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*National Renewable Energy Laboratory*

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## List of Acronyms

| | |
|---|---|
| CAISO | California Independent System Operator |
| DOE | U.S. Department of Energy |
| EGU | Energy generating unit(s) |
| ELCC | Effective load-carrying capability |
| ERCOT | Electric Reliability Council of Texas |
| FRCC | Florida Reliability Coordinating Council |
| IRA | Inflation Reduction Act of 2022 |
| ISO | Independent System Operator |
| ISONE | Independent System Operator of New England |
| MISO | Midcontinent Independent System Operator |
| MW | Megawatt |
| MWh | Megawatt-hour |
| LDC | Load duration curve |
| NLDC | Net load duration curve |
| NYISO | New York Independent System Operator |
| PJM | Pennsylvania-New Jersey-Maryland Interconnection |
| PV | Photovoltaic(s) |
| ReEDS | Regional Energy Deployment System |
| RTO | Regional transmission organization |
| SERTP | Southeastern Regional Transmission Planning |
| SPP | Southwest Power Pool |
| VRE | Variable renewable energy |

# Abstract

As deployment of variable renewable energy technologies and storage continue to significantly grow in the coming decades, these technologies will play increasingly important roles in maintaining the power systems' resource adequacy. Few analyses so far offer comprehensive comparisons of forward-looking average and marginal capacity credits of variable renewable energy and storage in the U.S. across a wide range of possible futures. To fill this research gap, we estimate the average and marginal capacity credits of solar photovoltaics (PV), onshore and offshore wind, and battery storage between 2026 and 2050 across the contiguous U.S power system to examine the temporal trends, spatial patterns, and trade-offs between these two capacity accreditation approaches. Across technologies, capacity credits of solar PV most clearly follow downward trends over time, reflecting the significant rise in solar PV generation share in the projected future of the U.S. grid. While battery storages' generation shares also rise significantly over time, their capacity credits remain high due to their capabilities to be dispatched strategically during critical periods. On the other hand, capacity credits of wind technologies in general follow slight upward trends. There are strong spatial variabilities of both average and marginal capacity credits across technologies, with capacity credits of solar PV displaying the most obvious spatial patterns with high values concentrating in wind-rich, solar-poor regions in SPP, PJM, and MISO, suggesting potential resource adequacy benefits of interconnection-wide planning for renewable energy deployments. Additionally, except for offshore wind, average capacity credits of all other renewable technologies tend to be higher than their marginal capacity credits, indicating that existing renewable resources tend to be accredited higher than new resources.

# 1 Introduction

The rate of global variable renewable energy (VRE) capacity additions has grown by almost 50% since 2022 and the total amount of capacity is on track to increase by 2.5 times by 2030 [1]. In the United States, declining capital costs of renewable energy [2–4] and climate policies such as the Inflation Reduction Act [5], and state-level renewable portfolio standards [6] have been major catalysts for significant growth in deployments of VRE and energy storage in the last few years. These policies, when paired with cost declines, are shown in multiple energy systems models to continue incentivizing large-scale increases in VRE and energy storage deployments in various possible scenarios in the coming decades [7]. In the United States, most new generation capacity is expected to be from VRE technologies and battery storage [8].

As VRE and energy storage capacities continues to grow, understanding their possible contribution to maintaining the power system's resource adequacy becomes increasingly important. Resource adequacy refers to the capability of a system's supply-side and demand-side resources to maintain the system's electricity services at any given time. Because VRE is inherently variable and uncertain, understanding how this growing VRE capacity could contribute to resource adequacy can be challenging. Additionally, VRE is spatially dependent, as resource quality can vary widely across a given geography. These aspects pose a challenge in appropriately quantifying the contribution of VRE, indicated by its capacity credit, to resource adequacy across time, planning regions, and technologies.

Capacity credit is a widely used metric in power systems planning to capture what fraction of an energy resource's nameplate capacity can be reliably expected to contribute to meeting demand during critical periods and thus maintain the power system's resource adequacy. Capacity credit generally ranges between 0 and 1[1], with 0 (0%) capacity credit meaning the resource has zero contribution to the system's resource adequacy and 1 (100%) capacity credit meaning all the resource's nameplate capacity contributes to the system's resource adequacy. Because of the importance of capacity credits in grid planning and policy-making at the state-, utility-, and regional transmission organization (RTO)-levels [9–13], it is useful to accurately quantify VRE capacity credits to avoid under- or over-planning for infrastructure and VRE deployment and thus minimize the costs of meeting system's reliability needs [14]. Quantification of VRE's capacity credits has been an ongoing research topic with different proposed methods resulting in different credit values [15]. So far, the effective load-carrying capability (ELCC) has been the a commonly recommended method to estimate VRE resources' capacity credits due to its probabilistic treatment of phenomena such as forced outages and VRE generation variability [12,15,16]. ELCC can be implemented in two different ways – the average ELCC, which estimates the average contribution of an existing generator or generators to system's resource adequacy, and the marginal ELCC, which estimates new resource's incremental contribution to system's resource adequacy. These two types of ELCC reflect different information (what is the contribution of what already exists versus what would be the contribution of something new) and can have very different estimates of capacity values for the same resource. Given this, decision makers should ensure they are selecting the right metric for the decision at hand [17–19]. For example, using an average

[1] It is also technically possible for capacity credit to be greater than 1, if the generator is expected to generate beyond its nameplate capacity during critical times, although such a situation is not common and not explored further in this report.

ELCC to anticipate the contribution of a new resource may overestimate its contribution when that resource has a declining marginal ELCC, as has been seen for solar PV [20].

Calculations of ELCC for VRE and storage has been extensively researched, in both proposed mathematical methods to estimate ELCC [21–28], as well as applications of ELCC calculation methods in analysis of real-life power systems [15,16,29–33]. However, few studies explore wide-scale ELCC of both solar PV and wind across large power systems [15,16]. Ssengonzi et al. [15] calculate ELCC for solar PV and wind resources across regions in the U.S. with different levels of VRE penetrations. They show the consistent declining trends of ELCC at higher levels of VRE penetrations corresponding with lower capacity factors across regions and technologies. Bromley-Dulfano et al. [16] calculate solar PV and wind ELCC across five regions in the Western Interconnection and find strong spatial variabilities for both solar PV and wind ELCC. They also emphasize the role of storage in increasing ELCC and decreasing spatial variability.

While studies that quantify multi-regional VRE ELCCs offer valuable insights into spatial variability of VRE contributions to resource adequacy to aid long-term planning, they share a few key gaps that this report can address.

First, prior studies focus on estimating average ELCC, not marginal. To date, we have found no analysis that compares the applications of average and marginal ELCCs across time and regions in interconnection-wide power systems. A more narrow comparison of average and marginal ELCCs has been performed from Aagaard and Kleit [34], which uses an analytical economic model to compare the impacts of average and marginal ELCCs of solar PV and fossil fuel resources on a hypothetical capacity market. They find that using marginal ELCC as a metric to measure the capacity values of the resources results in less market distortion than using average ELCC. In this work, we build on the nascent literature that compares marginal and average capacity credits by comprehensively examining marginal and average capacity credits of VRE and battery storage under a wide range of scenarios at high temporal and spatial resolutions.

Second, few studies focusing on application of capacity credits in power system planning have explicitly quantified the capacity credits of energy storage [35–37]. As its capital costs are declining [38,39], energy storage has increasing potential to contribute to system's resource adequacy, which makes quantification of their capacity credits more useful for power system planning. To contribute to this strand of literature, this study offers a more comprehensive analysis of average and marginal energy storage capacity credits under a wide range of scenarios across the contiguous U.S power system.

Finally, studies that quantify capacity credits of VRE over a long-time horizon, considering the possible evolutions of the future grids, are rare (e.g., [40]). Given the future changes in electricity demand, costs, resource availabilities, policies, and decarbonization targets, it is helpful to comprehensively capture how VRE capacity credits would change over time in response to the changes in the grids' infrastructures as well as to changes in deployment of VRE in other regions. We expand on previous works that explore forward-looking VRE capacity credits by examining capacity credits of a wide range of classes of VRE and storage across the U.S over the next few decades.

As discussed above, this study fills research gaps in the literature on the application of VRE and energy storage ELCC on the power systems to inform long-term planning. We use the Regional Energy Deployment System Model (ReEDS), a capacity expansion model, to estimate the average and marginal capacity credits of solar PV, wind, and battery storages at a high temporal and spatial resolution across the U.S. power system. Specifically, we use the outputs of the 2023 Standard Scenarios [41], simulated using ReEDS[2], as a source for this report's capacity credits. As explained more in the following methodology section, the ReEDS model estimates capacity credits using a load duration curve method (instead of calculating probabilistic ELCC). Previous studies have shown that the VRE ELCC values calculated using approximation-based method can capture ELCC values calculated using probabilistic method [15,27,42,43], with mean absolute error of less than 0.05 [15]. Using this simplified method of calculating ELCC allows us to quantify a wide range of VRE's and storage's average and marginal capacity credits across time and space, as well as examine how these capacity credits vary under different levels of VRE deployment, driven by uncertainties in future policies, costs, and resource availabilities. The wide range of sensitivities from the Standard Scenarios help us quantify the robustness of our results under future system uncertainties. To support more future long-term forward looking ELCC analysis, we also report and make available these approximated ELCC values as a publicly available dataset.

# 2 Methodology

## 2.1 Regional Energy Deployment System (ReEDS) Model

The Regional Energy Deployment System (ReEDS) Model is a mathematical linear programming model of the U.S. power sector developed by the National Renewable Energy Laboratory (NREL) [44–46]. ReEDS minimizes total system costs by optimizing new capacity deployment of energy generating units (EGUs) and transmission lines, dispatch of new and existing EGUs, retirements of existing EGUs, and inter-regional electricity flows at each model year. ReEDS includes a wide range of system-level and EGU-level constraints, including resources availability, clean energy policies, and the EGU's engineering and economic characteristics. Like many other macro-scale capacity expansion models [47–50], ReEDS runs myopically in sequential timesteps for a fixed planning horizon period. ReEDS is used to generate outputs for the 2023 Standard Scenarios [41], which we use to analyze the temporal and spatial patterns of average and marginal ELCCs of solar PV, wind, and battery storage.

## 2.2 The 2023 Standard Scenarios

The 2023 Standard Scenarios, released in early 2024, have 53 scenarios that can be broken down to three sets of scenarios with three different electric sector $CO_2$ trajectories–current policies, 95% $CO_2$ emission reduction by 2050, and 100% $CO_2$ emission reduction by 2035 (***Figure 1***). There are 18 scenarios under the current policies and the 95% $CO_2$ emission reduction by 2050 targets, and 17 scenarios under the 100% $CO_2$ emission reduction by 2035 target as we do not consider the no nascent technology scenario under this decarbonization trajectory. The scenarios under each decarbonization target include the mid-case scenarios which capture central assumptions in capital and fuel costs, resource availability, moderate electricity demand growth, and current federal and state policies as of September 2023. Additionally, each set of scenarios also include various

[2] The model version used for the 2023 Standard Scenarios is available publicly at https://github.com/NREL/ReEDS-2.0/tree/97a43f62039d5c3132a31fd2b5d7b708d24156d5.

sensitivity scenarios that diverge from the mid-case scenarios, capturing a wide range of parameters that drive system investments and operation, such as advanced generator performance assumptions, low and high fuel prices, low and high electricity demand, reduced renewable resources, etc. Details about the 2023 Standard Scenarios can be found in [41]. We use these scenarios because they capture a wide range of potential futures for the U.S. electricity system, allowing us to examine VRE and storage capacity credit across a wide range of conditions.

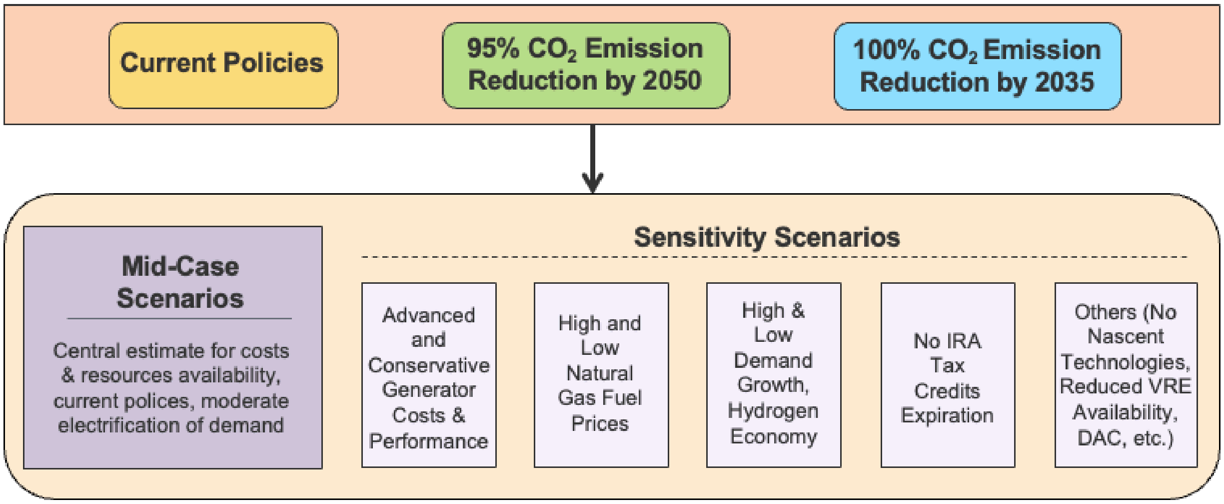


**Figure 1: Breakdown of the 2023 Standard Scenarios.**

## 2.3 Estimation of Average and Marginal Capacity Credits

Outputs from 2023 Standard Scenarios are used to quantify average and marginal capacity credits for solar PV, wind, and battery storages. Average capacity credits measure the average contribution that each existing resource can contribute to the system's resource adequacy in each region. It is equal to the total regional firm capacity divided by the total regional installed capacity for that technology. A resource's firm capacity refers to the portion of its nameplate capacity that can be available at the system's most critical periods (typically the high peak periods) to provide electricity services to maintain system's resource adequacy. Marginal capacity credits measure the incremental contribution that each new resource can contribute to the system's resource adequacy in each region. Some ISOs/RTOs might prefer the marginal capacity credits method because they argue that the value of the capacity of a resource at the margin would send accurate price signals to the capacity markets, and thus would incentivize investments in longer duration storage, and more balanced investments among wind and solar PV [20]. Others, on the other hand, might prefer the average capacity credits method as they argue that it would compensate resources' value to system's reliability more fairly by taking into consideration their total contribution [51]. Here we discuss how the average and marginal capacity credits are quantified in ReEDS.

### *2.3.1 Capacity Credits of VRE*

In this analysis, we calculate the average and marginal VRE capacity credits using an approximation method. Average capacity credits for each existing VRE resource and marginal capacity credits for each new VRE resource class are calculated at 11 ReEDS transmission regions (hereafter referred to as "regions") – California Independent System Operator (CAISO), Electric Reliability Council of Texas (ERCOT), Florida Reliability Coordinating Council (FRCC), Independent System Operator of New England (ISONE), Midcontinent Independent System

Operator (MISO), the Northern Grid, New York Independent System Operator (NYISO), Pennsylvania-New Jersey-Maryland Interconnection (PJM), Southeastern Regional Transmission Planning (SERTP), Southwest Power Pool (SPP), and the Western Connection (***Figure A. 1***). The overall process to calculate capacity credits in ReEDS is mapped out in ***Figure A. 2***, while an illustration of this method is shown in ***Figure 2*** [14].

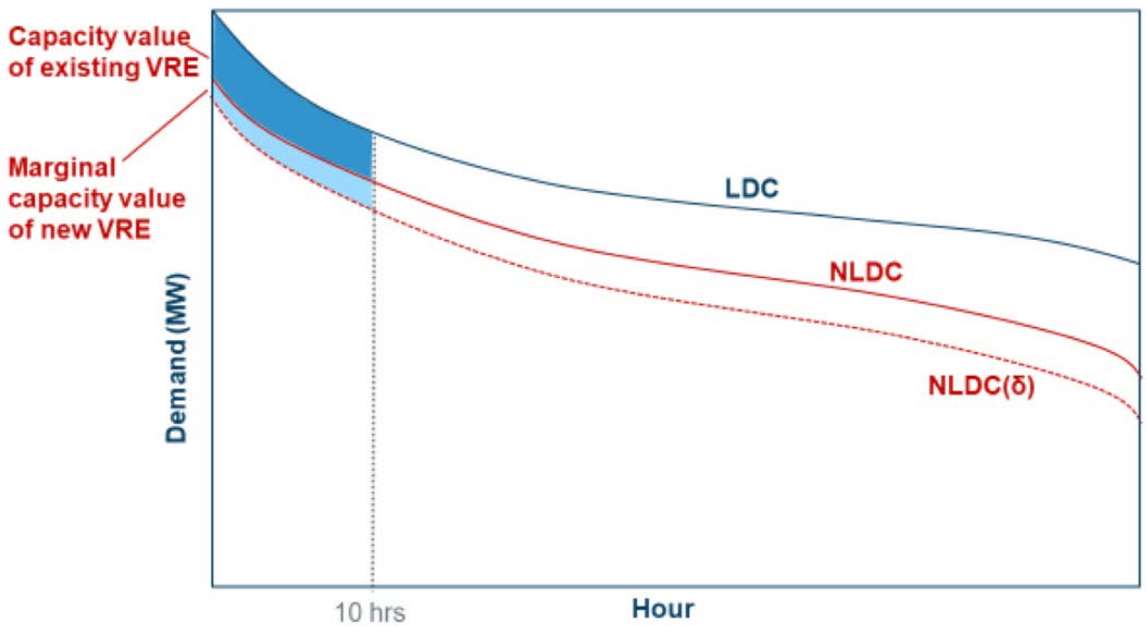


**Figure 2: Visualization of how average and marginal capacity credits (or capacity values) are approximated in ReEDS. Illustration taken from [14]**

***Average Capacity Credits of VRE***

Average capacity credit for each existing VRE resource is calculated using seven years (2007-2013) of hourly historical load and VRE normalized generation profiles. A load duration curve (LDC) is established in each region by sorting the region's seven years of hourly load from highest to lowest. Similarly, a net load duration curve (NLDC) is then established in each region by sorting the region's seven years of hourly net load (load minus hour corresponding forward-looking model projected VRE generation, which is calculated by multiplying installed capacity by the normalized generation profile) from highest to lowest. The total average capacity value for all existing VRE resources in the region is determined as the difference between the LDC and NLDC during the peak 10 hours (darker blue area in ***Figure 2***). This total VRE firm capacity during the peak 10 hours is then allocated to each VRE resource based on their generation share during those 10 hours. Each resource's average capacity credit is then calculated as its weighted firm capacity contribution value divided by its installed capacity. For example, if the net load duration curve is reduced by 100 MW during these top hours, and a 50 MW resource contributed 20% of the generation that led to that reduction, then that resource would get 20% of 100 MW = 20 MW of peak reduction value, for a capacity credit of 20 MW / 50 MW = 0.4, or 40%.

***Marginal Capacity Credits of VRE***

For assessing marginal capacity credit of VRE in each region, a new NLDC – NLDC(δ) is established for the region. NLDC(δ) is the difference between the NLDC and the region's hour corresponding additional generation of the new VRE resource. The total marginal capacity credit of a new VRE resource in the region is determined as the difference between the NLDC and the newly established NLDC(δ) (lighter blue area in ***Figure 2***). Each VRE resource class is assessed independently, allowing for a marginal value by technology and resource class to be calculated. The resource's marginal capacity credit is its marginal capacity value divided by the marginal amount of capacity added. For example, if a new 100 MW solar plant reduces the net peak load in the top 10 hours by 10 MW, then that solar plant would have a marginal capacity credit of 0.1 or 10%. In the case that the top 10 net peak load hours had shifted to nighttime, then adding new solar would not reduce the net peak demand, and its capacity credit would be 0.

Between solve years, ReEDS updates the average and marginal capacity credit for each VRE resource to calculate the resource's contribution to providing planning reserve requirements. Therefore, average and marginal capacity credits impact deployment decisions in the next solve year.

### 2.3.2 Capacity Credits of Battery Storage

While average capacity credit for battery storage is calculated the same way as average capacity credit for VRE (as the ratio of firm capacity over installed capacity), the way the firm capacity is calculated differs. The capacity value of battery storage is characterized by the increase in storage energy capacity (duration) that is needed to serve peak demand. To calculate this necessary energy capacity of the battery that can receive full capacity credit, the net load maximum is obtained by subtracting the battery power rating capacity from the peak load. The battery then must be discharged when the load exceeds this net load maximum and so this discharge is used to calculate the energy capacity required for the battery to receive full capacity credit. This process is repeated in each region and season over a wide range of battery power ratings (in 100-MW increments) to obtain a power-energy curve that allows us to estimate the marginal capacity credit for additional battery storage. With storage, the width of the net peak demand period is a major driving factor for determining its firm capacity. This is shown in ***Figure 3***.

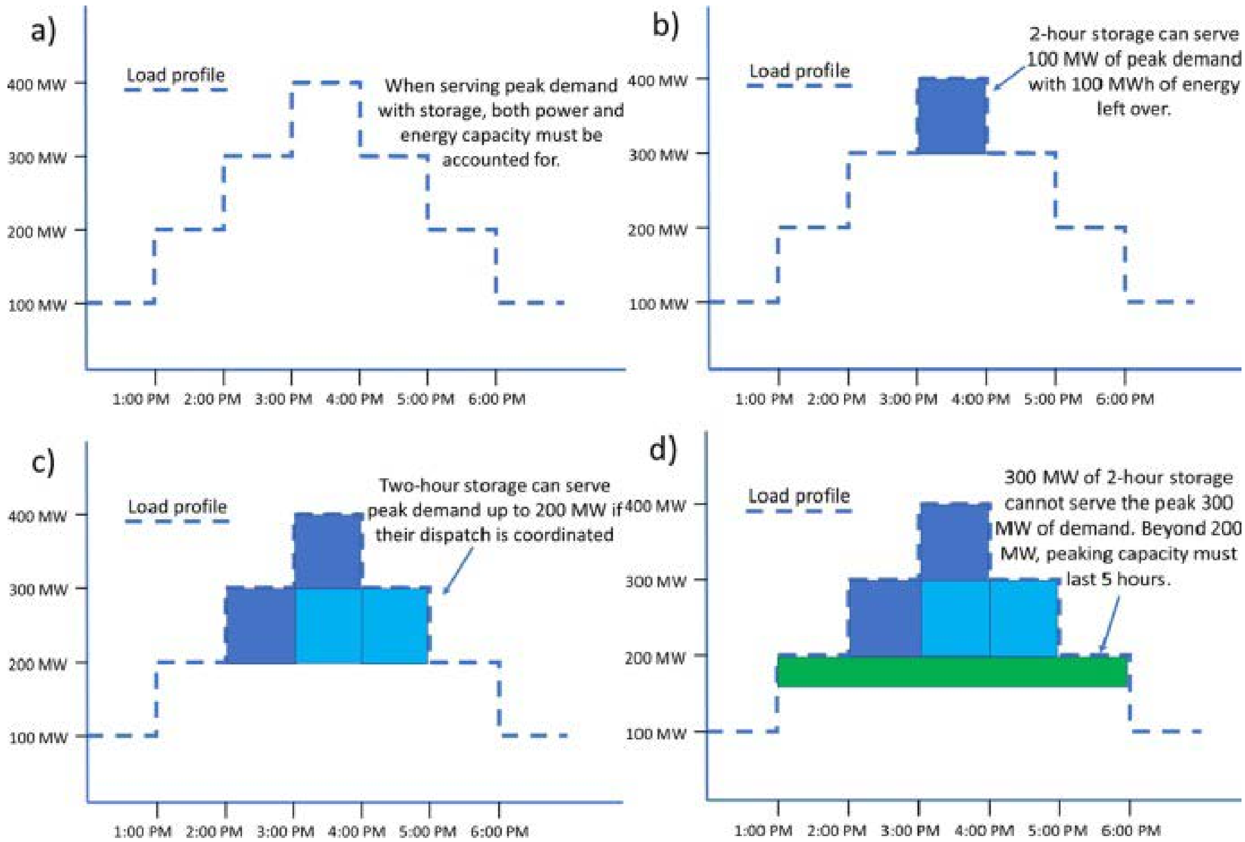


**Figure 3: Example illustrating how marginal capacity credit is determined for two-hour batteries of 100 MW (b), 200 MW (c), and 300 MW (d) power capacities. Illustration taken from [37].**

In ***Figure 3 (b)***, a 2-hour 100 MW battery can reduce peak demand by its power capacity (100 MW) over a 1-hour period, with 100 MW energy left over. Its capacity credit is therefore 100%. In ***Figure 3 (c)***, an additional 2-hour 100 MW battery can be dispatched in concert with the remaining energy in the first 2-hour battery to, together, reduce peak demand by its power capacity (100 MW), achieving capacity credit of 100%. ***Figure 3 (d)***, however, shows that adding a third 2-hour 100 MW battery cannot reduce peak demand by its power capacity (100 MW), because to do so it would need to have a duration of 5 hours. Therefore, in this case, the marginal capacity credit assigned to this battery would be 40% (2-hour/5-hour). In the case of the average capacity credit, the three batteries would have a combined capacity credit of 240 MW/300 MW = 0.8 or 80%, while the marginal capacity credit is the capacity credit of the next battery, or 40%.

More details on how ReEDS models marginal battery storage capacity credits with examples can be found in the ReEDS documentation [45] and Frazier et al. [37].

## 2.4 Method Limitations

Our method has a few methodological and data limitations that future modeling work can potentially address. First, to quantify capacity credits, we calculate approximation of ELCC instead of estimating the actual probabilistic ELCC. Our approach approximates ELCC using the 10 highest net peak load hours, which might not capture the times that the power system experiences the most stress, for example during extreme weather events that seriously impact system's resource adequacy or drive increases in outage rates [52]. Additionally, our approximated ELCCs are calculated at the transmission regions where the resources are deployed, therefore, might be undervalued when the resources export energy to other regions to contribute to resource adequacy elsewhere. Because of these and other assumptions in our approximation based ELCC method, our resulting capacity credits can yield different values compared to the probabilistic ELCC methods. Given the large number of scenarios as well as high temporal and geographical resolutions we consider in this work, the approximation method is still our preferred approach, relative to the probabilistic ELCC approach, which requires a more complex process and is significantly more computationally costly. However, given its limitations, future work would ideally explore methods that use more robust probabilistic quantification of ELCC in long-term planning models. Second, due to limited hourly weather data availability, we use seven years of weather and load data from 2007 to 2013, which is more than 10 years old. Since the resulting capacity credits calculated from different weather year data could be different, future works could extend the weather data to cover a longer time frame and/or to incorporate more recent or projected data to capture more recent climate change driven extreme weather events, into approximating ELCC.

# 3 Results

Across the 53 Standard Scenarios, we first discuss the how average and marginal ELCCs of solar PV, wind, and battery storage change over time between 2026 and 2050, as the power grid evolves. We then discuss the spatial patterns of average and marginal capacity credit of these technologies across the U.S. power system.

## 3.1 Average and Marginal Capacity Credit Trends over Time

### *3.1.1 Average Capacity Credits*

***Figure 4*** compares average capacity credits of solar PV (including utility-scale solar PV and distributed solar PV), onshore and offshore wind, and battery storage of 4-hour and 8-hour duration between 2026 and 2050 across 53 Standard Scenarios for all regions in the U.S power system. In each panel, for each modeled year, the range of average capacity credits of each technology across all regions and scenarios are graphed in a box and whisker plot. Values inside the box are between the 25$^{th}$ and 75$^{th}$ percentiles, while the whiskers show values below and above these quartiles. The dots outside of the whiskers are outliers.

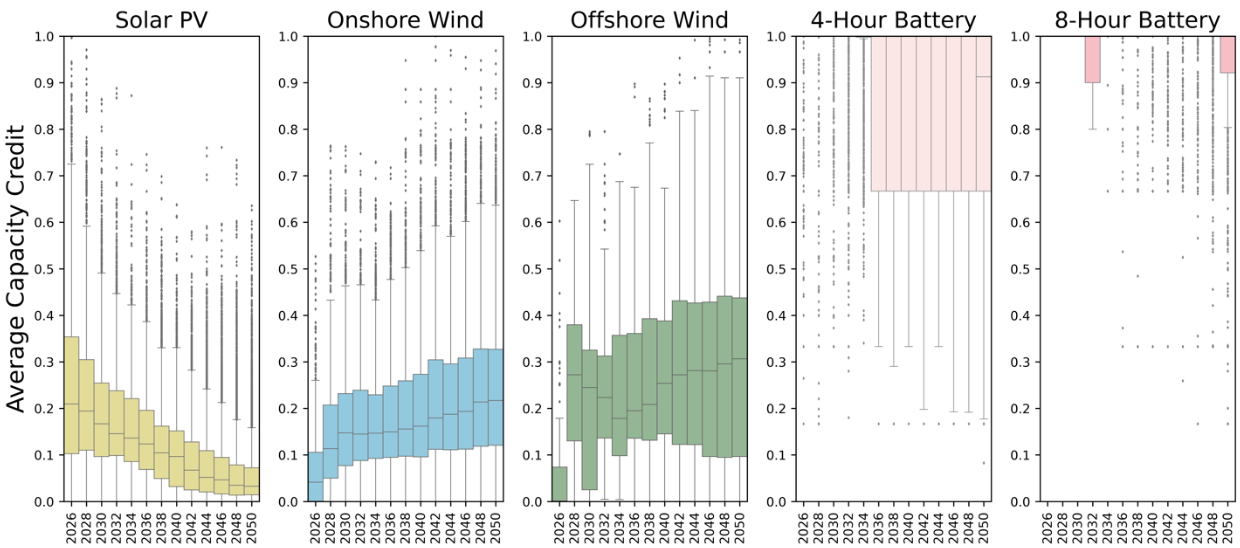


**Figure 4: National average capacity credits across technologies, 2026-2050.**

The average capacity credits of solar PV (***Figure 4***, ***panel 1***) in general gradually decreases between 2026 and 2050. In half of the cases, average solar PV capacity credits range between 11% and 36% with a median of 21% in 2026 and decline to between 1.6% and 6.5% with a median of 3.5% in 2050. Between regions and scenarios, average solar PV capacity credits differ widely, reflecting the regions' wide range of load shapes and resource availabilities. The maximum non-outlier average solar PV capacity credits also decline across time from 72% in 2026 to 17% in 2050. This downward trend in average solar PV capacity credits is largely due to the significant rise in solar PV deployment and solar PV generation shares across the nation over time (***Figure A. 7, panel 1***). These increased solar PV generation shares result in decreases in net loads during hours of high solar PV generation, driving a gradual shift of peak net load hours to hours with little solar PV generation, as also consistently shown in previous studies [14,15,33].

Regions and periods with lower solar PV generation shares have wider ranges of and in general higher average solar PV capacity credits (***Figure 5*****,** ***panel 1***). The relationship between levels of solar PV penetration and average capacity credits can be captured in a fitted quadratic regression with $R^2$ = 57% (***Figure A. 9)***. Average solar PV capacity credits vary across a wide range between 0% and 50% at low solar PV generation shares, even though the highest capacity credits still steadily decline (***Figure 5, panel 1***). The low capacity credit values, even for low PV generation shares, are typically due to winter peaking conditions, where peaks often occur after sunset, or in lower irradiation areas such as the Northeastern United States and the Southwest Power Pool. For conditions where solar PV reaches or exceeds about 50% generation share, its capacity contribution is generally low, and its range of average capacity credits narrows significantly to less than 5%. This is driven by both a decline in the marginal capacity credit (shown later) and large solar PV installed capacity with high solar shares. There are very few occasions when average solar PV capacity credits are higher than 72% in 2026 and higher than 40% in 2050 (around 0.2% of the time). These high average solar PV capacity credit outliers happen in several regions with relatively rich wind resources but poor solar PV resources in SPP, NYISO, and PJM (***Figure A. 15***). In these cases, these regions have relatively small amounts of solar with low solar generation shares, but the existing solar provides a high level of peak reduction.

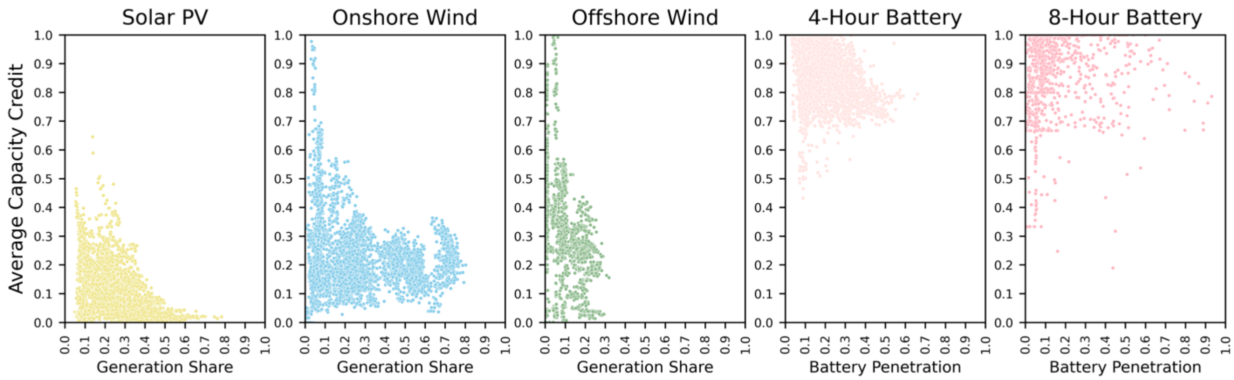


**Figure 5: National average capacity credits vs. generation shares across technologies. The x-axes are the ratios of solar PV generation, onshore wind, and offshore wind over total system generation, and ratios of 4-hour and 8-hour battery capacities over total system capacity.**

Across the 53 Standard Scenarios, average solar PV capacity credits' downward trends are consistent except for the low demand growth scenarios (***Figure A. 3***) where capacity credits stay relatively constant between 20% and 27% (utility-scaled solar PV) and between 13% and 16% (distributed solar PV). The low demand growth results in relatively low deployment of solar PV and non-increasing solar PV generation shares over time, which drive relatively high firm capacity and non-decreasing average capacity credits. In all other scenarios, this decreasing trend in average solar PV across time is consistent across different solar PV classes (***Figure A. 4***).

On the other hand, the average capacity credits of both onshore and offshore wind follow upward trends between 2026 and 2050 across scenarios (***Figure 4, panels 2 and 3***). Average onshore wind capacity credits start off much lower than solar PV but quickly increase after 2028. This trend can be attributed to poor alignment between performance of onshore wind and peak load. Correspondingly, compared to solar PV, onshore wind has higher range of penetration levels in the early years, which remain relatively non-increasing over time (***Figure A. 7***, ***panel 2***). Across regions and scenarios, average onshore wind capacity credits range from 5% to 21% with median of 11% in 2028 and gradually increase to reach a range from 12% to 32% with median of 21% in 2050, which is in the similar range with actual calculated average capacity credits of onshore wind from planning authorities [2]. Unlike solar PV, onshore wind's firm capacity grows steadily over time (***Figure A. 10**, **Figure A. 12***), reflecting the increasing values of existing onshore wind over time as solar shifts net peak demand periods to windier time periods and as wind technologies improve with higher towers and larger rotor areas which can better capture wind resources at lower wind speeds.

Like solar PV, onshore wind average capacity credits differ greatly across regions and scenarios and also share a negatively correlated relationship with generation shares (***Figure 5, panel 2***), which can be depicted in a fitted convex quadratic regression with $R^2$ = 58% (***Figure A. 9***). Average onshore wind capacity credits can have a wide range and can be very high at between 60% and 100% at generation shares of less than 10%. However, they decline quickly after reaching 30% penetration, at which level all average onshore wind capacity credits are lower than 40%. Despite decreasing in response to higher level of generation shares, average onshore wind capacity credits grow over time in all scenarios, reflecting narrowing and relatively stable ranges of generation shares of onshore wind over time (***Figure A. 7, panel 2***). This behavior is due to onshore wind deployment leveling off in later years ***(Figure A. 13***). Average onshore wind capacity credits of over 70% are extremely rare and only occur in a few regions with rich solar PV resources and relatively poor wind resources in CAISO, or in regions with relatively poor wind resources in PJM, NYISO, and ISONE under scenarios where onshore wind deployment and generation shares are relatively low such as low demand growth and reduced renewable resources scenarios (***Figure A. 16).*** Across classes, average onshore wind capacity credits fluctuate more compared to solar PV (***Figure A. 5***) with fluctuations occur the most often in 100% $CO_2$ emission reduction by 2035 scenarios.

Compared to onshore wind, average offshore wind capacity credits fluctuate more over time (***Figure* 4*, panel 3)***. They gradually decline in the short term between 2028 and 2036 due to sharp increase in offshore wind deployment (***Figure A. 13)*** and generation shares (***Figure A. 7***), driving steady increase in offshore wind firm capacity (***Figure A. 10***). Between 2036 and 2050, offshore wind deployments halt and its generation shares stagnate, resulting in increasing ranges of average offshore wind capacity credits, and constant levels of offshore wind firm capacity between 2036 and 2050. In half of the cases, average offshore wind capacity credits range between 0% and 7% in 2026, sharply rise to between 13% and 38% with median of 27% in 2028 and widen the range to between 11% and 44% with median of 30% in 2050. Overall, average offshore wind capacity credits also have a negatively correlated relation with generation shares, although offshore wind has much lower generation shares compared to onshore wind and solar PV ***(Figure A. 7)*** due to much lower deployment that is highly concentrated in only a few regions with good ocean wind quality in CAISO, NYISO, ISONE, and PJM (***Figure A. 14***). Generation shares of offshore wind are unlikely to exceed 32%, below which average offshore wind capacity credits can have a wide range, mostly between 5% and 60%, even though the highest capacity credits steadily decline as generation shares increase within this range.

Across scenarios, most regions have average capacity values equal to 100% for 4-hour battery until 2036 (***Figure 4, panel 4***), which reflects the relatively lower levels of deployment for this technology between 2026 and 2034 ***(Figure A. 13***). The battery deployment in later years increases due to lower battery costs [38] and increasing VRE deployment. As more batteries are deployed 4-hour battery start to have average capacity credits less than 100%. Between 2036 and 2050, most average 4-hour battery capacity credits range between 66% and 100% although they can be as low as below 20% in low demand growth scenarios where solar PV generation shares are low, which align with rare occasions of high average solar PV capacity credits.

There is no deployment of 8-hour battery before 2032 under all but one scenario, resulting in no average capacity credits for this technology during this time frame. 8-hour battery has lower penetration compared to 4-hour battery due to its higher costs, which result in 4-hour batteries being preferred as long as they retain high marginal capacity credits. In later years, 8-hour batteries start to be deployed due to their ability to provide firm capacity during longer critical periods. In most cases, 8-hour battery has average capacity credits of 100% (***Figure 4, panel 5***), emphasizing the ability of 8 hours of storage to deliver high capacity credits in most situations in the types of futures explored here. Average capacity credits of 8-hour battery lower than 20% occur rarely in a few scenarios with high hydrogen technology deployment and high electricity demand which require high deployment of this technology (over 200 GW), resulting in decrease in its average capacity credits.

### 3.1.2 Marginal Capacity Credits

***Figure 6*** reports marginal capacity credits of solar PV, onshore and offshore wind, and battery storage of 4-hour and 8-hour duration between 2026 and 2050 across 53 Standard Scenarios for all regions across the U.S power system. Like ***Figure 4*** above, in each panel of this figure, for each modeled year, the range of marginal capacity credits of each technology across all technology classes, regions, and scenarios are graphed in a box and whisker plot. Values inside the box are between the 25th and 75th percentiles, while the whiskers show values below and above these quartiles. The dots outside of the whiskers are outliers.

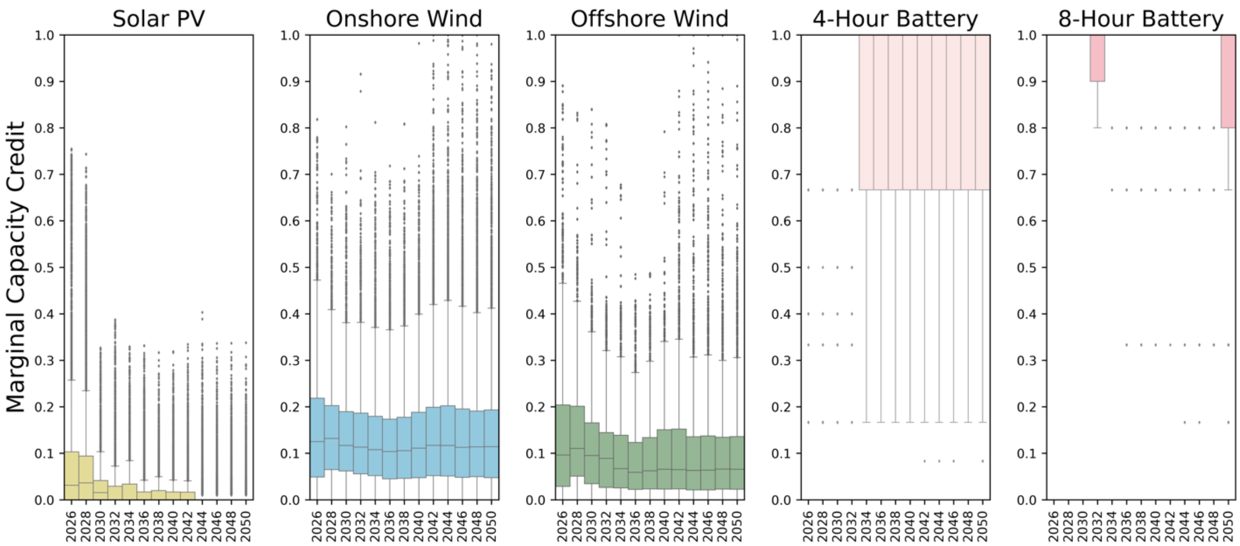


**Figure 6: National marginal capacity credits across technologies, 2026-2050.**

Like average capacity credits, marginal capacity credits of solar PV also follow a downward trend across the planning horizon (***Figure 6, panel 1***). They sharply decline between 2026 and 2030, afterward level off at around 2% until 2042, and in most cases no longer have any capacity values past 2042 when solar PV reaches significant generation shares (***Figure A. 7, panel 1***). The fact that marginal solar PV capacity credits decline very rapidly as solar PV generation shares increase, especially compared to other VRE and battery storage, is due to solar PV's daytime-only generation which prevents its contribution to resource adequacy during non-daytime hours, a phenomenon not faced by wind and storage.

Because capacity credits decline with higher solar PV penetration, marginal solar PV capacity credits are generally lower than average solar PV capacity credits. Marginal solar PV capacity credits also have narrower spread at lower generation shares compared to average capacity credits (***Figure 7, panel 1***). Even at lower generation shares less than 30%, marginal solar PV capacity credits are lower than 10% in most cases, and at 50% generation share, marginal solar PV capacity credits are close to zero. In rare occasions that marginal solar PV capacity credits are higher than 25%, they highly concentrate in a few regions in SPP and MISO where wind resources have been more cost-competitive than solar PV resources (***Figure A. 15, panel 2***).

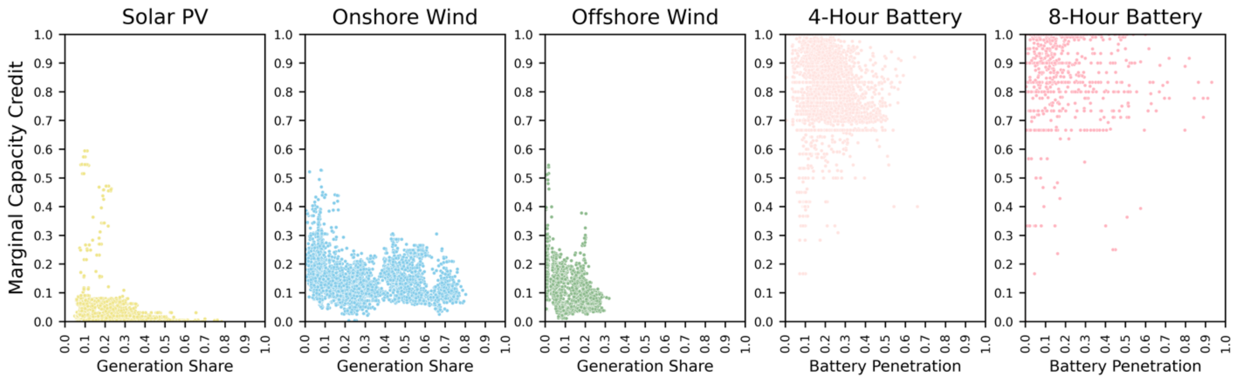


**Figure 7: National marginal capacity credits vs. generation shares across technologies.**

Marginal wind capacity credits, while having some fluctuations in some situations, tend more often to stay relatively constant over time (***Figure 6, panels 2 and 3***). Because wind generation is not as consistently focused during a contiguous time of the day, as compared to solar, , their capacity credits do not decline as sharply with higher generation shares as solar PV capacity credits do (***Figure 7, panels 2 and 3***). Marginal onshore wind capacity credits stay consistently in the range between 5% and 21% with median of 12% in 2026 and between 5% and 19% with median of 11% in 2050. Maximum marginal offshore wind capacity credits also stay relatively constant across time between 37% and 48% while outliers of over 75% are extremely rare and occur mostly only in the later period of the planning horizon after 2042. These high values only make up of 0.02% of the times, with over 75% of which in regions with low wind resources in CAISO (***Figure A. 16***).

Marginal offshore wind capacity credits follow a downward trend over time (***Figure 6, panel 3***). In the beginning of the planning horizon until 2036, they decline with most values range between 4% and 21% with median of 10% in 2026 and between 3% and 13% with median of 6% in 2036. This initial decrease is due to the sharp increase in offshore wind deployment (***Figure A. 13***), driving increase in offshore wind generation share during this period (***Figure A. 7***). Between 2036 and 2050, marginal offshore wind capacity credits level off at between 3% and 12% with median of 6% in 2050. During this time, offshore wind deployment and generation shares already level off. Marginal offshore wind can reach over 60% in rare occasions in upper MISO and the upper Northern Grid under highly decarbonization scenarios with low demand growth assumptions which de-incentivizes deployment of offshore wind (***Figure A. 17***).

Like average capacity credits, marginal capacity credits of batteries have stable ranges across time (***Figure 6, panels 4 and 5***). Most 4-hour battery's marginal capacity credits range between 67% and 100% with very rare occasions where they are lower than 20% under low demand scenarios. 8-hour battery has high marginal capacity credits at 80% to 100% most of the times and only decrease to below 20% under rare instances requiring high deployment of this technology. Unlike solar PV and wind, marginal capacity credits of batteries do not generally decline over time and do not decline as greatly with increasing development, largely because they can be discharged optimally during critical hours without being constrained by natural resources like solar PV and wind. These results emphasize the valuable role of batteries at the margin in resource adequacy, even in a grid already with a lot of existing battery resources.

## 3.2 Spatial Patterns of Average and Marginal Capacity Credits

***Figure 8*** compares average capacity credits of solar PV, wind, and batteries across eleven ReEDS transmission regions in the US. power system (***Figure A. 1***).

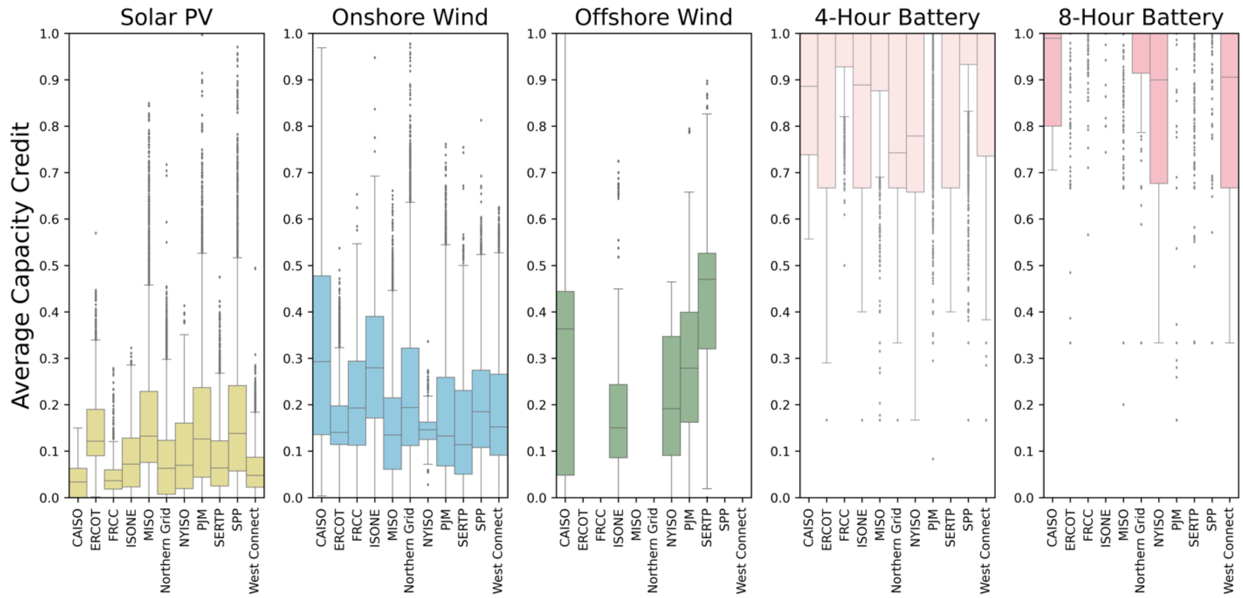


**Figure 8: Regional average capacity credits across technologies. See *Figure A. 1* for map of these 11 regions.**

Average capacity credits across VRE technologies have strong spatial variability. Median average solar PV capacity credits vary from 3% to 13% across transmission regions, while their maximum values can vary from 16% to 53% across regions. Average solar PV capacity credits are highest in SPP, PJM, and MISO where, in most cases, range between 4% and 24%, 3% and 23%, and 7% and 23% respectively (***Figure 8***, ***panel 1***). SPP, PJM, and MISO have many regions with the best wind resources in the nation but lower quality solar PV resources, resulting in low solar PV deployments (***Figure A. 14***) and generation shares (***Figure A. 8***), which drive high values of their existing solar PV capacity. These regions are also the only areas where average solar PV capacity credits of over 75% are observed under low demand growth scenarios which have even lower deployment of solar PV in these regions (***Figure A. 15***).

Average onshore wind capacity credits vary spatially more than solar PV, with median values ranging between 11% to 29% and maximum values ranging between 22% and 98% across transmission regions (***Figure 8, panel 2***). Although the spatial patterns of wind capacity credits are not as clear as solar PV, average onshore wind capacity credits are highest in regions with relatively low wind quality – CAISO, ISONE, and the part of the Northern Grid adjacent to CAISO, which have the least amount of onshore wind deployment (***Figure A. 14)*** and firm capacity (***Figure A. 12***).

Due to resource availability constraints, only five regions out of 11 in our study have offshore wind deployments and thus average offshore wind capacity credits (***Figure 8, panel 3***). Even though relatively more spatially concentrated, average offshore wind capacity credits vary greatly across regions, with median values ranging from 14% to 47% and maximum values ranging from 45% to 100%. Unsurprisingly, average offshore wind capacity credits are highest in coastal areas with low wind resources, such as CAISO and SERTP and lowest in coastal regions with high wind resources such as ISONE.

Because deployment and discharge of 4-hour battery is highly correlated spatially with that of solar PV (***Figure A. 8, panels 1 and 4***) to contribute to resource adequacy during critical periods where solar PV resources are not available, high solar PV capacity credit areas such as SPP, PJM, and MISO also have the highest average capacity credits for this type of battery (***Figure 8, panel 4***), with most values stay above 88%. Additionally, FRCC also observes high average capacity credits for 4-hour battery of mostly above 90%. Average capacity credits of 8-hour battery do not have clear spatial patterns, probably because 8-hour battery is more likely to dispatched strategically whenever the grid is stressed. Therefore, this technology has high average capacity credits in all regions (***Figure 8, panel 5***).

***Figure 9*** compares marginal capacity credits of solar PV, wind, and batteries across the same eleven transmission regions.

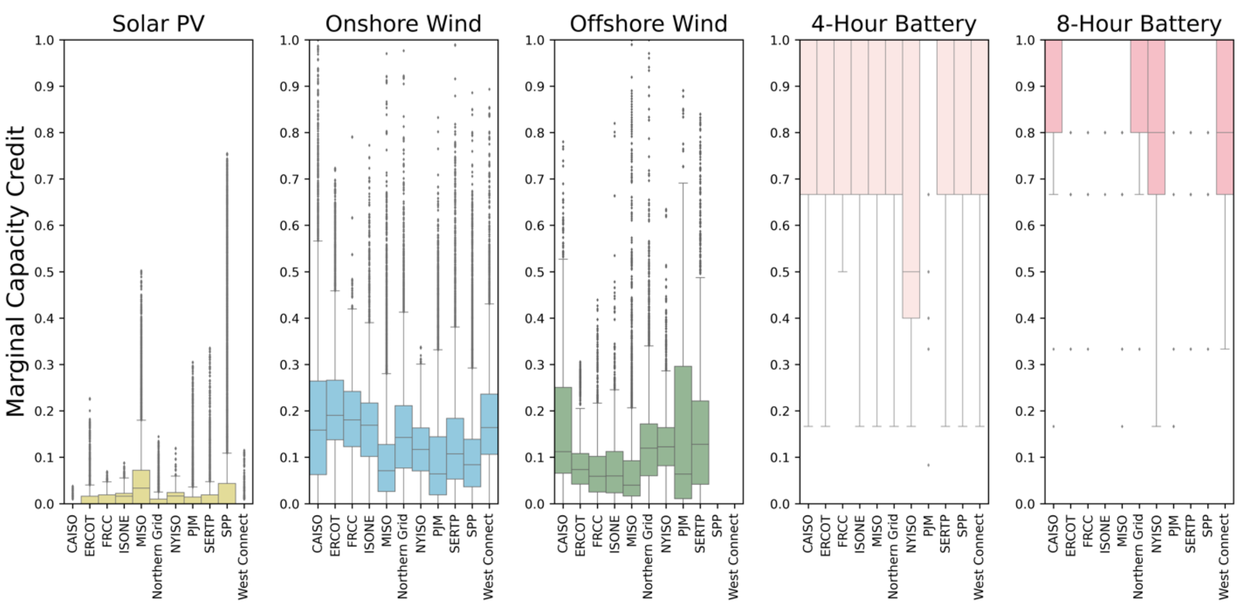


**Figure 9: Regional marginal capacity credits across technologies.**

Compared to average capacity credits, marginal capacity credits vary less across regions, even though some similar spatial patterns to average capacity credits are still observed. Marginal solar PV capacity credits are still highest in wind richest but solar poor regions in SPP and MISO (***Figure 9, panel 1***). Marginal onshore wind capacity credits are also generally higher in the western regions in CAISO, the Northern Grid, and West Connect (***Figure 9, panel 2***). Marginal offshore wind capacity credits spread out across regions more compared to average capacity credits (***Figure 9, panel 3***), indicating the potential benefits of deploying offshore wind more widely. Finally, 4-hour battery has very even marginal capacity credits spatially, corresponding well the relatively even distribution of marginal solar PV capacity credits. These capacity credits are also consistently high across regions, suggesting that adding more of this technology in the resource mix has high resource adequacy values everywhere.

# 4 Discussion

In this report, we quantified the average and marginal capacity credits of solar PV, wind, and battery storage across the U.S. in a wide range of scenarios that represent many possible future evolutions of the U.S power grid. We found different trends over time across technologies and between average and marginal capacity credits. Consistent with previous literature, we also found negatively correlated relationships between capacity credits and generation shares across all VRE technologies. Both average and marginal capacity credits of solar PV follow downward trends between 2026 and 2050, driven by the increasing deployment and generation shares of solar PV over time. Average and marginal capacity credits of batteries are both consistently high at any given time, emphasizing their capability to be dispatched flexibly and strategically to complement solar PV to contribute to the system's reliability during the critical periods when solar PV and/or wind resources are unavailable. Of the technologies studied in this analysis, wind is displayed the greatest differences between the average and marginal capacity credits. Average capacity credits of both onshore and offshore wind increase over time, whereas their marginal capacity credits have declining and relatively flat trends, respectively. In later years higher capacity credits can be extracted from existing wind resources while lower capacity values can be obtained from new wind resources.

We also found strong spatial patterns for average and marginal solar PV capacity credits, with the highest capacity credits tend to occur in regions in SPP, MISO, and PJM with rich wind resources but poor solar resources and thus low solar deployment and firm capacity. These consistent spatial patterns of solar capacity credits suggest that there might be potential reliability benefits in expanding more long-distance transmission capacity between SPP, MISO, and PJM and other solar resource rich regions in the west. Spatial patterns for wind and battery storage capacity credits are less obvious, largely because compared to solar PV, wind resources are less constrained to specific hours within the day, and battery resources can be more flexibly dispatched to serve load during critical hours.

The values in this analysis do not solely determine which capacity credits would be best to use under any scenarios but may be helpful to grid planners and utilities seeking to understand the ranges and trends between average and marginal capacity credits. This may assist with efficient capacity markets design. While the Federal Energy Regulatory Commission approves of both approaches [53,54], the differences between average and marginal capacity credits could mean substantially different capacity payments to resource owners and drive very different long-run market signals, resulting in different future deployments. Across all VRE technologies except offshore wind, we found that average capacity credits are generally declining more gradually, thus are generally higher than marginal capacity credits across the planning period, implying that more capacity payments can be credited to existing VRE plants than new VRE plants at almost any time.

For solar PV, average capacity credits are most likely to be higher than marginal capacity credits (around 90% of the time). In the rare scenarios when marginal solar PV capacity credits are higher than average solar PV capacity credits (around 10% of the time), they are most likely to occur in regions with low solar irradiation in SPP, MISO, PJM, and several small regions in the northern US. This is also true for scenarios where there are no average capacity credits, but marginal capacity credits are non-zeros. Due to having low solar irradiation, these regions under these scenarios do not have or have little existing solar PV and thus higher capacity credits for new solar

PV, sending market signals to incentivize new deployment there. Onshore wind in general also has higher average capacity credits compared to marginal capacity credits, however, it is less clear in which regions marginal capacity credits are most likely to be higher than average capacity credits for this technology. Accrediting solar PV and onshore wind resources with average capacity credits could be argued as providing resource owners and developers equitable and fair compensation which incentivizes more long-term investments of these technologies. In principle, marginal capacity credits might be more aligned with efficient capacity market design, where capacity prices better communicate the value of adding another generator.

Marginal capacity credits of offshore wind are generally higher than its average capacity credits (around 78% of the time). Only less than 22% of the time are marginal offshore wind capacity credits are lower than their average capacity credits. This phenomenon is observed only in coastal-proximity regions in the east coast and west coast in ISONE, NYISO, PJM, SERTP, and CAISO, which are the only transmission regions where offshore wind resources are deployed. This spatial pattern of offshore wind capacity credits suggests there might be resource adequacy benefits in developing more offshore wind in non-ocean water bodies, such as in the Great Lakes.

# 5 Conclusions

Driven by economic incentives and energy policies, deployment of renewable resources and storage are expected to continue to grow significantly in the coming decades, making an understanding of their contribution to power system's resource adequacy increasingly important. To inform long-term capacity planning, we estimated the average and marginal capacity credits of solar PV, onshore and offshore wind, and batteries over time across multiple possible futures of the power system, using the outputs from the 2023 Standard Scenarios simulated by the ReEDS Model.

We found declining trends over time in both types of capacity credits for solar PV, constant trends for batteries, increasing trends for average wind capacity credits, but declining trends for marginal wind capacity credits. Across regions, capacity credits of solar PV display clear spatial patterns, with high values concentrated in wind resource rich but solar resource poor regions in SPP, MISO, and PJM, while spatial patterns of wind and battery capacity credits are less obvious. These strong spatial variabilities suggest that the power system can benefit from planning for solar PV and wind development widely at the interconnection-scale. Additionally, across VRE technologies, average capacity credits are in general higher than marginal capacity credits. Because of this, resource developers and utilities might find average capacity credits preferrable as this approach provides more stable and higher returns to their clean energy investments.

# Data Availability

2023 Standard Scenarios datasets of average and marginal capacity credits are available at

https://doi.org/10.7799/2466151

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# Appendix A. Additional Figures

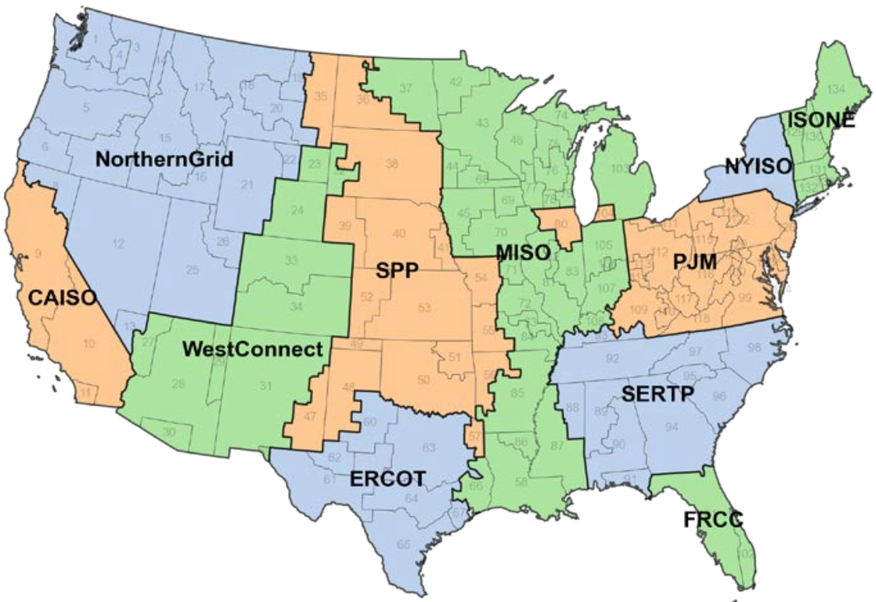


**Figure A. 1: Map of the 11 transmission regions where capacity credits are calculated in ReEDS.**

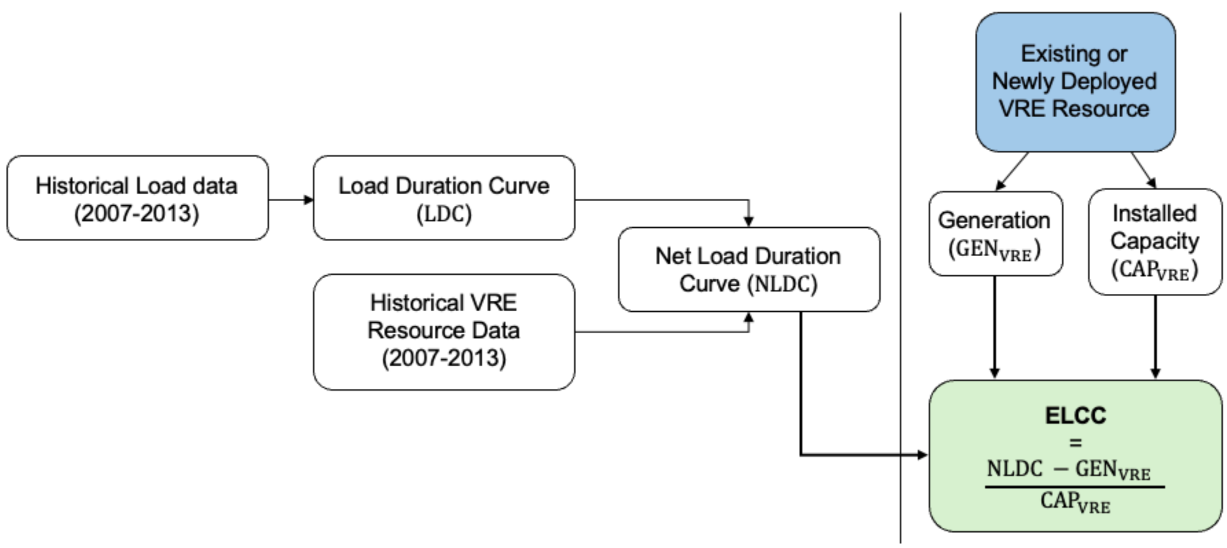


**Figure A. 2: Process of calculating ELCC for VRE in ReEDS. This calculation is applied to the hours with the most risk for loss of load (top 10 hours).**

## A.1 Capacity Credits by Technology Class

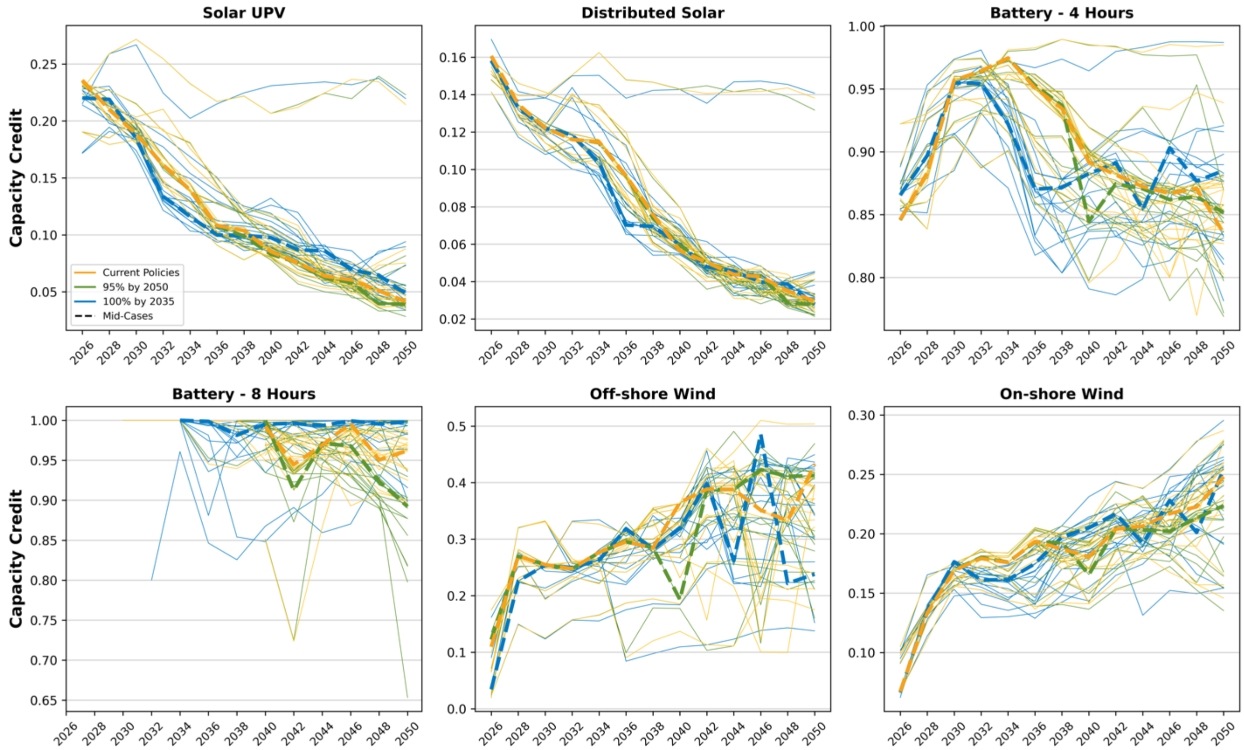


**Figure A. 3: National average capacity credits across technologies by scenarios, 2026-2050.**

The different resource classes reflect different resource qualities based on the annual average global horizontal irradiance (for solar PV classes) or wind speed (for wind classes) that determine these resources capacities.

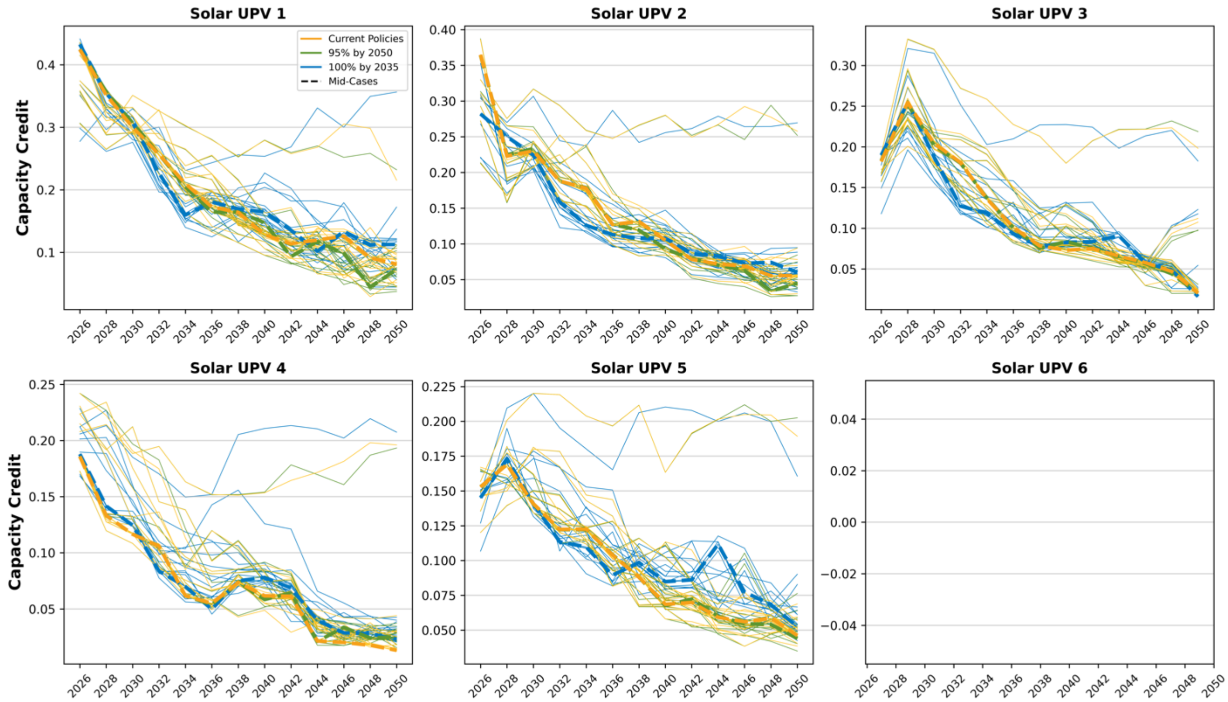


**Figure A. 4: National average solar UPV capacity credits by class across scenarios, 2026-2050.**

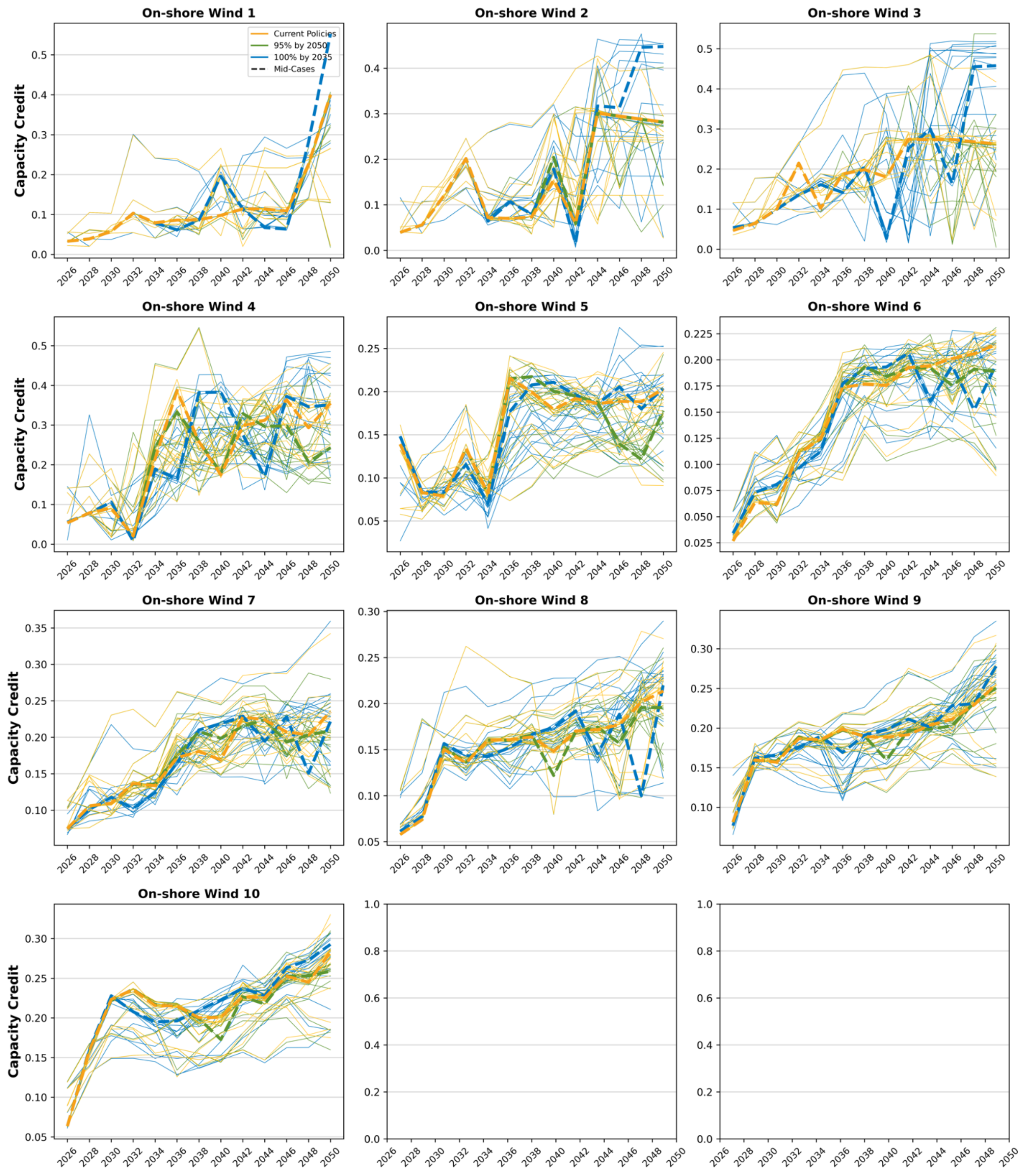


**Figure A. 5: National average onshore wind capacity credits by class across scenarios, 2026-2050.**

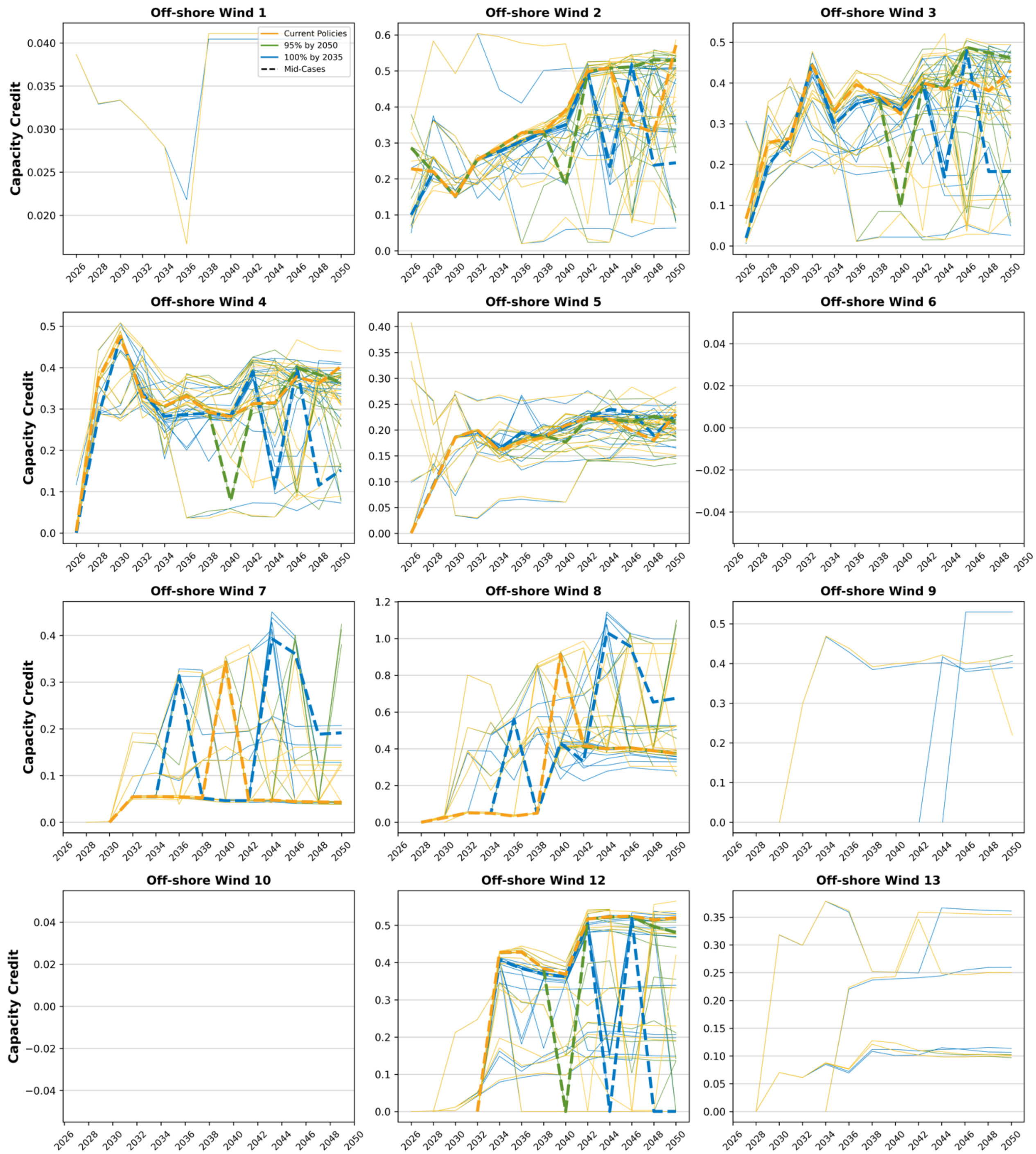


**Figure A. 6: National average offshore wind capacity credits by class across scenarios, 2026-2050.**

## A.2 Generation Shares of Technologies

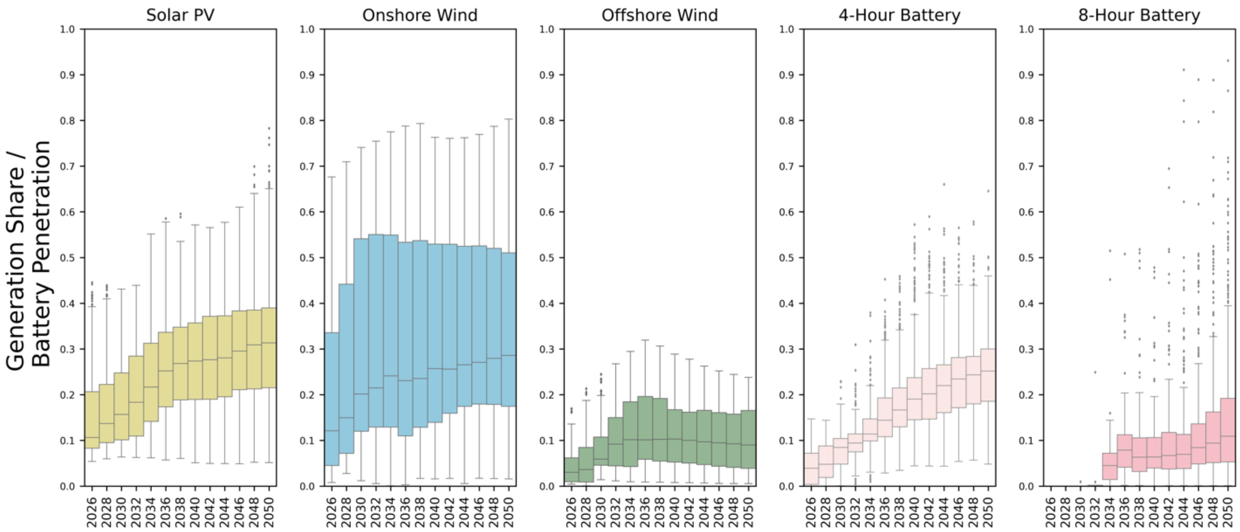


**Figure A. 7: Generation shares (solar PV and wind) and ratio of installed capacity over peak demand (batteries), across time.**

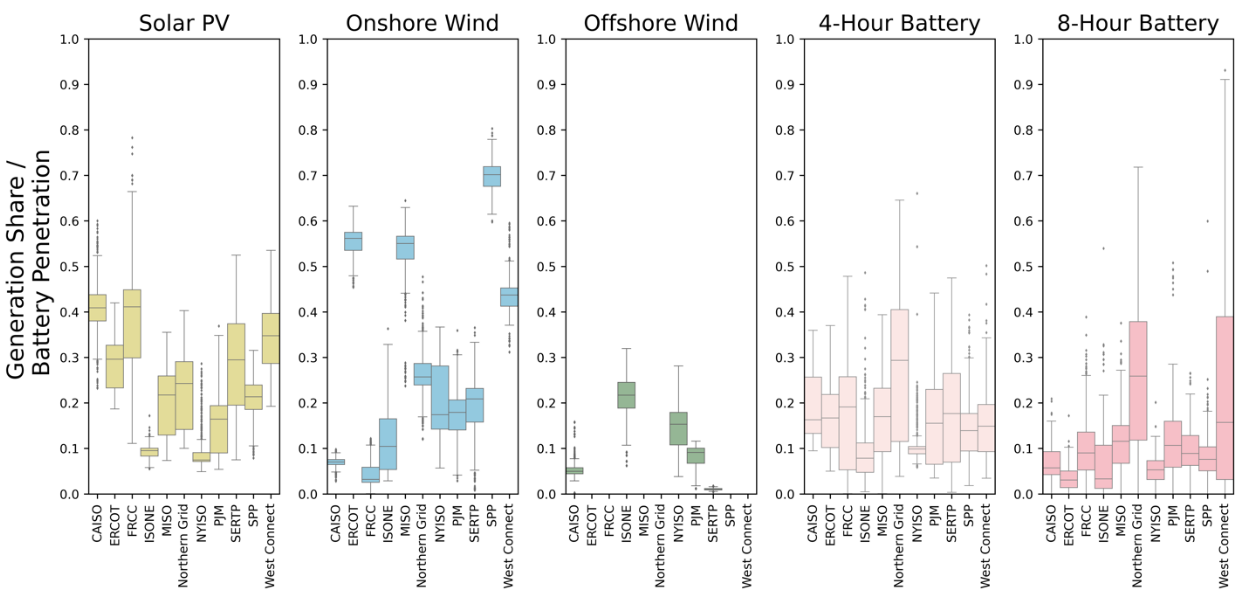


**Figure A. 8: Generation shares (solar PV and wind) and ratio of installed capacity over peak demand (batteries), across transmission regions.**

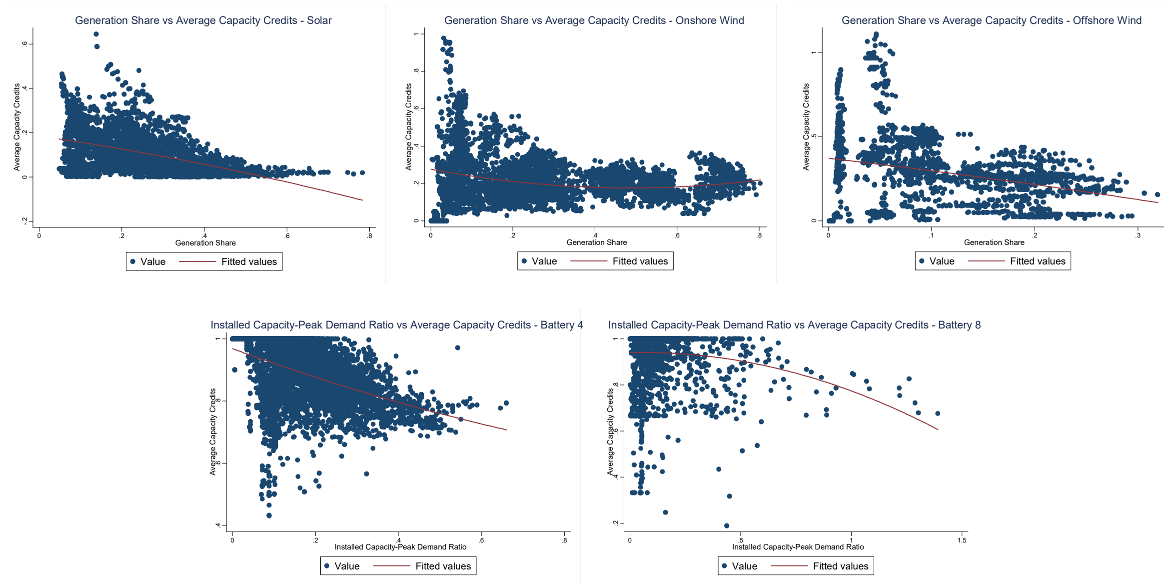


**Figure A. 9: Fitted quadratic regressions of generation shares (for solar PV and wind), installed capacity-peak demand ratios (for battery storage) vs. average capacity credits.**

## A.3 Firm Capacity

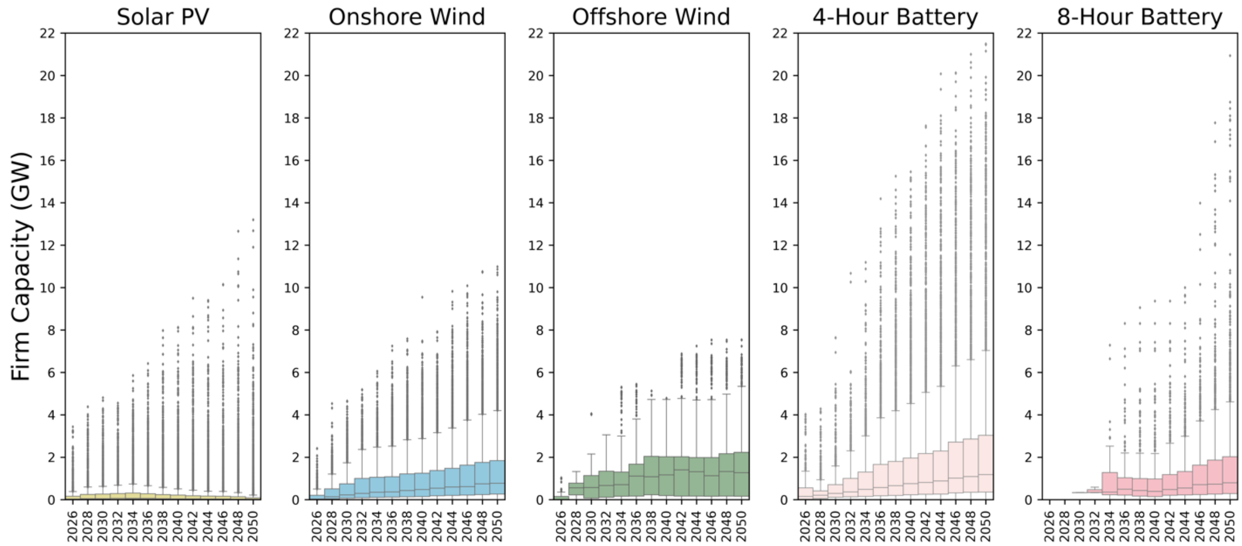


**Figure A. 10: Firm capacity of technologies across time.**

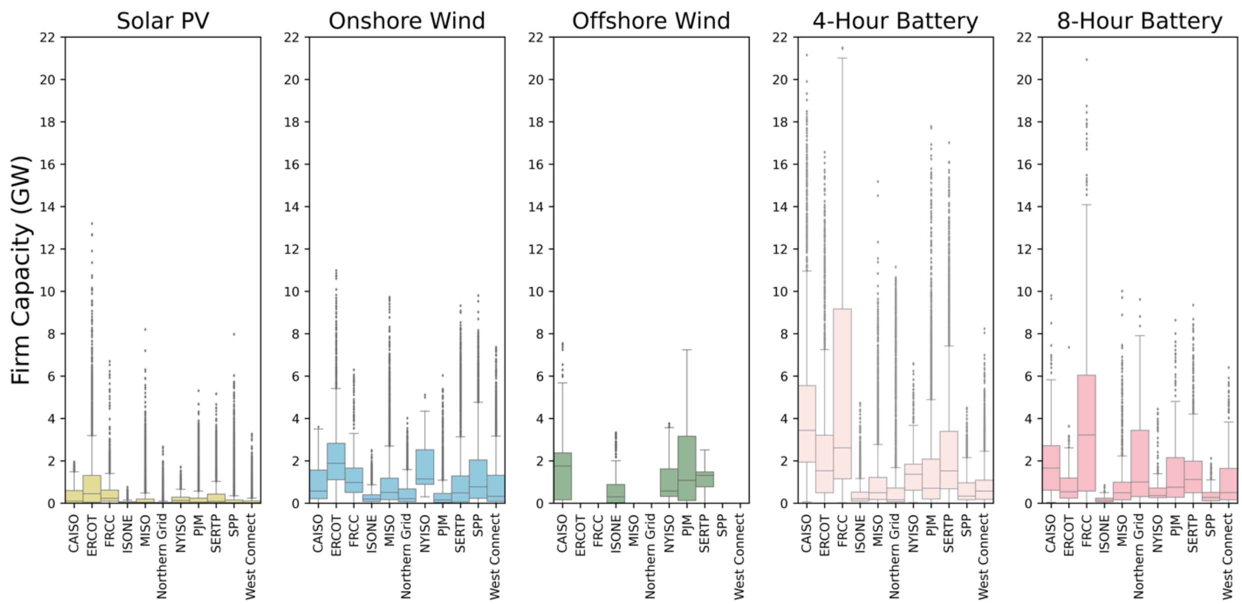


**Figure A. 11: Firm capacity of technologies across transmission regions.**

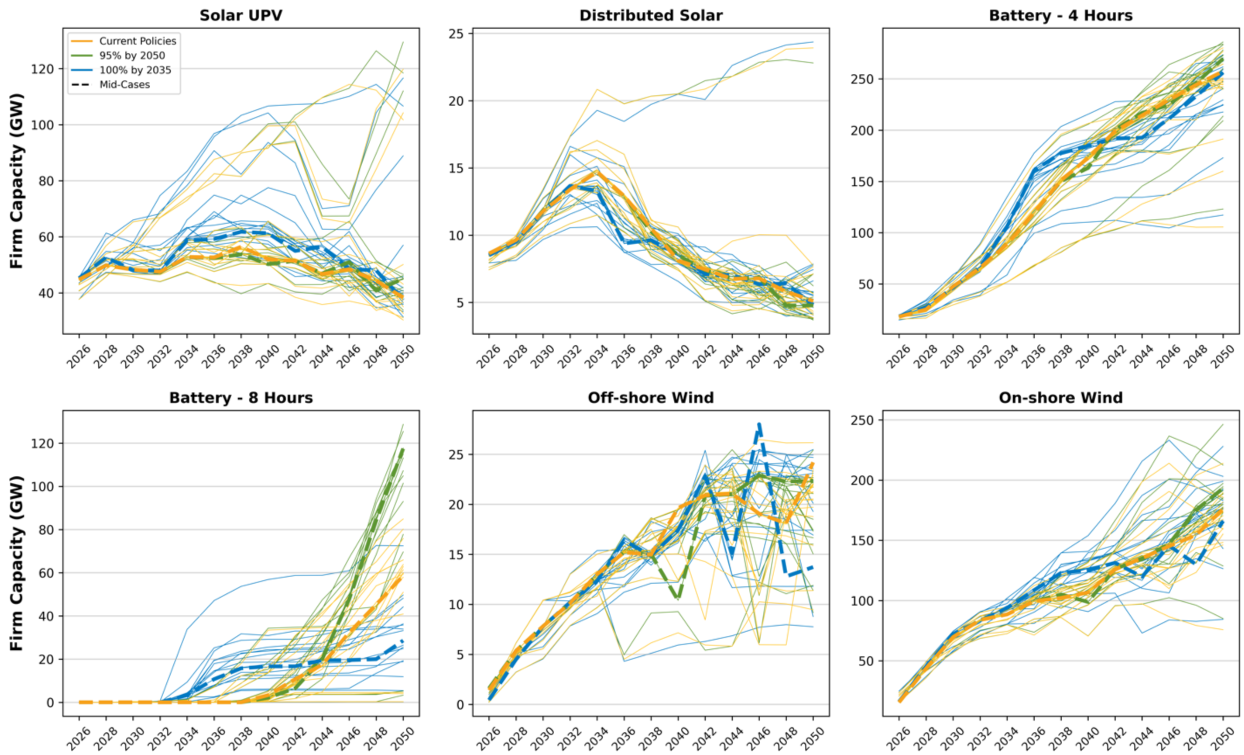


**Figure A. 12: Firm capacity of technologies across time by scenarios.**

## A.4 Installed Capacity

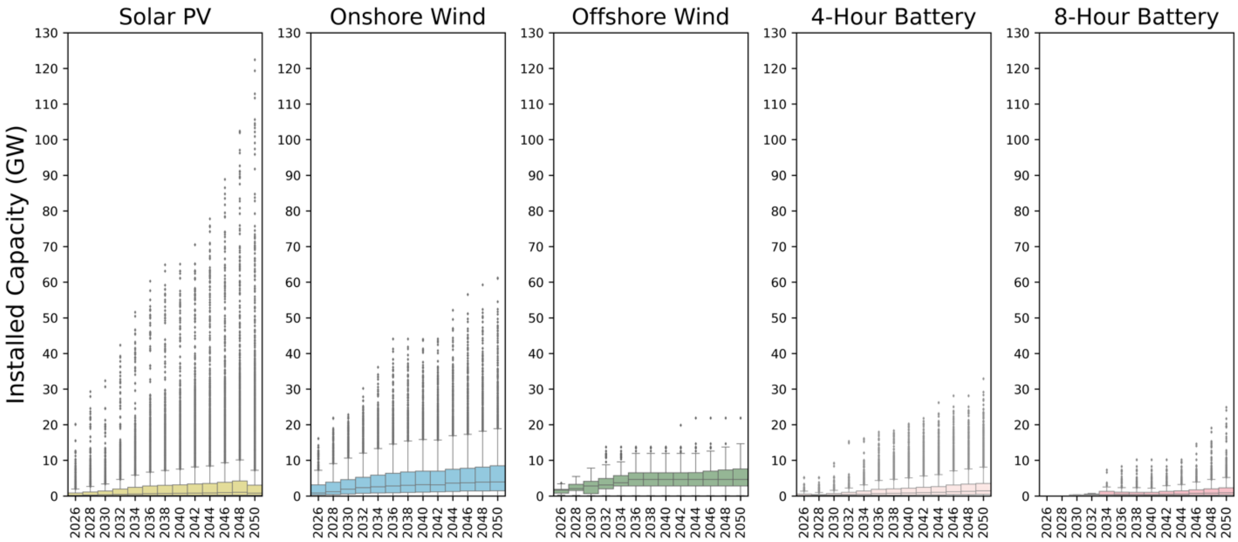


**Figure A. 13: Installed capacity of technologies across time.**

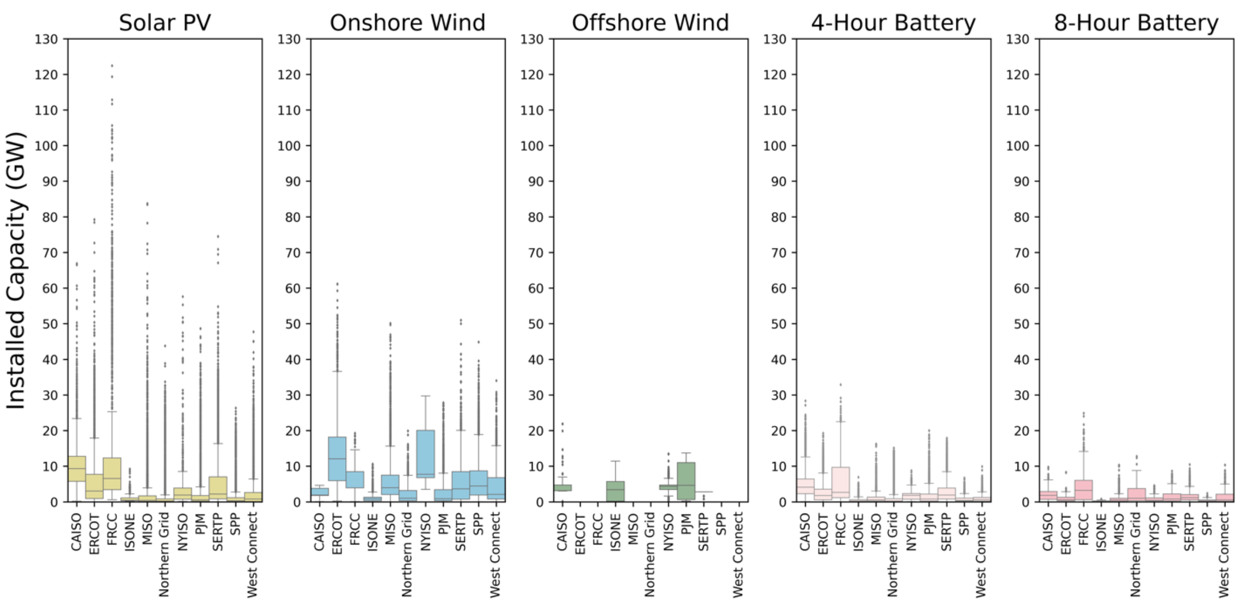


**Figure A. 14: Installed capacity of technologies across transmission regions.**

## A.5 Spatial Patterns of Average and Marginal Capacity Credit Outliers

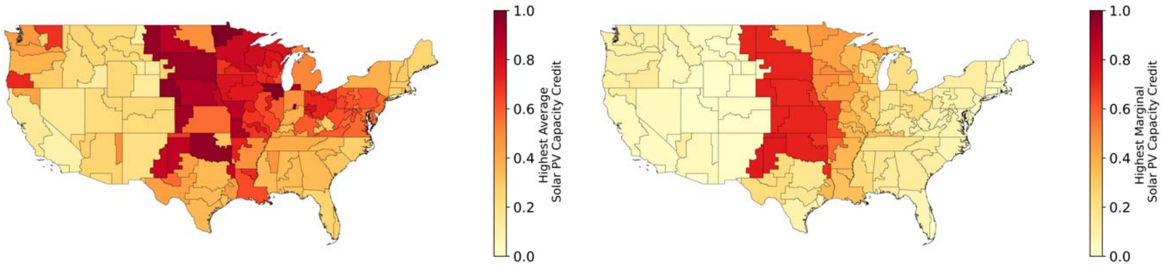


**Figure A. 15: Highest average (left) and marginal (right) solar PV capacity credits across the US.**

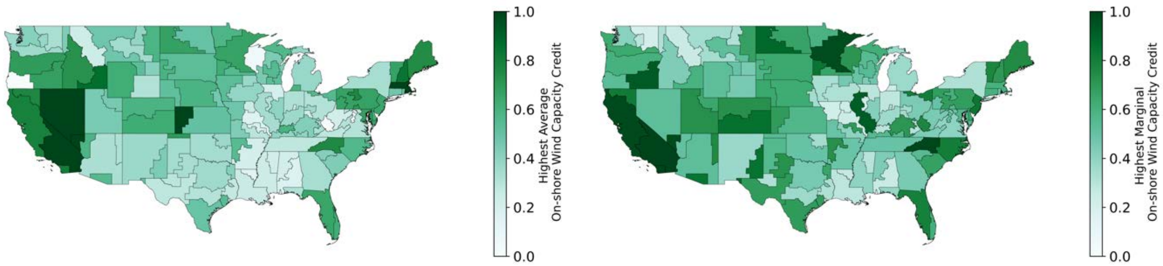


**Figure A. 16: Highest average (left) and marginal (right) onshore wind capacity credits across the US.**

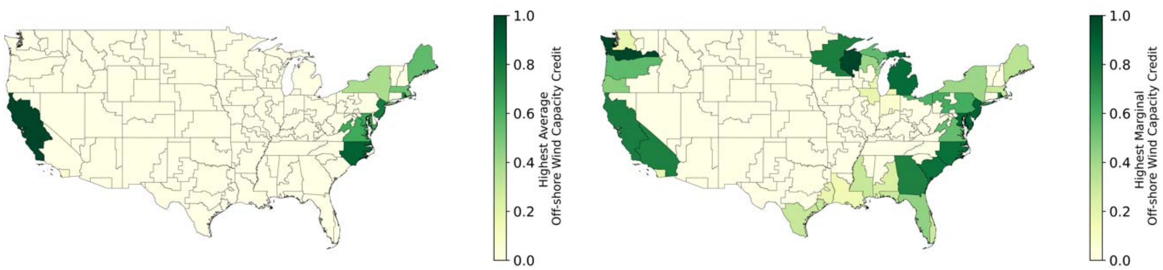


**Figure A. 17: Highest average (left) and marginal (right) offshore wind capacity credits across the US.**

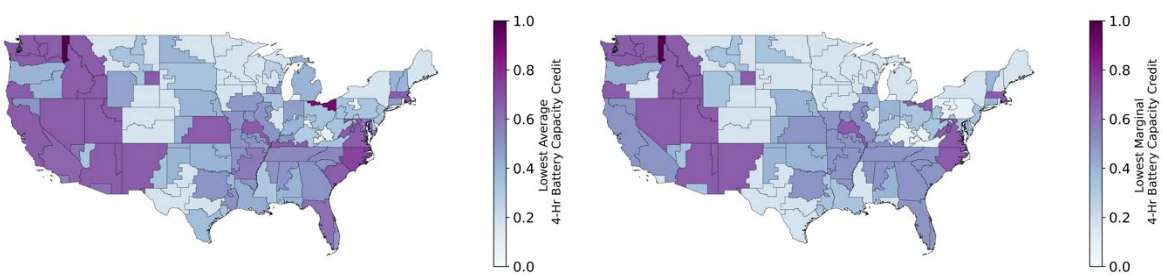


**Figure A. 18: Lowest average (left) and marginal (right) 4-hour battery capacity credits across the US.**

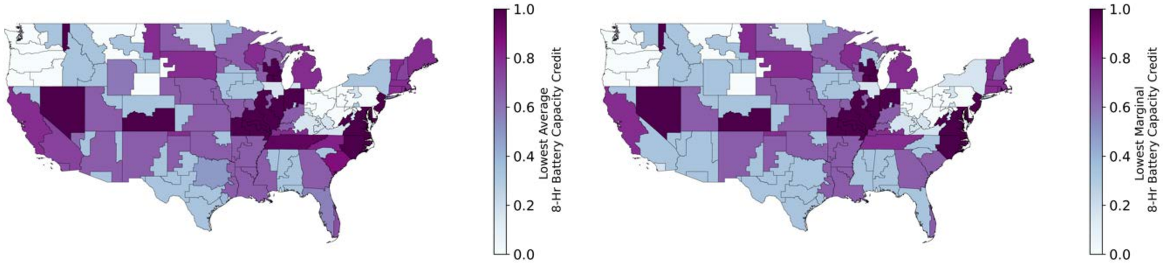


**Figure A. 19: Lowest average (left) and marginal (right) 8-hour battery capacity credits across the US.**