential elimination of differences between the county and balancing area resolution models is performed to better understand the factors that lead to differences between the spatial resolutions.

Fig. A11- Fig. A13 show the absolute difference of installed land-based wind and UPV for county resolution relative to the balancing area resolution for each sensitivity scenario. As each sensitivity layer is added, differences in the model outcomes persist motivating a deeper dive. In Sensitivity Scenario 3 the objective function value for the county solution is 9.7 % lower than the balancing area objective in 2050, a substantial enough difference to suggest that underlying modeling differences still exist despite the systematic removal of sources of deviation. To diagnose this the objective function values, starting with the first year (2010) and continuing forward, are compared between the spatial resolutions. Already in 2020 the operational and investment (capital cost) components of the objective function differ by 1.3 % and 3 % respectively, indicating that the initial capacities available in the balancing area and county resolution models are not consistent. In comparing the 2020 capacities, the total across technologies between the balancing area and county resolutions match, however in the case of land-based wind there is a discrepancy in the contribution from each specific technology class. In the balancing area model there is a greater share of class 10 land-based wind which is compensated for by a greater share of class 4 land-based wind in the county resolution model. This can be attributed to the methods used to enforce some constraints in ReEDS which create inherent differences in the availability of certain technology classes across the spatial resolutions. For instance, planned (prescribed) builds are included in the model by requiring that the total model investment in prescribed capacity equals the amount that is exogenously defined. This constraint is enforced across each model region, in each model year, and for each technology, however it is not enforced on the specific resource class. Therefore at the balancing area resolution the model has the flexibility to select the best wind resource across a larger geographic scope to meet this constraint, meanwhile the county-level resolution may not have as diverse a selection of technology classes within the model region boundaries. This incongruity also exists for UPV, however the relative homogeneity of UPV in ERCOT helps to avoid differences in resource class availability as a result of spatial resolution. The same three sensitivity scenarios are considered for WI with similar findings; the balancing area and county resolutions do not converge to the same solution despite eliminating meaningful differences between the models. Ultimately the differences between the balancing area and county resolution results in 2050 stem from the discrepancies that pervade the model as the initial generation fleet is endogenously configured.

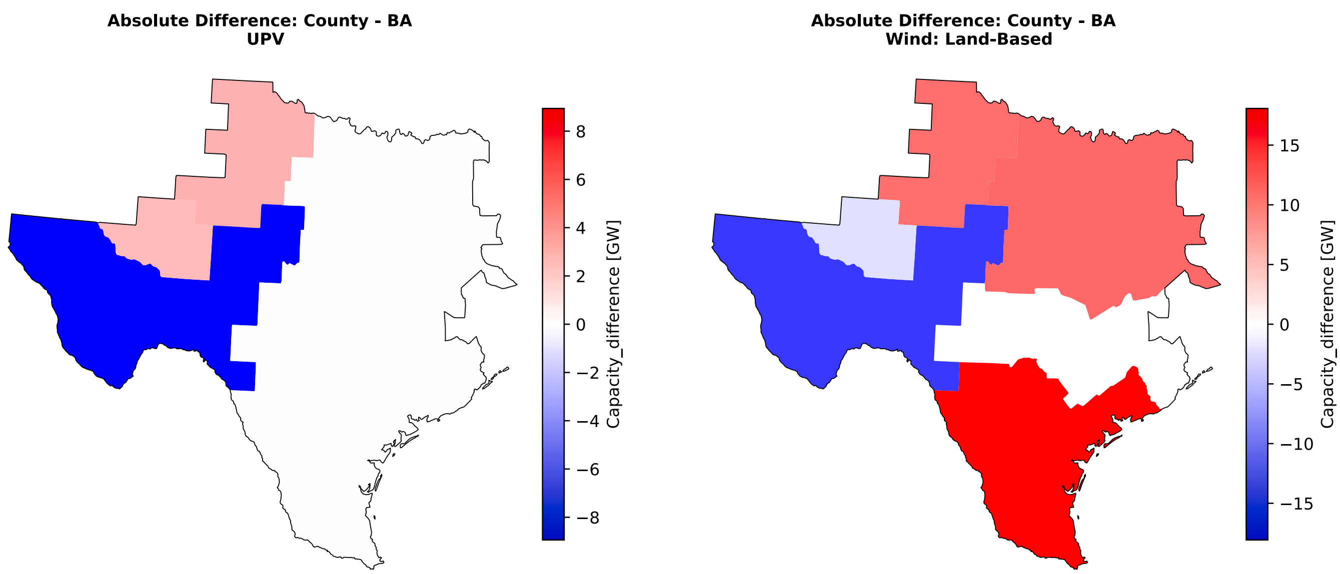

Fig. A11. Absolute difference of installed land-based wind (right) and UPV (left) for county resolution relative to the BA (balancing area) resolution for Sensitivity Scenario 1.

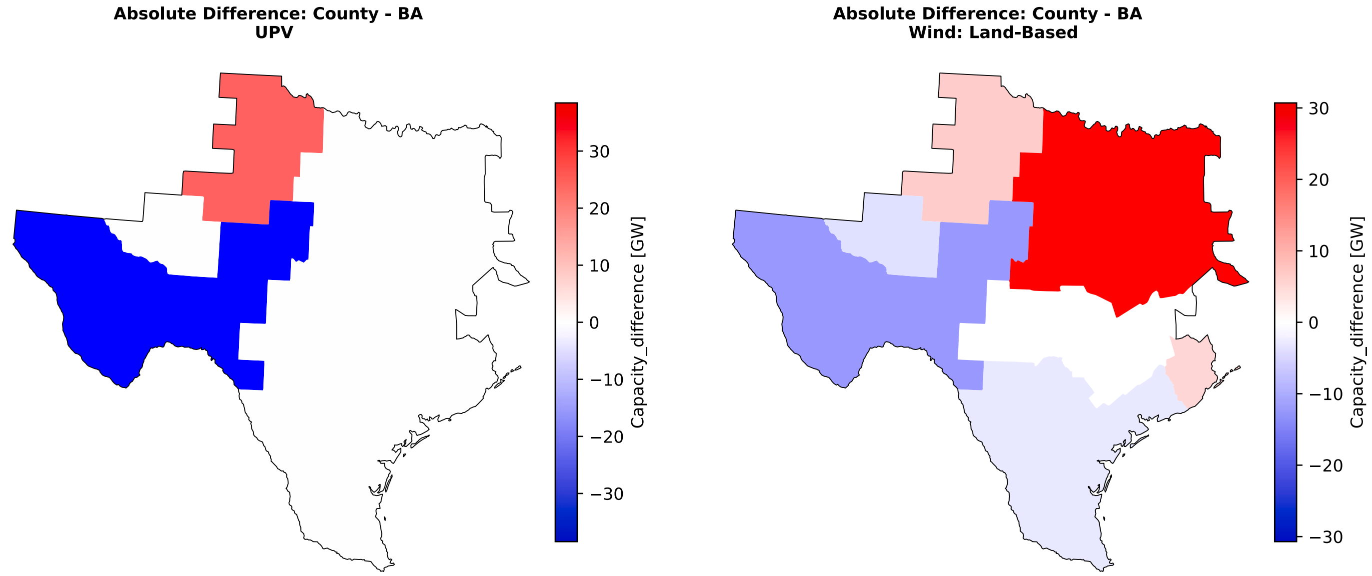

Fig. A12. Absolute difference of installed land-based wind (right) and UPV (left) for county resolution relative to the BA (balancing area) resolution for Sensitivity Scenario 2.

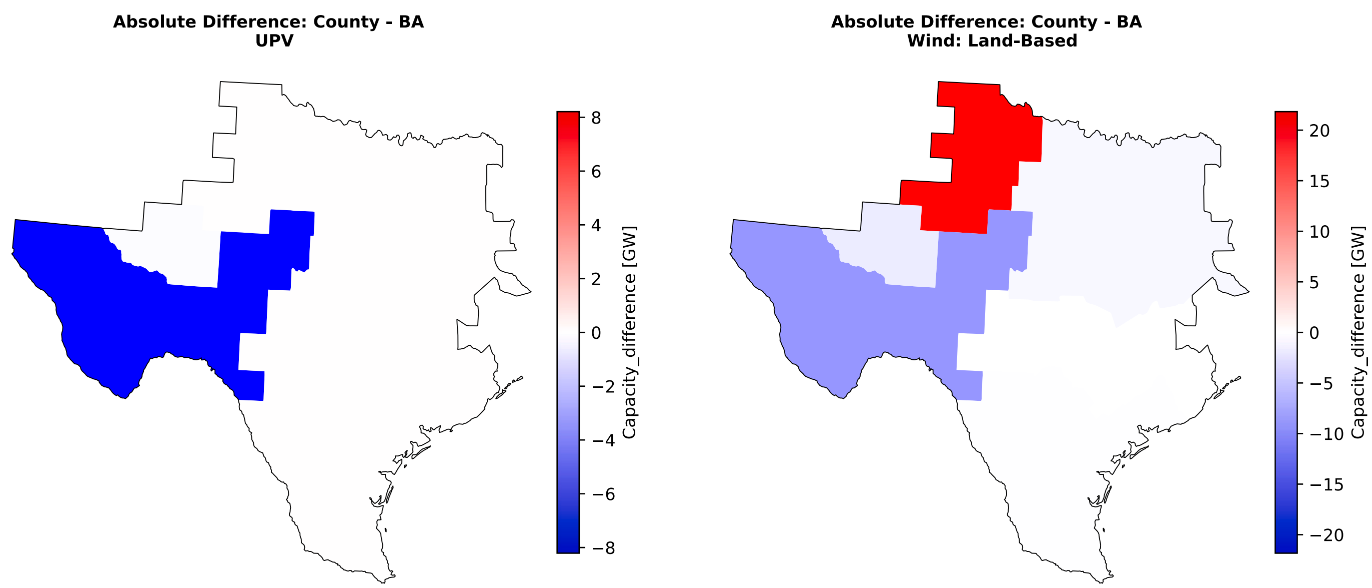

Fig. A13. Absolute difference of installed land-based wind (right) and UPV (left) for county resolution relative to the BA (balancing area) resolution for Sensitivity Scenario 3.

A.8. Mixed Resolution Capability

The results of this work indicate runtime as a considerable challenge for increasing the spatial resolution in capacity expansion models. To address this a mixed resolution capability has been developed in ReEDS. With this feature focus areas could be modeled at the county resolution while retaining the interactions with the surrounding regions modeled at the balancing area resolution. For instance, Fig. A14 shows an example of the Western Interconnection at mixed resolution with the state of Idaho represented at county resolution and the reaming states at balancing area resolution. Similarly, an example of the Pacific census division is shown in Fig. A14 with the state of Washington represented at county resolution while California and Oregan are represented at balancing area resolution. Table A4 summarizes the number of model regions associated with each spatial resolution and Table A5 summarizes the impact on runtime. More analysis is needed to better understand the implications of running at mixed resolution, however the preliminary example cases indicate this capability as a reasonable compromise between high spatial resolution and runtime.

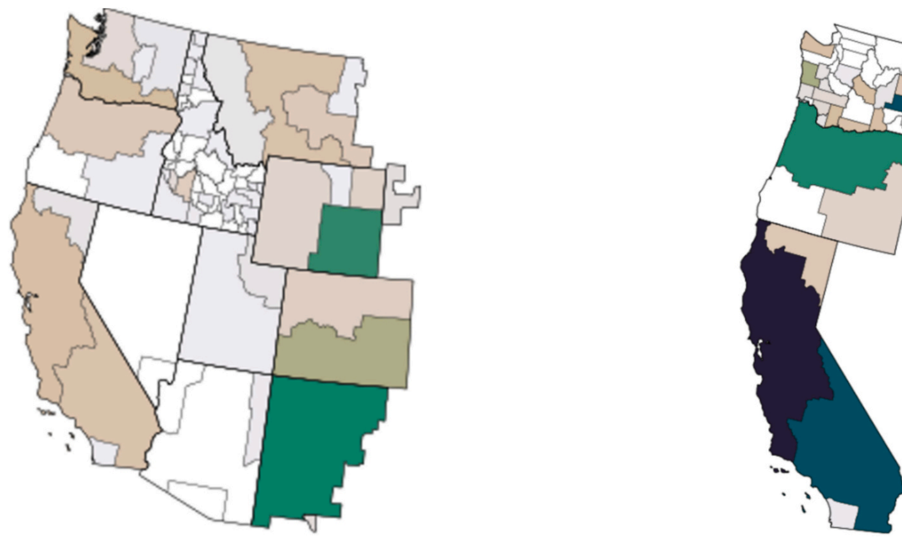

Fig. A14. Maps illustrating the Western Interconnection (left) and the Pacific Census Division (right) at mixed resolution.

Table A4
Summary of the number of model regions at each spatial resolution for the Western Interconnection and Pacific Census Division.

Region	County	BA	Mixed
Pacific	133	11	46 (WA county = 39 Remaining BAs = 7)
Western Interconnection	403	35	76 (ID county = 44 Remaining WI BAs = 32)

Table A5
Summary of runtime at different spatial resolutions.

	Runtime (h)
WI County	15
WI BA	0.44
WI mixed	3.7
Pacific County	10
Pacific BA	0.4
Pacific Mixed	1

Data availability

The data and model used in this paper are publicly available at https://github.com/NREL/ReEDS-2.0.

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