Complementarity of Renewable Energy-Based Hybrid Systems

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DOE/GO-102023-5896

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office and Water Power Technologies Office. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government .

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Complementarity of Renewable Energy-Based Hybrid Systems

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April 2023

Abstract

Increased attention has focused on scenarios of rapid and deep decarbonization of the U.S. electricity supply, with least-cost solutions typically involving significant expansion of renewable energy, energy storage, and transmission assets. Strategies that enable the integration of renewable energy projects while minimizing transmission expansion could be especially valuable in the future. It is within this context that the concept of hybrid power plants (or hybrid energy systems) has gained prominence. One specific example is the FlexPower concept,[1] which seeks to demonstrate how coupling variable renewable energy (VRE) and energy storage technologies can result in renewable-based hybrid power plants that provide full dispatchability and a full range of reliability and resiliency services, similar to or better than fuel-based power plants.

To help inform and evaluate the FlexPower concept, this report quantifies the temporal complementarity of pairs of colocated VRE (wind, solar, and hydropower) resources, based on their native generation profiles. The combined output from complementary resources—i.e., resources whose generation profiles are anticorrelated or out of phase with one another—will be spread more evenly across time, resulting in reduced variability. In turn, hybrid power plants comprising complementary resources can have increased capacity factors, reduced curtailment, and cost synergies due to smaller interconnection and energy storage requirements for smooth and dispatchable generation.

Through the evaluation of two complementarity metrics over annual and seasonal timescales, we find evidence that combining multiple VRE resources can reduce the variability in daily plant output across many regions of the United States. In general, complementarity signals are strongest for resource pairs that involve solar photovoltaics (PV), including wind-PV and hydropower-PV combinations. Complementarity varies on a seasonal and regional basis, both in terms of the strength of potential synergies and the resource pairs for which synergies are observed.

In the western United States, colocated wind and PV resources are complementary in the Central Valley of California, and output from hydropower dams complements that of colocated PV along the Colorado River, near Tahoe, California, and in northern Utah. In the wind belt and surrounding regions, colocated wind and PV are highly complementary, and generation from hydropower dams in the northern latitudes complements colocated PV (although these dams tend to have small capacities, ≤ 20 megawatts). In the Northeast, both wind and hydropower resources are moderately-to-strongly complementary with colocated PV, while the synergies between wind and hydropower are more muted. In the Southeast, complementarity among all evaluated resource pairs is moderate.

This report focuses on the temporal complementarity of pairs of wind, solar, and hydropower resources[2], but complementarity on its own cannot predict the competitiveness of hybrid energy systems. The economics of a power plant ultimately depend on its ability to deliver power during periods of greatest need and value, and high complementarity may not be optimal from a net economic perspective, accounting for all cost and value categories. In addition, complementarity provides initial insights into where the FlexPower concept could generate transmission and/or interconnection benefits, but the goals of FlexPower are much broader. Insights derived from this complementarity analysis can help with scenario design in operational models to provide a more complete picture of the value proposition of the FlexPower concept, including the addition of energy storage.

[1] "NREL Researchers Study Synergistic Value Streams in Hybrid Power Plants," National Renewable Energy Laboratory, September 1, 2021, https://www.nrel.gov/news/program/2021/flexpower.html.
[2] Complementarity results for all resource pairs, metrics, and locations evaluated in this study are available at https://github.com/NREL/Renewable-Complementarity.

Summary

Increased attention has focused on scenarios of rapid and deep decarbonization of the U.S. electricity supply. Analysis to date indicates a wide range of generation, storage, and transmission portfolios could meet current and projected demands for electricity (Denholm et al. 2022), including those associated with newly electrified end uses and pathways for decarbonized fuels and chemicals. A common theme among these candidate portfolios is the significant expansion of low-cost renewable energy sources and energy storage, the latter of which helps ensure alignment of weather-dependent generation with the timing of electricity demand. Such scenarios often involve significant expansion of long-distance transmission, which is needed to connect high-quality renewable resource regions to load centers and enables bidirectional energy and capacity trades between regions (Hurlbut, Harrison-Atlas, and Gu 2022).

Observed and expected barriers to new long-distance transmission projects make the possibility of significant transmission expansion highly uncertain. Therefore, strategies that enable the interconnection of renewable energy projects while minimizing transmission expansion could be especially valuable in the future. It is within this context that the concept of hybrid power plants (or hybrid energy systems) has gained prominence. In this report, we adopt the U.S. Department of Energy (DOE) definition of hybrid energy systems, which states that they involve "multiple energy generation, storage, and/or conversion technologies that are integrated—through an overarching control framework or physically—to achieve cost savings and enhanced capabilities, value, efficiency, or environmental performance relative to the independent alternatives" (DOE 2021). Prominent motivating factors for hybridization include increased capacity factors and shared balance of station infrastructure and costs.

Many different forms of hybrid energy systems have been proposed, which span a wide variety of energy generation, storage, and conversion technologies; include various architectures and forms of coupling; are designed for front-of-the-meter, behind-the-meter, and off-grid applications; and produce electricity and other energy products or services. One specific example is the FlexPower concept,[1] which seeks to demonstrate how combining multiple colocated variable renewable energy (VRE) resources and energy storage can result in renewable-based hybrid power plants that provide full dispatchability and a full range of reliability and resiliency services, similar to or better than fuel-based power plants. The FlexPower concept is further defined by the use of advanced controls and improved forecasting, which are designed to reduce curtailment, increase energy production, and reduce variability.

In this report, we evaluate the generation sources that could contribute to the FlexPower concept—namely wind, non-powered dams (NPDs), existing hydropower dams (EHDs), and solar photovoltaics (PV). A fully dispatchable plant would likely involve energy storage as well, but we seek to inform the nature and sizing of that energy storage via complementarity analysis. In particular, we evaluate the temporal complementarity of pairs of colocated VRE resources, where temporal complementarity is greatest when generation profiles are anticorrelated (or out of phase with one another). Colocated complementary resources will have a combined output that is less variable (i.e., it will be more even across time), such that combining them into a single power plant can lead to cost synergies due to smaller interconnection and energy storage requirements for smooth and dispatchable generation.

To evaluate the complementarity of pairs of wind, NPDs, EHDs, and PV, we rely on generation profiles derived from historical weather data including wind speeds (Draxl et al. 2015), solar irradiance (Sengupta

[1] "Clusters of Flexible PV-Wind-Storage Hybrid Generation (FlexPower)," Grid Modernization Initiative, https://gmlc.doe.gov/projects/6.1.1.
"NREL Researchers Study Synergistic Value Streams in Hybrid Power Plants," National Renewable Energy Laboratory, September 1, 2021, https://www.nrel.gov/news/program/2021/flexpower.html.

et al. 2018; Freeman et al. 2018), and United States Geological Survey (USGS) stream gauge data. PV and wind resource data are rooted in 2012 weather year data for all locations across the United States, which represents more than 1.7 million sites (not considering any geographic restrictions on where solar or wind projects may be viable). NPD and EHD resource data are limited to dams with adequate USGS stream gauge data, which are used to derive original generation profiles for select dams based on (a) a spatial join between dam locations and nearby stream gauges and (b) filtering to ensure adequate data quality. Altogether, this process results in original hourly generation profiles for 1,165 MW of NPD capacity (based on assumed dam characteristics) and 2,594 MW of EHD capacity.[1] Because hydropower generation exhibits strong annual variations, we evaluate complementarity of hydropower-based hybrids using the single representative year between 2010 and 2019 with the highest-quality flow data.

The complementarity analysis in this report spans two previously defined metrics—the Pearson correlation coefficient and the stability coefficient (Table ES-1). In this report, both metrics are formulated to provide insights into the *daily complementarity* of VRE resource pairs, but the evaluated metrics are rooted in distinct information. The daily Pearson correlation coefficient quantifies complementarity based on *daily* capacity factors and thus does not capture the potential for complementarity over shorter timescales.

The stability coefficient quantifies the daily complementarity of a pair of colocated resources, based on the timing and relative strengths of their *hourly* generation profiles. In evaluating the stability coefficient, we define the baseline technology as PV (which offers the clearest indication of diurnal variations) or wind (only in the case of the hydropower-wind complementarity assessment). We further assume the capacity ratio involves equal capacities of each resource (e.g., a 1:1 ratio of PV-to-wind capacity or adding 20 MW of colocated PV to a 20 MW hydropower dam). Therefore, the stability coefficient quantifies the extent to which adding a second VRE resource helps smooth output compared to the baseline VRE resource (most often PV) over the course of a day, assuming comparable nameplate capacities for each resource.

Table ES-1. Summary and Description of Complementarity Metrics Evaluated in this Report

General Characteristics			**Specific to the Formulation in This Report**
Metric	**What it Measures**	**Interpretation**	**Insights Provided**
Pearson correlation coefficient	Strength of the linear association between pairs of VRE generation profiles	-1 = perfect complementarity 0 = no correlation +1 = perfect synchrony (or lack of complementarity)	Whether production from each resource tends to occur on the same *day* or on different *days*
Stability coefficient	Reduction in the coefficient of variation for the capacity factor of a hybrid system relative to that of a standalone VRE generator	+1 = complete mitigation of variability from the underlying VRE generation profile (i.e., flat-block generation) 0 = no reduction in variability through hybridization	The extent to which hybridizing VRE generators of comparable nameplate capacities can reduce plant-level variability, compared to a *standalone PV or wind* plant at the same location

[1] Our generation profiles cover 11% of NPD capacity and 3% of EHD capacity in the contiguous United States, primarily due to the screening steps involved with joining dam locations and nearby USGS stream gauges.

Altogether, this analysis explores the daily temporal complementarity of each pair of resources across the contiguous United States, considering both annual and seasonal trends[1], based on a single representative weather year. Therefore, the analysis does *not* fully capture interannual variability in the timing and strength of wind, hydro, and solar generation profiles, which would vary in magnitude based on the underlying features that drive the relevant weather patterns (e.g., topography versus atmospheric conditions). A multiyear analysis could show a more complete picture of what it would look like to depend on hydropower for balancing colocated PV or wind; it would be especially valuable to include the sensitivity of the metrics to projected effects of climate change on hydropower availability and timing. Complementarity results for all resource pairs, metrics, timescales and locations evaluated in this study are available at https://github.com/NREL/Renewable-Complementarity.

The full suite of analysis results reveals that hybridizing multiple VRE resources can reduce the variability in plant output, but the details vary by metric, region, resource pair, and season. We find that complementarity between VRE resource pairs is highly nuanced, and it should be evaluated with multiple metrics and over multiple timescales to generate the full set of relevant insights. The remainder of this Summary describes five key insights that are meant to inform decision makers as they consider renewable energy-based hybrid power plants in the grid of the future.

Insight 1: Complementarity is Observed Throughout the Country, but it is Most Apparent Over Shorter Timescales

Figure ES-1 summarizes the stability coefficient results for all resource pairs involving solar PV: shading in the base map indicates wind-PV complementarity, and shading of square (circle) symbols indicates NPD-PV (EHD-PV) complementarity. For both the base map and symbols, dark blue shading indicates the combined output of the colocated resources is approaching a "flat block" profile, such that generation of comparable strength is available during most hours of the year.

In general, the dark shading in Figure ES-1 indicates that wind-PV complementarity is relatively strong in the central and eastern United States, accounting for both the timing and strength of wind and solar generation at a given location. The lighter shading in Figure ES-1 indicates locations where the variability in the combined output of the colocated resources is comparable to that of PV on its own. Wind-PV complementarity is more variable in the western United States, and hydropower-PV complementarity varies from dam to dam (with less-pronounced regional trends). In both cases, a location with a reduced complementarity signal could indicate overlap in the timing of generation and/or significant differences in the relative strengths of the colocated resources. In other words, lighter shading in the base map of Figure ES-1 could indicate a location where the wind output is concentrated during non-solar hours but it is significantly lower or significantly higher than the PV output (assuming the same nameplate capacity).

Different complementarity patterns arise from the daily Pearson correlation coefficient (not shown), which are readily explained by the fact that the daily Pearson correlation coefficient quantifies complementarity based on *daily* capacity factors; therefore, it does not capture the potential for complementarity over shorter timescales. For all VRE resource pairs, the daily Pearson correlation coefficient is near-zero throughout most of the United States: this means that there is not a strong association between the total amount of daily generation from wind, solar, or NPDs/EHDs in a given location. From a complementarity standpoint, the daily Pearson correlation coefficient result could be misleading, primarily because of the longer timescale over which it is being evaluated: the lack of

[1] Annual and seasonal trends refer to complementarity signals based on simulated generation throughout the entire year and restricted to an individual month, respectively.

correlation between the total daily output from colocated resources could be masking potentially beneficial (negative) correlations over shorter timescales, which are captured by the stability coefficient.

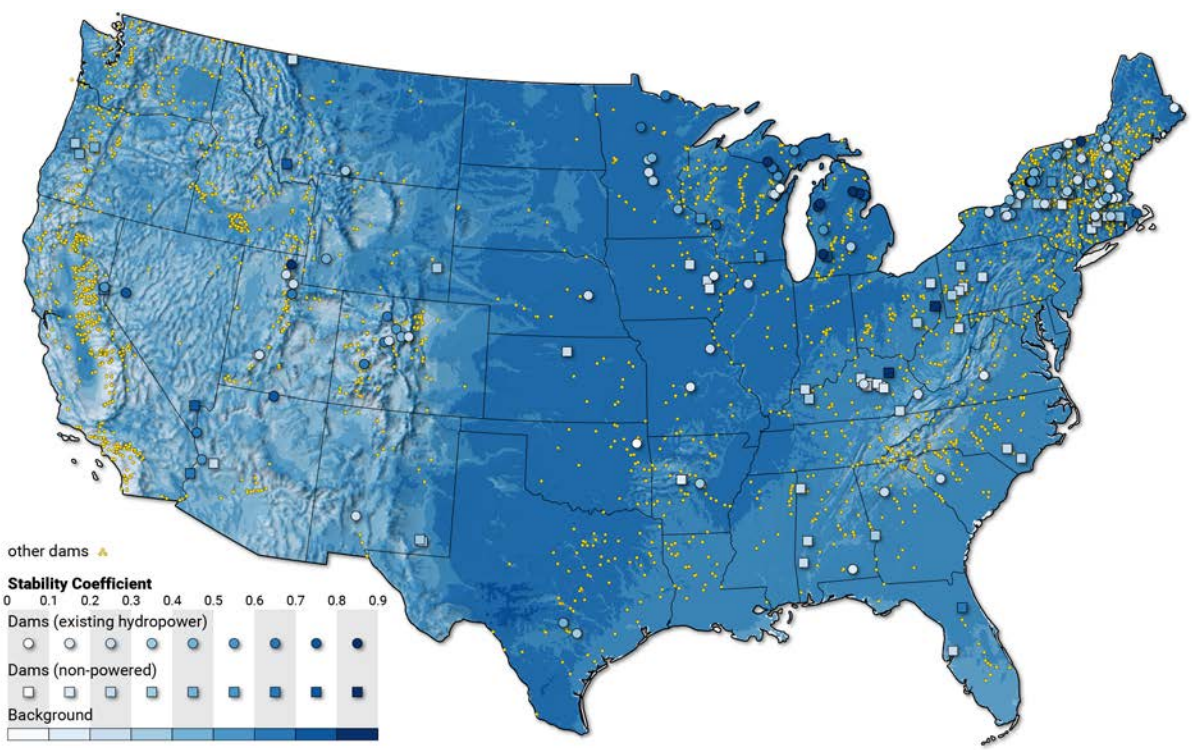

Figure ES-1. Stability coefficient results for wind-PV (base map), NPD-PV (square symbols), and EHD-PV (circle symbols), where darker blue shading indicates greater complementarity

Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

The Central Valley of California serves as a useful case study for demonstrating this point. The daily Pearson correlation coefficient for the Central Valley of California indicates a strongly *positive* correlation, which points to a sunny day also tending to be windy (or a lack of complementarity). However, the stability coefficient for colocated wind and PV in the Central Valley of California is relatively high (Figure ES-1), which means the combined output from colocated wind and PV resources is considerably less variable than the singular output of the baseline PV system. In other words, wind generation tends to be stronger during non-daylight hours, and it is of comparable strength as the colocated PV (assuming the same nameplate capacities).

Combining the indicators from the daily Pearson correlation coefficient and stability coefficient metrics, we find that a sunny day tends to be windy, but the *hours* of strong generation do not overlap (Figure ES-1). Therefore, the stability coefficient is a more reliable indicator of complementarity, and if demand for electricity is also high on that day, a positive correlation from the daily Pearson correlation coefficient could actually be beneficial.

Because complementarity based on more aggregate (daily) information can be misleading for certain applications, the remaining insights in this Summary are primarily rooted in stability coefficient results.

Insight 2: Complementarity Varies Regionally and is Most Pervasive for Pairings that Involve Colocated Solar PV

To help inform decision makers as they consider the potential for candidate hybrid power plants, we characterize complementarity for each pair of evaluated resources across the nation and on a regional basis. In general, we observe strong wind-PV complementarity in the central United States (base map of Figure ES-1), which corresponds to the locations with the strongest wind resources overall (i.e., the highest wind capacity factors). The combined output of wind-PV hybrids would also be less variable (than standalone PV) for locations in the Central Valley of California and throughout the non-mountainous regions of the Eastern United States. Variability in the combined output of colocated wind and PV in the Western United States is more comparable to the variability of standalone PV, which reflects the greater degree of overlap in the timing of wind and solar generation (i.e., the two hourly generation profiles tend to be more aligned than staggered) in this region.

We observe more limited reductions in variability associated with the combined output of NPD-wind (Figure ES-2) or NPD-PV (Figure ES-1) pairs, as indicated by the light shading for most square symbols. Greater complementarity is observed for a larger *number* of NPD-PV pairs (compared to NPD-wind pairs), but this corresponds to a comparable amount of NPD-PV and NPD-wind *capacity*.

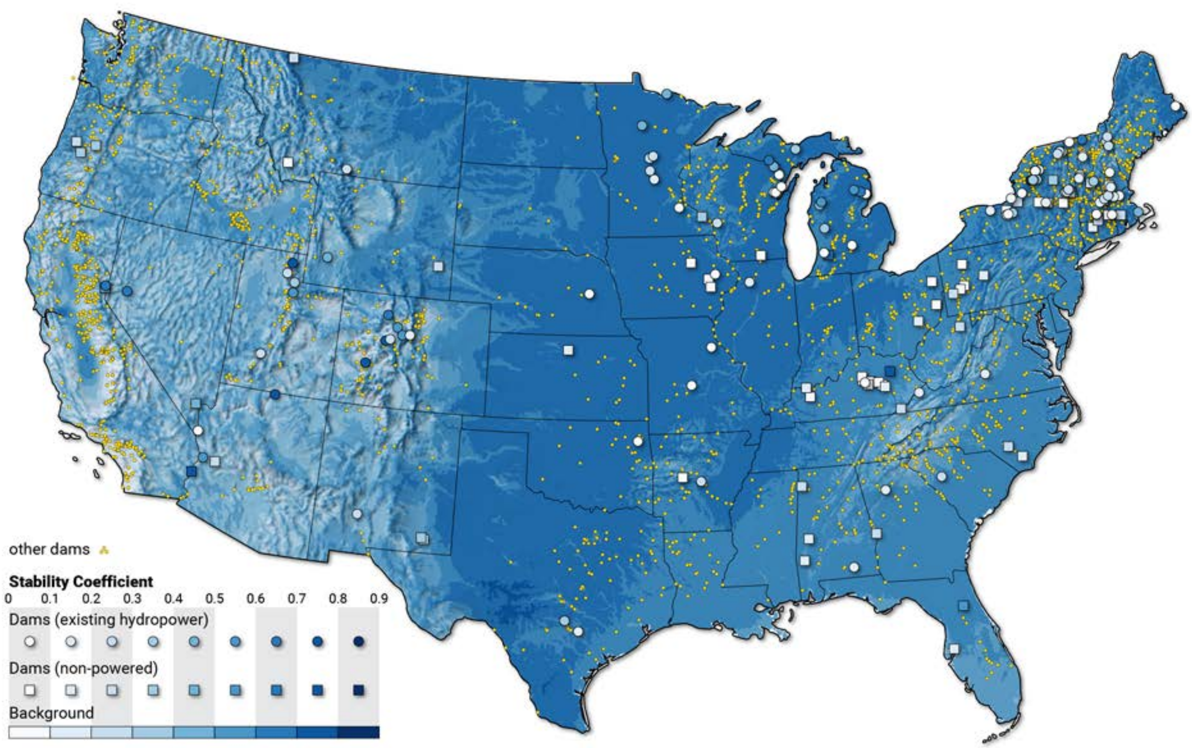

Figure ES-2. Stability coefficient results for wind-PV (base map), NPD-wind (square symbols), and EHD-wind (circle symbols), where darker blue shading indicates greater complementarity

Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

Hydropower-based complementarity is more pronounced for EHDs—as indicated by the presence of darker blue *circles* in Figure ES-1 and Figure ES-2—but it is also concentrated in large-capacity hydropower dams (e.g., Glen Canyon Dam with a capacity of 1,312 MW). Beyond Glen Canyon Dam, the remaining EHDs that substantially mitigate variability in output from colocated PV or wind are located throughout the Western United States. In the northern latitudes of the Eastern Interconnection—including the Midwest, New York, and New England—EHDs are more effective at mitigating the variability of colocated PV (Figure ES-1) than they are at mitigating the variability of colocated wind (Figure ES-2).

Recall that our complementarity analysis for hydropower-based hybrids is limited to dams with nearby USGS stream gauges and adequate flow data. In total, we evaluate complementarity metrics for dams that represent 11% of NPD capacity and 3% of EHD capacity nationwide. Therefore, the findings of this report should not be interpreted as absolute potential for hydropower-based hybrid power plants, but rather as (a) an initial exploration of the metrics that could be used to evaluate candidate locations and (b) initial findings regarding regional variation in hydropower-based complementarity.

Finally, for each U.S. census region and division, we identify which resource pairs indicate the greatest complementarity and, in turn, potential benefits under the FlexPower concept.

West Census Region

In the West Census Region, the most consistent complementarity signal arises from reductions in the variability of the combined output from colocated hydropower and PV (compared to standalone PV). This form of complementarity is observed for both NPDs and EHDs, with the strongest signals observed along the Colorado River, near Tahoe, California, and in northern Utah. There is a large volume of dams with unavailable or inadequate flow data (yellow circles), especially in the Pacific Census Division, which points to the need for improved flow and/or generation data to better quantify complementarity in hydropower-based hybrid configurations using the present methodology.

The relatively muted wind-PV complementarity signal in the West Census Region highlights the role of topography in influencing weather patterns that drive the timing and strength of solar and wind resources. In the easternmost portions of the Mountain Census Division (neighboring the wind belt), the combined output from colocated wind and PV is significantly less variable than that of standalone PV.

Midwest Census Region

The East-North Central Census Division indicates strong complementarity among multiple resource pairs. The strongest complementarity signal is observed for EHD-PV pairs (i.e., the dark blue circles in Michigan), although these dams tend to be smaller (≤ 20 MW). The combined output from colocated wind and PV in this region is also substantially less variable than that of standalone PV.

The West-North Central Census Division indicates similarly strong temporal complementarity between wind and PV resources, and a windy day has similar likelihood of being sunny or overcast. Hydropower dams with adequate flow data generally indicate limited complementarity with colocated PV or wind. However, the combined output from colocated EHD-PV pairs along the Mississippi River in Minnesota is significantly less-variable than that of standalone PV.

South Census Region

The dominant form of complementarity in the West-South Central Census Division reflects reduced variability in the combined output of colocated wind-PV pairs (compared to standalone PV). There are fewer hydropower dams in the region overall, and only five dams in the region have adequate flow data for evaluating complementarity with the present methodology. In the East-South Central and South

Atlantic census divisions, wind-PV complementarity is more moderate, and the number of dams with adequate flow data is low. For many hydropower dams with inadequate flow data, select nearby dams (e.g., one in Kentucky and one in Florida) indicate the potential for significant complementarity with either PV or wind.

Northeast Census Region

There are many hydropower dams in the Northeast Census Region, many of which have adequate flow data to enable complementarity analysis with the present methodology. In general, the combined output of colocated hydropower-PV pairs is less-variable than that of standalone PV, but the complementarity of colocated hydropower-wind pairs is more muted. The most pronounced complementarity is observed for EHD-PV pairs. In terms of the broader characteristics of the U.S. bulk power system, this region is characterized by higher transmission interconnection costs, which may favor the formation of hybrid power plants at EHDs if capacity is available on their existing transmission and interconnection services.

In summary, the diversity of weather patterns (including sun, wind, and precipitation) across the expansive contiguous United States intuitively leads to a range of complementarity signals when considering pairs of VRE resources. The regional trends described above (and summarized in Table ES-2) are designed to help inform initial discussions and considerations for hybrid power plant locations and resource combinations, based on complementarity that is evaluated over an annual timescale. However, complementarity can also vary seasonally, and the feasibility of a hybrid power plant depends on more than just complementarity signals, as discussed in the following two insights.

Table ES-2. Summary of Regional Complementarity Trends by Census Region and Division

Region	Division	Complementarity Findings (Annual Results)
West	Pacific	Wind and PV resources in the Central Valley of California are moderately complementary, and there are many dams for which better flow data are needed to facilitate a complementarity assessment
	Mountain	Hydropower dams along the Colorado River, near Tahoe, California, and in northern Utah indicate complementarity with colocated PV, and wind-PV resources neighboring the wind belt are highly complementary
Midwest	East-North Central	EHDs and wind both indicate complementarity with colocated PV
	West-North Central	Wind and EHDs along the Mississippi River in Minnesota both indicate complementarity with colocated PV
South	West-South Central	Colocated wind and PV resources are highly complementary
	East-South Central	Colocated wind and PV resources are highly complementary
	South Atlantic	Colocated Wind and PV resources are highly complementary
Northeast	Middle Atlantic	EHDs and wind both indicate complementarity with colocated PV
	New England	EHDs and wind both indicate complementarity with colocated PV

Insight 3: Complementarity Varies Seasonally

Our discussion to this point has focused on complementarity evaluated over annual timescales, but the underlying weather that informs wind, solar, and hydropower generation profiles varies seasonally. Figure ES-3 illustrates this seasonality by presenting the stability coefficient results based on generation for each month of the year, for all resource pairs involving PV. This figure indicates there is strong seasonal variation, such that regions that exhibit complementarity across the year have varying degrees of complementarity from month to month.

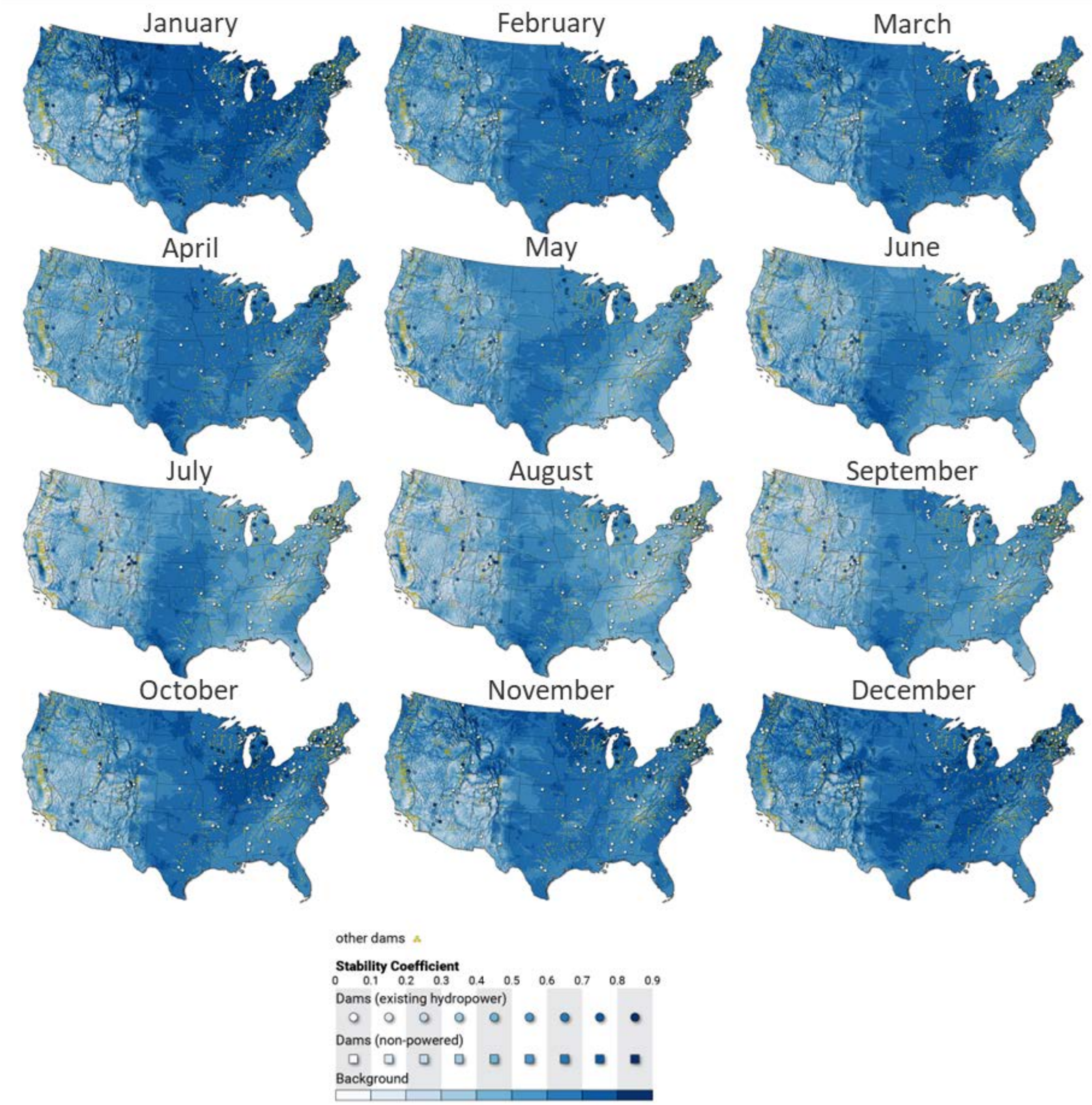

Figure ES-3. Stability coefficient results for wind-PV (base map), NPD-PV (square symbols), and EHD-PV (circle symbols) for each month of the year, where darker blue shading indicates greater complementarity

Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

The base map in Figure ES-3 presents the wind-PV stability coefficient, where the darker and greater extent of blue shading in the top and bottom rows indicate greater wind-PV complementarity during the winter months. For most of the country, the warmer months (May–August) indicate lesser wind-PV complementarity, which reflects lower wind capacity factors, higher PV capacity factors, and a greater number of solar hours during the summer months. It is interesting to note the relatively *high* stability coefficient values in the Central Valley of California and southern Texas during the summer months (Figure ES-3), which help explain the greater degree of *annual* complementarity in these regions as well (Figure ES-1).

Though the overall trends appear consistent with the annual findings, there are notable seasonal nuances in regional wind-PV complementarity findings (Table ES-2). For example, while the Mountain Census Division indicates limited wind-PV complementarity during the summer months, larger portions of the northern latitudes within this region indicate complementarity during the winter. In addition, the strongest wind-PV complementarity shifts further east during the winter, such that the East-South Central and East-North Central regions outperform the West-North Central and West-South Central regions (which indicate the greatest wind-PV complementarity on an annual timescale).

The temporal complementarity of hydropower and PV (symbols in Figure ES-3) also varies strongly across seasons, especially in regions with seasonal flows. For example, the complementarity of colocated PV and hydropower dams along the Colorado River or in northern Utah is more limited during the winter months, when water levels tend to be relatively low. On the other hand, the same dams indicate strong complementarity with colocated PV during the spring and summer months, which are the months with the greatest flow rates due to snow melt and monsoon season, respectively. The timing of this enhanced hydropower-PV complementarity (darker symbols) is especially noticeable because it corresponds to periods of relatively low wind-PV complementarity (lighter base map shading). Seasonality in hydropower's complementarity is similarly observed for (a) colocated PV in the Northeastern United States, albeit with stronger complementarity in the winter months (Figure ES-3), and (b) colocated wind (not shown), with similar regional trends.

Given these seasonal variations, the value of hybrids may be most apparent during particular months of the year, and the resource pairs that offer the greatest complementarity may further depend on the season. There could be significant value in combining seasonal complementarity results with corresponding data for electricity demand, transmission ratings, transmission utilization, and resource adequacy (e.g., peak load or net load) when evaluating candidate hybrid power plant locations and resource combinations. These other sources of potential value for hybrid power plants are the focus of our final insight below.

Insight 4: Complementarity is Only Part of the Hybrid Value Proposition

Though this Summary focuses on the temporal complementarity of pairs of wind, solar, and hydropower resources, we conclude with a discussion about additional cost and value considerations for hybrid power plants. First and foremost, it is important to note that capturing the reduced-variability benefits of combining multiple VRE resources does not require hybridization. Regional resource balancing has long been leveraged as a means of smoothing variability across a portfolio of generation assets, and such an approach may be preferred in regions with vertically integrated electric utilities. Therefore, while complementarity can help inform locations where hybridization could reduce plant-level variability, other strategies may be preferred or offer alternative benefits.

Second, our analysis shows that complementarity between VRE resource pairs is multifaceted, and a single metric or timescale cannot offer all the insights that are needed to evaluate a candidate hybrid power plant. In addition, different metrics and timescales capture different aspects of complementarity, so care must be taken to select and evaluate the metric that most closely aligns with the sought-after-benefits of hybridization. For example, to evaluate the potential for avoided transmission investment (due to shared interconnection capacity and greater transmission utilization), it is recommended that one evaluates complementarity based on hourly (or subhourly) generation and by season, as more aggregate information could be misleading for that application. Such an assessment could further consider historical transmission congestion, future transmission buildout, and voltage issues as well, all of which require relatively fine temporal resolution to derive meaningful insights.

Third, complementarity further depends on the chosen design and configuration of a candidate hybrid power plant. This analysis was limited to pairs of resources with equal nameplate capacities, so complementarity signals could be rooted in strong differences in resource strengths (e.g., in the case of Glen Canyon Dam). Such apparent limitations could be addressed through design choices, including oversizing a wind component relative to PV in the Southwest, or oversizing PV relative to hydropower in New England. Of the two metrics evaluated here, only the stability coefficient captures the effects of sizing on complementarity.

Finally, complementarity is not inherently an indicator of economic value, and economic value underpins any investment decision. The *value* of a power plant ultimately depends on its ability to deliver power during periods of greatest need, which vary over both short and long timescales. Therefore, a "flat block" of generation would be suboptimal if one could avoid the deployment of PV panels or wind turbines that would primarily increase generation during very low-value periods of the day or year. This concept is especially important when considering the energy storage aspect of the FlexPower concept, which would both facilitate shifting of generation to periods with high value (or away from periods with especially low value or transmission congestion), as well as expand the range of reliability services that the plant could provide and be compensated for. Finally, hybrid power plants have the potential to realize balance of station cost savings through shared (and reduced) point of interconnection and transmission costs, reduced permitting and siting times, and shared land use. None of these factors were analyzed in this study, but they would likely influence the economics and broader market viability of hybrid power plants on a regional basis.

Acknowledgments

Primary funding support for the FlexPower project is provided by the DOE Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office (WETO) and Water Power Technologies Office (WPTO). We especially thank Jian Fu (DOE-WETO) for her support and leadership on this report and throughout the FlexPower project. We also thank Samuel Bockenhauer (DOE-WPTO), David Corbus (National Renewable Energy Laboratory), and Hill Balliet (Idaho National Laboratory) for their valuable feedback on a draft version of this technical report, which helped to improve the quality and clarity of this publication. Any errors and omissions are the sole responsibility of the authors.

Special thanks go to colleagues at the National Renewable Energy Laboratory, including Billy Roberts for graphics support; Michael Rossol for data analysis support; and Mike Meshek for editing support.

Acronyms and Abbreviations

API	application programming interface
DOE	U.S. Department of Energy
EHD	existing hydropower dams
FlexPower	Flexible PV-Wind-Storage Hybrid Generation
HUC	hydrologic unit code
NPD	non-powered dam
NSRDB	National Solar Radiation Database
PV	photovoltaics
REST	representational state transfer
reV	Renewable Energy Potential model
SAM	System Advisor Model
USGS	United States Geological Survey
VRE	variable renewable energy
WIND	Wind Integration National Dataset

Contents

Figures

Tables

1 Introduction

Increased attention has focused on scenarios of rapid and deep decarbonization of the U.S. electricity supply. Analysis to date indicates a wide range of generation, storage, and transmission portfolios could meet current and projected demands for electricity (Denholm et al. 2022), including those associated with newly electrified end uses and pathways for decarbonized fuels and chemicals. A common theme among these candidate portfolios is the significant expansion of low-cost renewable energy sources and energy storage, the latter of which helps ensure alignment of weather-dependent generation and the timing of electricity demand. Such scenarios often involve significant expansion of long-distance transmission capacity to connect high-quality renewable resource regions to load centers and enable bidirectional energy and capacity trades between interconnected regions (Hurlbut, Harrison-Atlas, and Gu 2022).

Many challenges are anticipated under scenarios that envision a U.S. electricity supply that is dominated by variable renewable energy (VRE) resources, which has motivated research into a range of solutions. One prominent strategy for enabling the integration of large shares of VRE resources involves their spatial aggregation, which leverages a geographic smoothing effect to decrease variability of the aggregated output (Berger et al. 2020; Mills et al. 2009; Holttinen et al. 2021; Widen 2011; Klima and Apt 2015; Olauson and Bergkvist 2016; Solomon, Kammen, and Callaway 2016; Shaner et al. 2018; Risso, Beluco, and Marques Alves 2018; Ren et al. 2019; Gonzalez-Salazar and Poganietz 2021; Karadöl, Yıldız, and Şekkeli 2021). Other approaches include improved generation forecasting (Brancucci Martinez-Anido et al. 2016; Wang et al. 2016; Sobri, Koohi-Kamali, and Rahim 2018), as well as flexibility in electricity supply (de Sisternes, Jenkins, and Botterud 2016; Mallapragada, Sepulveda, and Jenkins 2020) and demand (Lund et al. 2015; Paterakis, Erdinç, and Catalão 2017; Mai et al. 2018). Finally, transmission expansion is often considered a key strategy in least-cost solutions for a decarbonized U.S. electricity supply (Jacobson and Delucchi 2011; Engeland et al. 2017; Denholm et al. 2021), but observed and expected barriers to new long-distance transmission projects make the possibility of significant transmission expansion highly uncertain. Strategies that enable the integration of renewable energy projects while minimizing transmission expansion could be especially valuable in the future.

It is within this context that the concept of hybrid power plants (or hybrid energy systems) has gained prominence. In this report, we adopt the U.S. Department of Energy (DOE) definition of hybrid energy systems, which states that they involve "multiple energy generation, storage, and/or conversion technologies that are integrated—through an overarching control framework or physically—to achieve cost savings and enhanced capabilities, value, efficiency, or environmental performance relative to the independent alternatives" (DOE 2021).

Many different forms of hybrid energy systems have been proposed (Figure 1.). In this report, we focus on a subset of the hybrid energy systems universe (Figure 1): namely electricity-only hybrids comprising colocated renewable energy resources. This subset of hybrid energy systems is consistent with the concept proposed in DOE's Grid Modernization Laboratory Consortium project titled Clusters of Flexible PV-Wind-Storage Hybrid Generation (FlexPower[1]). It proposes a pioneering approach to demonstrate how technology hybridization can fully leverage the value of variable utility-scale wind and solar generation, in combination with hydropower generation, to take them from simple VRE resources to ones that provide dispatchability, flexibility, capacity, and a full range of reliability and resiliency services to the bulk power system—similar to or better than conventional plants. The project will demonstrate the ability of hybrid plants to operate in grid-forming mode and provide reliability and resilience services (black start, islanded operation) in a multi megawatt-scale system.

[1] "NREL Researchers Study Synergistic Value Streams in Hybrid Power Plants," National Renewable Energy Laboratory, September 1, 2021, https://www.nrel.gov/news/program/2021/flexpower.html.

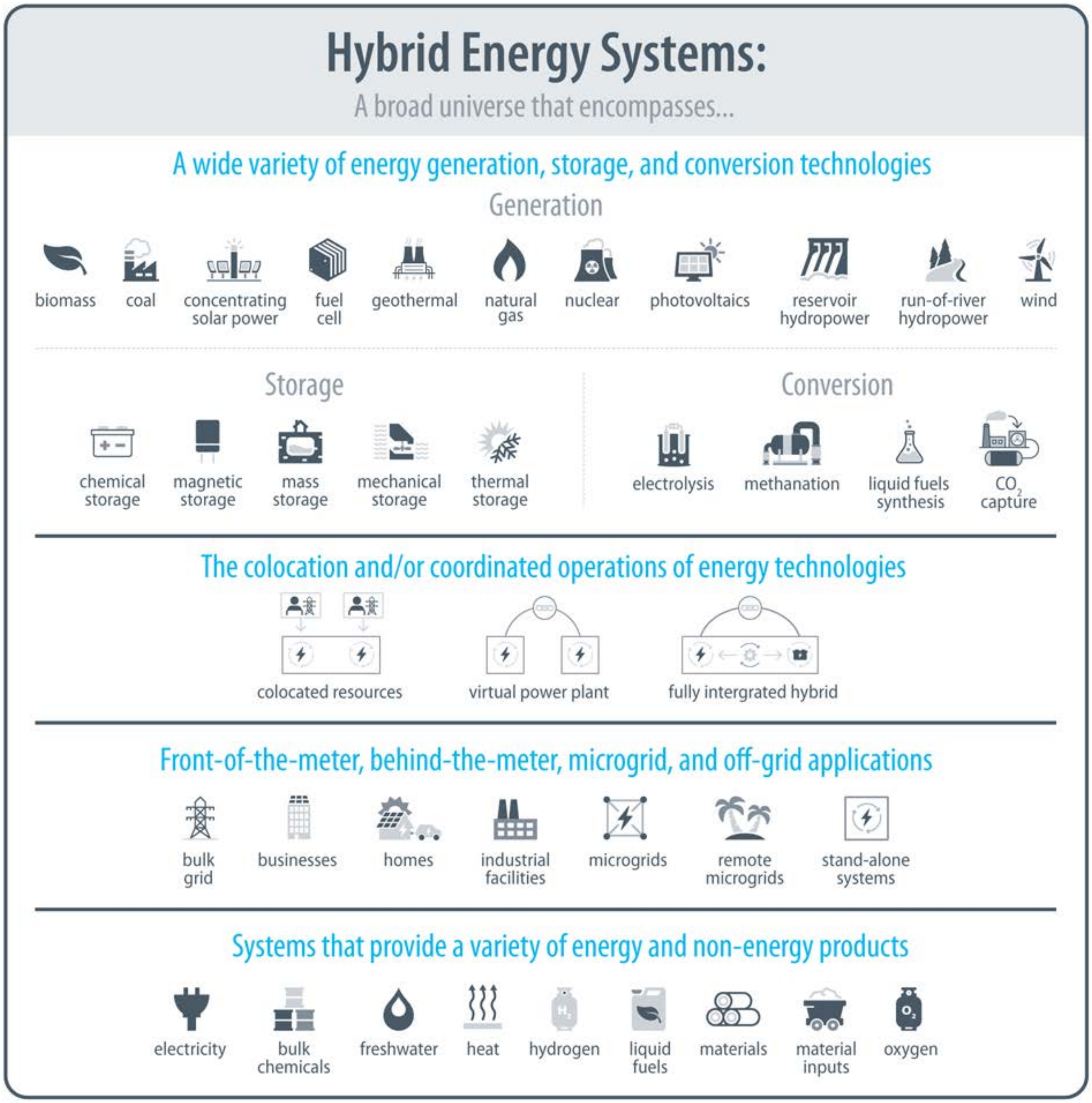

Figure 1. Summary of dimensions that define hybrid energy systems

Source: (DOE 2021)

This analysis is formally part of the FlexPower project, which involves multiple tasks. First, the project will develop a FlexPower demonstration platform. Second, the project will implement and demonstrate a FlexPower control system. Finally, the project will perform a regional integration study. In this report, we present the results of the first stage of the regional integration study, which involves evaluating hybridization potential across the contiguous United States based on synergies in resource availability to mitigate short-term variability. To this end, we analyze VRE resource pair *complementarity*, of which there are three primary types:

- Temporal Complementarity: a measure of whether generation profiles from colocated resources are out of phase or in sync with one another.
- Spatial Complementarity: a measure of whether generation profiles from geographically distinct resources are out of phase or in sync with one another over a particular period.
- Spatiotemporal Complementarity: a measure of whether generation profiles from resources are out of phase or in sync with one another, considering variations across space and time (for a particular region and period).

Because the FlexPower concept involves colocated VRE resources, the focus of this study is on *temporal* complementarity.

1.1 Literature Review: Temporal Complementarity

To date, studies of varying geographic scope have covered different aspects of the temporal complementarity of VRE resources using a variety of metrics. In this section, we review the relevant literature related to the temporal complementarity of colocated VRE resources; additional synthesis is available in recent reviews that cover the emerging complementarity literature in detail (Jurasz et al. 2020; Weschenfelder et al. 2020; Yan et al. 2020).

Research regarding the temporal complementarity of VRE resources in the literature spans many decades and metric formulations (Weschenfelder et al. 2020; Jurasz et al. 2020; Yan et al. 2020). In the absence of a uniformly established approach for evaluating temporal complementarity, researchers have used a diverse set of metrics and definitions to quantify synergies among renewable energy source pairs. Their methods can readily be classified into statistical metrics and indices. Statistical metrics involve descriptors of variability in resource or generation profiles, such as standard deviation, coefficient of variance, and robust coefficient of variance; these descriptors are then related to one another through various forms of correlations, such as the Pearson correlation coefficient, Kendall's Tau, Spearman's Rank, cross-correlation, and canonical correlation analysis (Harrison-Atlas et al. 2022). Numerous indices have also been proposed to quantify aspects of hybrid plant performance that reflect different characteristics of temporal complementarity. These include, for example, indices for quantifying load tracking (Zhu et al. 2018), system reliability (Jurasz et al. 2020), smoothing effects (Sterl et al. 2018; Hoicka and Rowlands 2011), and ramp rate (Widen 2011).

Such metrics have largely been applied to evaluate the temporal complementarity of VRE resource pairs (Murphy, Schleifer, and Eurek 2021), with wind-solar pairings appearing most often (Jurasz et al. 2020). That being said, all combinations of wind, solar, and hydropower—including the complementarity of pairs and trios—have been studied in the literature (Kougias et al. 2016; H. Li et al. 2019; François et al. 2016; Aziz, Mufti, and Ahmad 2017; Borba and Brito 2017; Zhu et al. 2018; Han et al. 2019; Canales et al. 2020). Most temporal complementarity studies to date examine resource variability using historical time series data, and they are most relevant for the planning and design of hybrid systems. In some cases, studies have synchronized time series data for load and generation in order to evaluate impacts of complementarity on load balancing objectives (Sun and Harrison 2019).

The temporal complementarity of VRE resources has been studied at multiple spatial scales, including globally (Kapica, Canales, and Jurasz 2021), continentally (Miglietta, Huld, and Monforti-Ferrario 2017; Prasad, Taylor, and Kay 2017; Viviescas et al. 2019), nationally (Clark et al. 2022), and subnationally (Beluco, de Souza, and Krenzinger 2008; Takle and Shaw 1979; Solomon, Kammen, and Callaway 2016; Slusarewicz and Cohan 2018; W. Li, Stadler, and Ramakumar 2011; Nikolakakis and Fthenakis 2011), as well as for offshore resources (Soukissian, Karathanasi, and Zaragkas 2021). In general, the larger the geographic scope considered, the coarser the resolution applied to the complementarity analysis.

Previous work has demonstrated that wind and PV generation are temporally staggered in many regions across the United States (Takle and Shaw 1979; Solomon, Kammen, and Callaway 2016; Slusarewicz and Cohan 2018; W. Li, Stadler, and Ramakumar 2011; Nikolakakis and Fthenakis 2011; Clark et al. 2022), which indicates high wind-PV complementarity. Separate work under this project presented the first national-scale, high spatial fidelity, systematic analysis of the temporal complementarity of U.S. wind and solar resources based on *hourly* generation profiles (Harrison-Atlas et al. 2022). Using coincident generation profiles from advanced solar photovoltaic (PV) and wind technologies, the authors evaluated the temporal complementarity of wind and PV resources across seven years of weather data (2007–2013) and four complementarity metrics.

The results from Harrison-Atlas et al. (2022) yielded many key findings. Evaluating the hourly complementarity of wind and PV capacity factors based on various statistical correlation metrics (Pearson, Spearman's rank, and Kendall's Tau) and the stability coefficient yields similar findings in terms of which regions indicate the greatest wind-PV complementarity. The central United States consistently indicates the greatest wind-PV complementarity (or anticorrelation), whereas mountainous regions typically involve a lower degree of wind-PV complementarity. These results are consistent across monthly and annual timescales; across resource data for all weather years; and for the multiple wind tower heights considered by Harrison-Atlas et al. (2022).

1.2 Report Outline

In this report, we build on the previous literature by evaluating temporal complementarity based on high-resolution spatial data that spans the contiguous United States, three VRE resource types, two distinct metric formulations, and multiple timescales. In particular, we evaluate both the Pearson correlation coefficient and the stability coefficient, which allows us to gauge the consistency of findings across multiple complementarity metrics. Ultimately, the full suite of results and discussion reveal which resource pair or pairs indicate the greatest potential for beneficial hybridization in each region of the United States—this ultimate finding is based on the complementarity of the underlying resource pairs, but we further discuss the additional information needed to understand economic potential.

Section 2 summarizes the methodologies employed in this study, including methods for producing spatially and temporally aligned generation profiles for each VRE resource with high spatial resolution (2-km x 2-km resolution and individual dams), as well as the complementarity metrics employed. Section 3 presents complementarity metric results for all resource pairs and regions of the contiguous United States. We discuss the implications of our complementarity analysis results in Section 4, and we conclude in Section 5. The appendices provide additional details regarding the development of hydropower generation profiles and access to the full suite of complementarity results.

2 Methods

In this section, we describe our approach to evaluating complementarity of VRE resource pairs that are relevant for the FlexPower concept. Our broad spatiotemporal analysis evaluates the local complementarity of resource pairs across the contiguous United States, including combinations of wind, NPDs, EHDs, and PV. The general approach involves evaluating correlations between, as well as variance reduction that can be achieved through, the combination of pairs of colocated VRE resources (Figure 2). We evaluate complementarity metrics over *daily* timescales using both daily aggregated resource data as well as a metric that is designed to capture variability in hourly generation over the course of a day.

Sections 2.1 and 2.2 present our approaches for developing generation profiles for each VRE resource with high spatial (2-km x 2-km and individual dams) and temporal (hourly) resolution. Section 2.3 describes our approach for spatially and temporally aligning generation profiles for all three VRE resources, as well as the underlying calculations for evaluating the complementarity of each pair of resources over monthly and annual timescales.

2.1 Wind and Solar Generation Profiles

We calculate wind-PV capacity factors using representative configurations for each of the underlying technologies (Table 1). Adopting the same PV and wind configurations at all locations enables us to compare performance across space and time while holding the technology constant.

These PV and wind system configurations are input into the Renewable Energy Potential (reV) model (Maclaurin et al. 2019), which estimates potential electrical output across broad geographic extents. The reV model uses the System Advisor Model (SAM) to estimate system performance at each location (Freeman et al. 2018). The resulting capacity factor time series data are useful for comparing regional resource quality, for estimating the technical potential for solar and wind systems, as well as for evaluating the temporal complementarity of generation profiles.

Table 1. Underlying wind and PV technology definitions for our complementarity analysis

	Wind	PV
Technology Type	Advanced Onshore Wind Turbine	Monofacial 1-axis tracking (no tilt)
Component Sizing	7-MW Turbine 135-m hub height 200-m rotor diameter	PV panel capacities are sized at 1.3x the inverter capacity (i.e., DC/AC ratio of 1.3)
Inverter Characteristics	N/A	96% efficiency
Losses	9.4% (net), which reflects wind turbine availability, electrical losses, wake effects, turbine performance, environmental losses (blade coatings, cleaning, cold weather packages) and curtailment (Clifton, Smith, and Fields 2016)	14.08%, which reflects soiling, shading, inverter mismatch, wiring and connection losses, light-induced degradation, and nameplate losses and availability (Freeman et al. 2018)

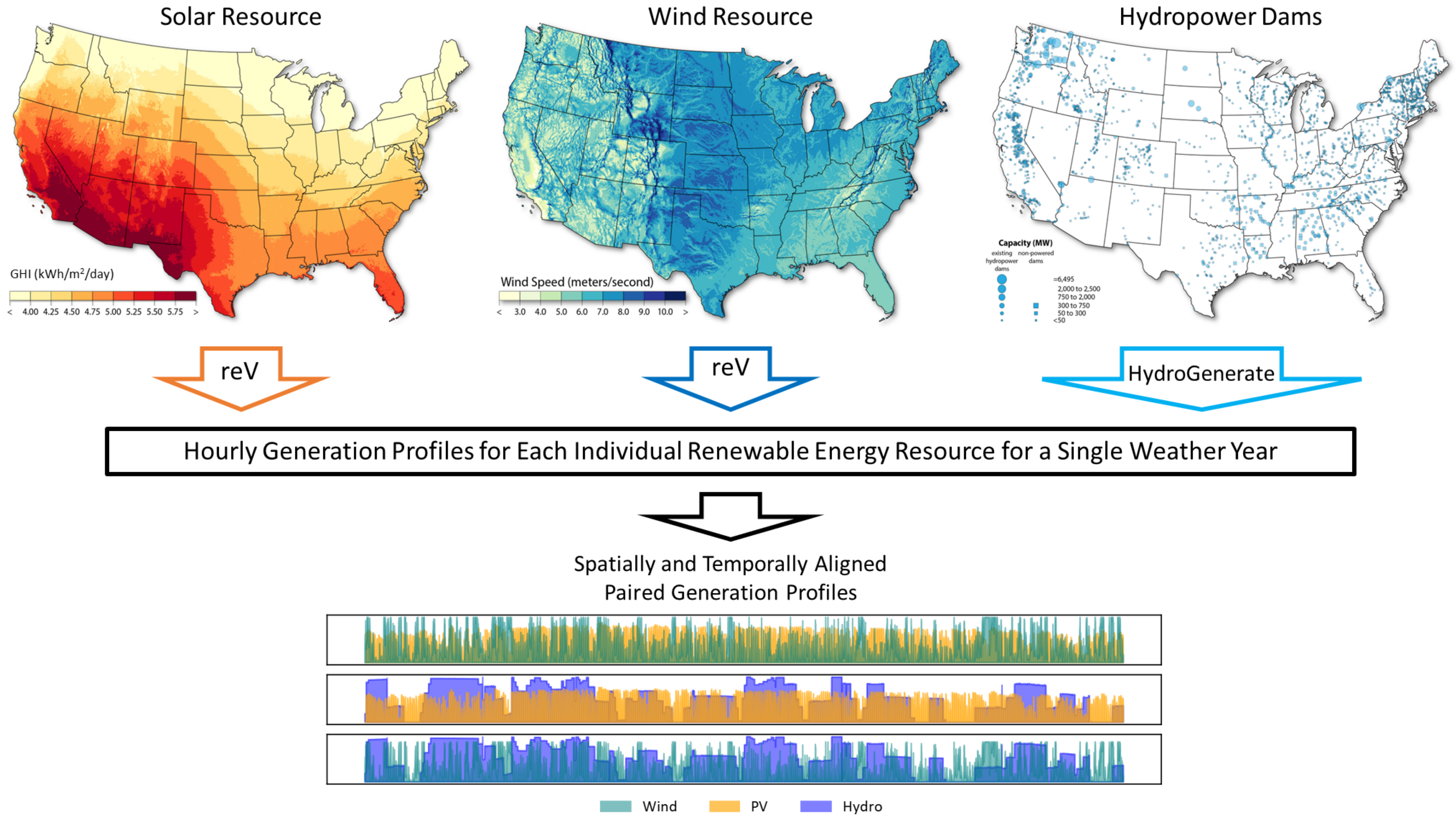

Figure 2. An illustration of our approach to evaluating correlations between, as well as variance reduction associated with, the generation of colocated VRE resource pairs

GHI = global horizontal irradiance; reV = Renewable Energy Potential model.
The bottom panel presents an overlay of hourly capacity factors for each pair of VRE resources for one weather year, based on the location of a non-powered dam in northern Florida.

In addition to requiring information about system configurations, highly resolved spatiotemporal solar and wind resource data sets serve as inputs for the reV model. For calculating PV capacity factors across the country, the National Solar Radiation Database (NSRDB) is used to represent solar resource (Sengupta et al. 2018). The NSRDB is a spatiotemporal time series data set that provides numerous weather variables at half-hour resolution and 4-km spatial resolution. The reV model calculates PV generation at a location based on many variables in the NSRDB, including direct normal irradiance, diffuse horizontal irradiance, air temperature, and wind speed.

To estimate potential wind capacity factors across the country, we rely on the Wind Integration National Dataset (WIND) Toolkit as a high-fidelity representation of wind resource (Draxl et al. 2015). The WIND Toolkit provides modeled hourly weather variables at 2-km spatial resolution for the contiguous United States. The reV model computes wind power generation based on many variables in the WIND Toolkit including wind speed, pressure, and temperature (at 135 meter hub height for the present analysis).

The reV model produces time series profiles of generation for each location, and the temporal resolution of the reV outputs is determined by the granularity of the resource data. For example, the half-hour resolution of the NSRDB data set translates to 17,520 electrical output time-steps in a representative year while the hour resolution of the WIND Toolkit data set yields an output time series of 8,760 time steps. We standardize the absolute instantaneous electrical output at each time-step by deriving the system's capacity factor, which ranges from 0 to 1 and represents how fully a system's peak capacity is used over a given period. For this analysis, our wind and PV resource information is based on 2012 weather data.

2.2 Hydropower Generation Profiles

The hydropower generation profiles are produced using the open-source tool HydroGenerate (Mitra et al. 2021). Figure 3 presents a high-level overview of (and Appendix A details) the methods implemented to obtain a database that relates the discrete location of dams to associated hydropower generation profiles, which are compatible with the PV and wind generation time series data described in Section 2.1.

In HydroGenerate, the hydrological data are specified as a flow time series in units of cubic feet per second (cfs). Normally, the flow duration curves in a hydropower resource assessment are created using approximately 10 years of data, but in this analysis, the hydrological input data are based on a representative year for each site. The representative year for each site was determined by computing the median flow of the available data for the years 2010-2020 (which contain the smallest number of missing values) and choosing the year for which the yearly mean was closest to the median value. A single year may not be sufficiently representative, particularly given the dynamics of interannual variability in precipitation, leading to "dry" and "wet" years.

The corresponding output from HydroGenerate is a power generation time series in megawatts (MW). There is no minimum number of data points required (like in the case of a flow-duration curve), nor is there a time step resolution constraint, given that there is no dependency between each time step. The formulation computes an estimate of the power generation for a given turbine type, based on a flow data point and head height value. The calculation can be further informed by inputs such as the nameplate capacity of the turbine, which is especially useful for EHDs or NPDs where such a value exists. Based on these variables, HydroGenerate produces a hydropower generation profile that is consistent with normal operations and avoids excessive generation for periods of outlier flow values.

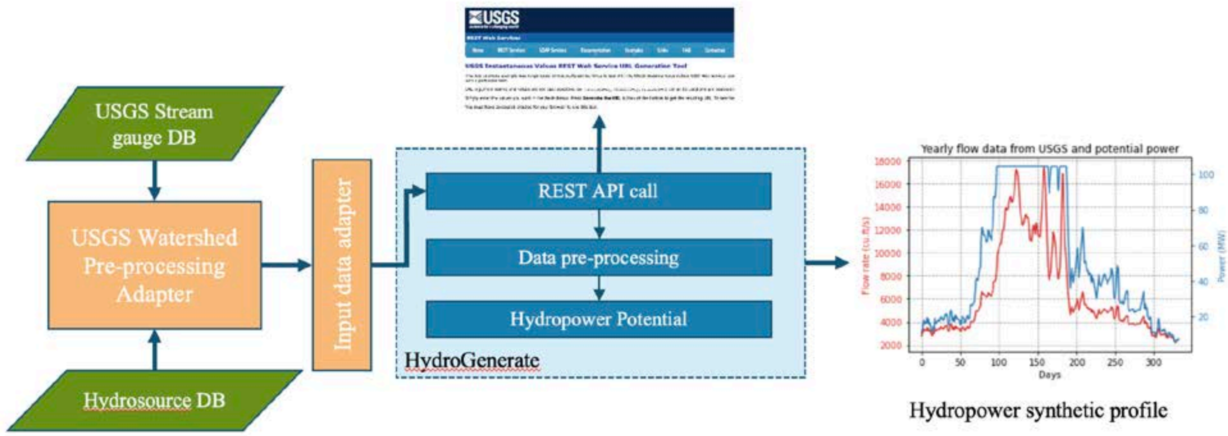

Figure 3. Workflow for creating NPD and EHD generation profiles for complementarity analysis

Unlike the methods for wind and PV generation (which assume a standard technology configuration), there is no specific technology or configuration of subcomponents defined for the hydropower analysis. The heterogeneity of the hydropower resource and varying range of capacities make such a determination nearly impossible. Instead, we assume a system that contains a penstock leading to a turbine, where the type depends on the size of the head height, unless provided.

This workflow (Figure 3) produces a time series that contains flow rate and estimated power at 15-minute intervals. Further post-processing is conducted to (a) resample the time series to hourly values (based on the mean of the 15-minute data points) and (b) compute the capacity factor using the recorded capacity (in MW) for each NPD and EHD. It is important to note that the need to limit our analysis to dams with nearby USGS stream gauges and adequate flow data means that we only evaluate dams that represent 11% of NPD capacity (based on assumed dam characteristics) and 3% of EHD capacity in the contiguous United States.

2.3 Complementarity Analysis

To evaluate temporal complementarity, the time series profiles for electricity output from each resource must match in their spatial and temporal resolution. Temporal alignment is achieved by matching the time-steps for wind, PV, and hydropower generation. Spatial alignment of the wind and solar data sets is achieved using the nearest neighbor relationship, which results in nominal 2-km x 2-km grid cells; spatial alignment with hydropower is achieved by performing a spatial join between these grid cells and discrete locations for each NPD and EHD site.

These time-synchronized, spatially aligned data yield for a location a set of paired generation profiles:

$$\left\{\left(g_1^s, g_1^{s'}, \cdots, g_n^s, g_n^{s'}\right)\right\} \tag{1}$$

where g_t^s and $g_t^{s'}$ are hourly generation time series for the pair of resources being considered. In addition, for the correlation analysis outlined below, we aggregate the generation time series to produce an equivalent time series for each resource type that describes its daily average output. Throughout, we use capacity factors to standardize generation time series to a range between 0 and 1.

In this study, we focus on two complementarity indicators—the Pearson correlation coefficient and the stability coefficient—which are summarized in Table 2 and detailed in Appendix B. The Pearson correlation coefficient is the most commonly applied metric for assessment of complementarity (Jurasz et al. 2020), and it takes the form of a statistical correlation. We evaluate the Pearson correlation using the daily aggregation of the generation time series described above. Using the daily average capacity factor allows us to answer the question of whether a sunny day tends to be a low or high wind (or hydropower) day and vice versa; by contrast, examining correlations using *hourly data* would tell us whether a sunny hour tends to be a low or high wind (or hydropower) hour and vice versa.

Though statistical correlations offer foundational insights into associations between the generation potential of different VRE sources, they are an incomplete indicator of the potential benefits of hybridization. For example, resources may appear complementary even if the quality of the resource is insufficient for practical utilization; in this case, hybrid systems would appear to be strongly synergetic even if their absolute generation potential is low (Sterl et al. 2018). Conversely, a location with consistently strong winds throughout the day and night may not be highly rated in terms of its complementarity with solar, even though the wind offers sufficient generation at night and could compensate for the lack of PV production during those hours. Relatedly, focusing on the average quality of a VRE resource (as measured through its annual capacity factor) could preclude certain sites as candidates for a hybrid system despite having robust temporal synergy (e.g., in cases where a single technology such as wind or PV may not be viable if considered as an independent system).

Table 2. Summary and Description of Complementarity Metrics Evaluated in this Report

General Characteristics			Specific to the Formulation in This Report
Metric	**What it Measures**	**Interpretation**	**Insights Provided**
Pearson correlation coefficient	Strength of the linear association between pairs of VRE generation profiles	-1 = perfect complementarity 0 = no correlation +1 = perfect synchrony (or lack of complementarity)	Whether production from each resource tends to occur on the same *day* or on different *days*
Stability coefficient	Reduction in the coefficient of variation for the capacity factor of a hybrid system relative to that of a standalone VRE generator	+1 = complete mitigation of variability from the underlying VRE generation profile (i.e., flat-block generation) 0 = no reduction in variability through hybridization	The extent to which hybridizing VRE generators of comparable nameplate capacities can reduce plant-level variability, compared to a *standalone PV or wind* plant at the same location

The stability coefficient overcomes these limitations of the Pearson correlation by quantifying the reduction, over the course of a day, in the coefficient of variation for the *hourly* capacity factor of a hybrid system relative to a standalone VRE generator. Our consideration of the stability coefficient allows for a deeper assessment of the potential synergies between VRE resource pairs, in that it accounts for the quality (or strength) of each component resource. In evaluating the stability coefficient, we assume a one-to-one capacity ratio for a given resource pair (i.e., equal amounts of PV and wind capacity or PV and hydropower capacity, independent of the site-specific capacity factors).

By definition, locations with higher stability coefficients (for a given pair of VRE resources) are those in which a hybrid plant's production could approach a flat-block generation profile. The most common baseline over which to evaluate the stability coefficient is that of PV production, which has the benefit of a relatively predictable diurnal production pattern. This is the approach employed for wind-PV, NPD-PV, and EHD-PV hybrid systems in this report. We also present stability coefficient results for NPD-wind and EHD-wind hybrid systems, for which the wind generation profile is used as the baseline.

Together, the combination of daily Pearson correlation coefficient and stability coefficient results reveals unique complementarity insights based on statistical correlations and reduced variability of combined output (relative to a single VRE baseline). We hypothesize that obtaining qualitatively similar results across different metrics could increase the robustness of our findings and broaden support for hybrid synergies, while discrepancies would require further investigation. At the same time, we exclude additional statistical correlation metrics (e.g., Kendall's Tau, Spearman's Rank) because recent research indicates similar insights are derived across the multiple formulations (Harrison-Atlas et al. 2022).

3 Results

In this section, we present the results of our temporal complementarity analysis for all metrics and VRE resource pairs evaluated. To visualize temporal complementarity throughout this report, we use dark blue shading to indicate greater degrees of complementarity, which is most consistent with the vision of the FlexPower concept. For the Pearson correlation coefficient, dark blue shading (or a negative value) indicates that the *daily* generation profiles for the two resources are anticorrelated, or tend to be out of sync; for example, days with high PV output tend to have low wind output and vice versa. For the stability coefficient, dark blue shading (or a value approaching 1) indicates the combined output of the colocated resources is approaching a "flat block" profile, such that generation of comparable strength is available during most hours of the day (throughout the year). We refer to larger stability coefficient values (e.g., > 0.5) as complementarity between two resources, which corresponds to the combined output from a pair of colocated resources being significantly less variable than the output of a single VRE (e.g., PV) baseline.

By contrast, red shading indicates a lack of complementarity, such that *daily* output from each VRE resource is synchronous—days with low/high output of one resource type also tend towards having similarly low/high output of a different resource type. This corresponds to a positive correlation and a positive value for the Pearson correlation. Finally, white shading indicates a lack of correlation, which generally means a windy day has roughly equal chances of being either sunny or overcast, and a sunny day has roughly equal chances of having low or high generation at a colocated NPD or EHD.

The figures presented in this section summarize complementarity across all resource pairs: shading in the base map indicates wind-PV complementarity, whereas the shading of square (circle) symbols indicates the complementarity of an NPD (EHD) and either wind or PV. The smaller yellow circles correspond to dams for which flow data were incomplete or inadequate; these dams were not included in our complementarity analysis.

3.1 Pearson Correlation

Figure 4 presents the Pearson correlation coefficient results for all pairs of wind, NPD, EHD, and PV, based on daily average capacity factors for each resource. This figure reveals that the Pearson correlation coefficient is near-zero in many regions of the United States for all resource pairs, which means daily average VRE capacity factors are only *slightly* correlated or anticorrelated with one another.

Zooming in on colocated wind and PV resources (base map), complementarity patterns are complex and geographically variable. Some regions indicate strongly positive correlations between colocated wind and PV generation (like the southwestern United States, Washington, Kansas, and South Texas); in other words, high-wind days tend to be sunny, and low-wind days tend to be cloudy. These patterns primarily reflect the effect of considering daily average PV output, which reduces the influence of the diurnal cycle of PV generation in terms of its complementarity with wind power.

We find evidence for daily wind-PV complementarity (darker blue shading) in much of the Pacific Northwest, Northern Rockies, and along the Sierra Nevada, with more modest complementarity (lighter blue shading) in non-coastal portions of the Eastern United States. There appears to be a general lack of correlation between the daily average capacity factors for colocated wind and PV resources in the central United States and along the East Coast, when looking across the entire year.

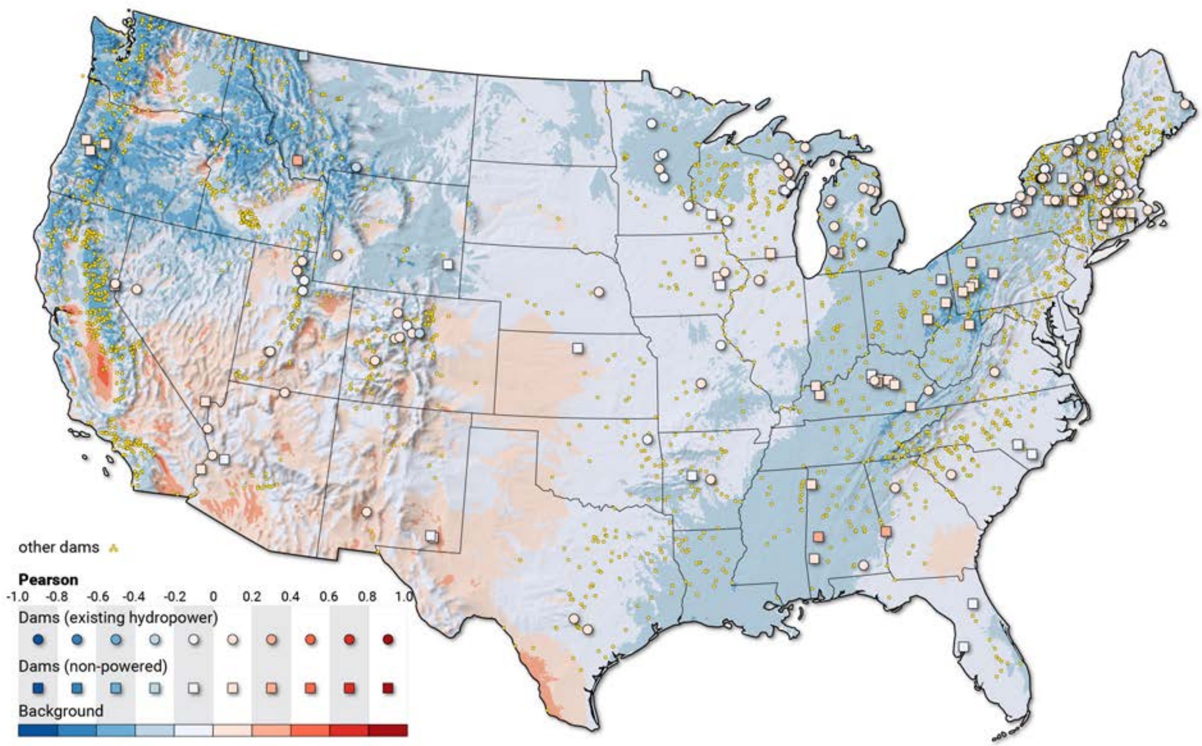

Figure 4. Daily Pearson correlation coefficient results for wind-PV (base map), NPD-wind (square symbols), and EHD-wind (circle symbols), where darker blue shading indicates greater complementarity over the course of a year

Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

The symbols in Figure 4 and Figure 5 present hydropower-wind and hydropower-PV complementarity (respectively), with the larger symbols representing individual NPDs (squares) and EHDs (circles) with adequate flow data for evaluating complementarity. In general, we observe limited daily complementarity between the evaluated hydropower dams and colocated wind: most symbols in Figure 4 having a very light shading, and darker red symbols (e.g., in Montana and the Southeast) indicate overlap in the days with strong (or weak) wind and hydropower output. Only a handful of dams in the western United States indicate modest complementarity (anticorrelations) in wind and hydropower generation, based on the daily Pearson correlation coefficient.

Nationwide, the daily complementarity signal is also largely muted for colocated hydropower and PV (Figure 5), though notable exceptions are found in the western United States. Interestingly, the NPD in southern Montana that indicated a relatively strong positive correlation (lack of complementarity) with wind has a relatively strong *anti*correlation (complementarity) with PV. Another NPD near the border of Nevada and Arizona also indicates strong complementarity with PV. The other strong signals in the western United States take the form of strong positive correlations, particularly in Northern Utah.

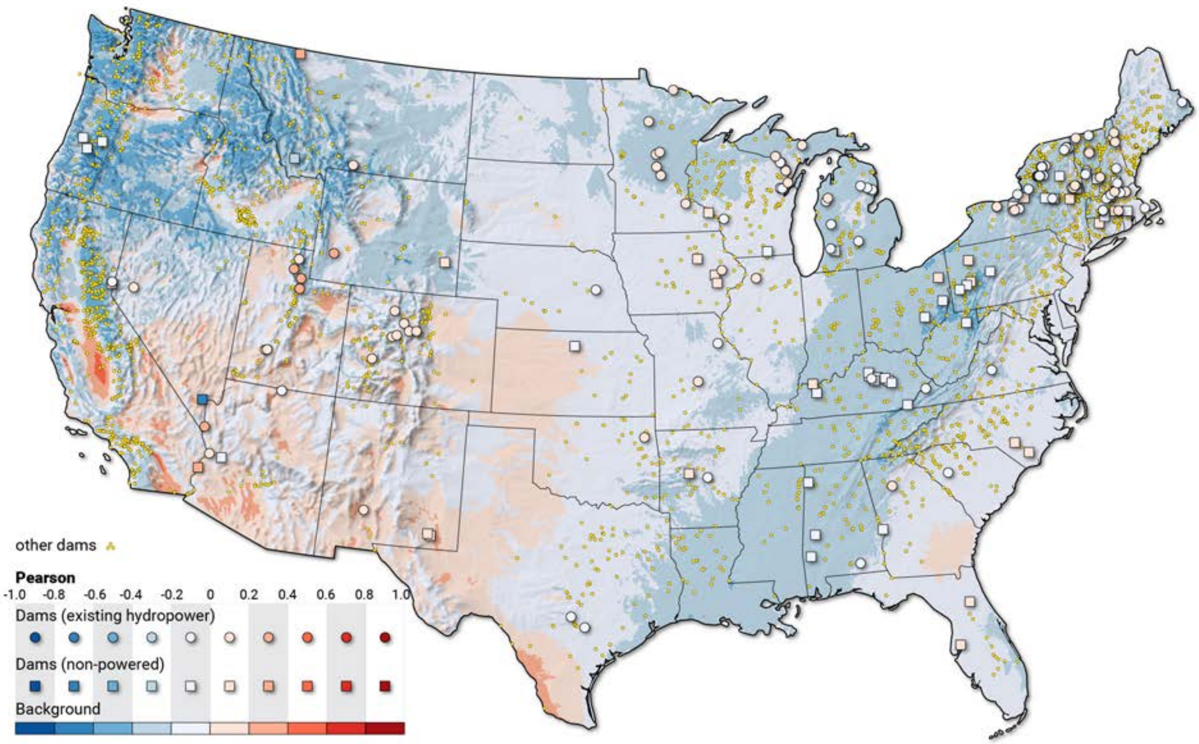

Figure 5. Daily Pearson correlation coefficient results for wind-PV (base map), NPD-PV (square symbols), and EHD-PV (circle symbols), where darker blue shading indicates greater complementarity over the course of a year

The base map in Figure 5 is identical to the base map in Figure 4; it is only the hydropower symbols that differ between the two figures. Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

3.2 Stability Coefficient

The stability coefficient also evaluates complementarity over the course of a day, but it is rooted in hourly generation profiles. In turn, the stability coefficient quantifies the extent to which adding a VRE resource helps smooth the variability of another VRE resource of comparable size (in this analysis) over the course of a day. Regions with higher stability coefficient values are those in which a hybrid plant's production could approach a flat-block generation profile. Recall that evaluating the stability coefficient with a PV-only baseline has the benefit of a characteristic diurnal production pattern; this is the approach employed below for wind-PV, NPD-PV, and EHD-PV resource pairs, as presented in Figure 6.

Considering first colocated wind and PV resources (base map in Figure 6), we find that the stability coefficient values primarily range from 0.3 to 0.7 on an annual basis; this indicates that combining wind and PV resources drives a reduction in variability throughout much of the United States. The highest wind-PV stability coefficient values occur in the wind belt (including Texas), the Midwest, California's Central Valley, the Eastern Seaboard, and pockets throughout the Northeast. In many of these regions, PV capacity factors are lower than wind capacity factors, so the ability of colocated wind to influence the variability of the combined wind-PV output is relatively enhanced.

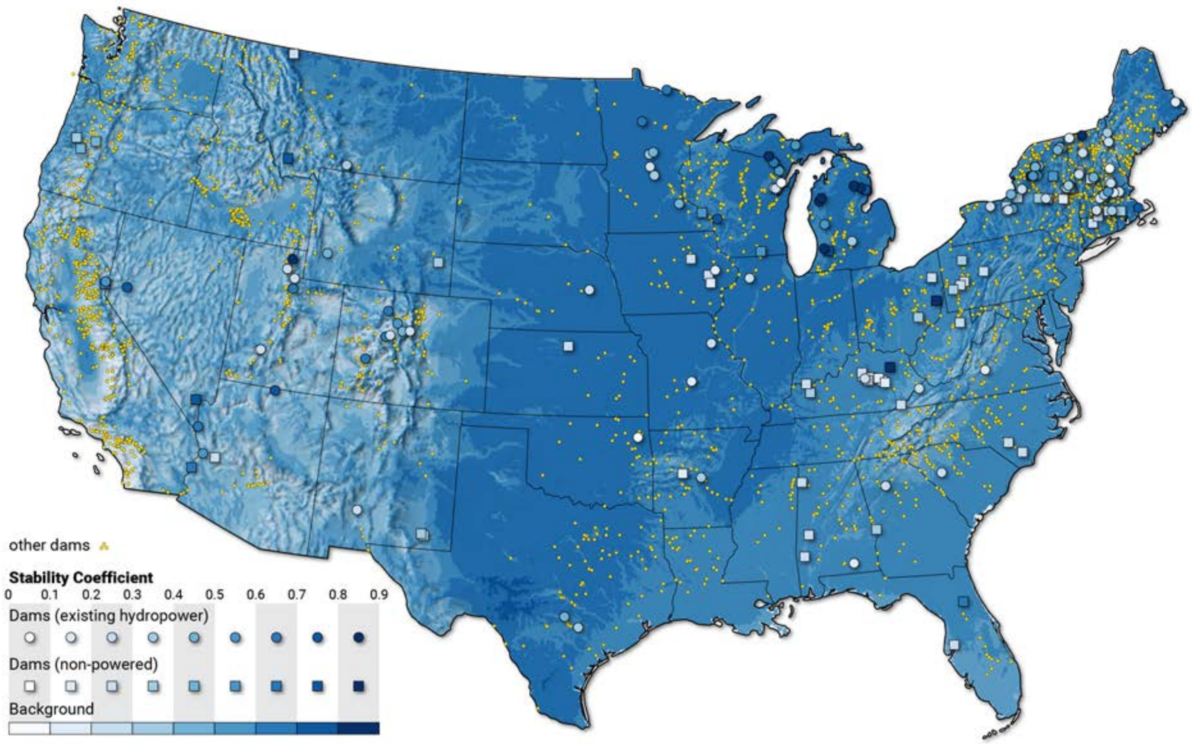

Figure 6. Stability coefficient results for wind-PV (base map), NPD-PV (square symbols), and EHD-PV (circle symbols), where darker blue shading indicates greater complementarity

Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

The lowest stability coefficient values for colocated wind and PV are observed in the mountainous regions of the western United States. A similar spatial pattern is also observed for hourly statistical correlation metrics (Harrison-Atlas et al. 2022), which indicates that the trend reflects a greater degree of overlap in the timing of wind and solar generation (i.e., the two hourly generation profiles tend to be more aligned than staggered) in the Western United States.

The symbols in Figure 6 present similar results in terms of reductions in the variability of combined output from colocated hydropower and PV (compared to that of standalone PV). Compared to the daily Pearson correlation coefficient results in Figure 5, we observe stronger signals in terms of hydropower's ability to mitigate the variability of colocated PV at individual dams scattered throughout the country (darker blue symbols in Figure 6) when accounting for hourly generation patterns. Hydropower-PV complementarity is often more muted, with white symbols indicating a given NPD or EHD does not meaningfully reduce variability in PV output; but it exceeds wind-PV complementarity in select locations (i.e., darker symbols overlaying a lighter base map).

Focusing on hydropower dams with stability coefficients greater than 0.5, we find 11 NPDs nationwide (totaling 131 MW of capacity) that significantly mitigate variability in the output of colocated PV. Hydropower-based complementarity is more pronounced for EHDs—as indicated by the presence of darker blue *circles* in Figure 6. We find 42 EHDs that have a stability coefficient value that exceeds 0.5 when considering colocated EHDs and PV; those 42 dams represent 1,937 MW of hydropower capacity, over half of which is from the Glen Canyon Dam (1,312 MW). The remaining EHDs that indicate complementarity with colocated PV are located throughout the western United States and in the northern latitudes of the Eastern Interconnection, including the Midwest, New York, and New England.

Finally, Figure 7 presents stability coefficient results for resource pairs including wind. In this figure, the symbols involve a wind baseline, such that they represent hydropower's ability to reduce the variability in output from colocated wind. In general, we observe more-muted complementarity for colocated hydropower and wind. This trend likely reflects the more complex weather patterns that drive wind generation, which does not follow a predictable diurnal cycle.

There are 16 EHDs with a stability coefficient value that exceeds 0.5 when considering colocated EHDs and wind, totaling 1,546 MW of hydropower capacity (Figure 7). Beyond Glen Canyon Dam, the EHDs that exhibit complementarity with the colocated wind resource are concentrated in the west and in Michigan. Comparing the results of Figure 6 and Figure 7, we find a larger *number* of NPDs indicate greater complementarity with colocated PV (11 dams) than with colocated wind (4 dams), but comparable amounts of NPD *capacity* indicate complementarity with colocated PV (131 MW) and wind (97 MW).

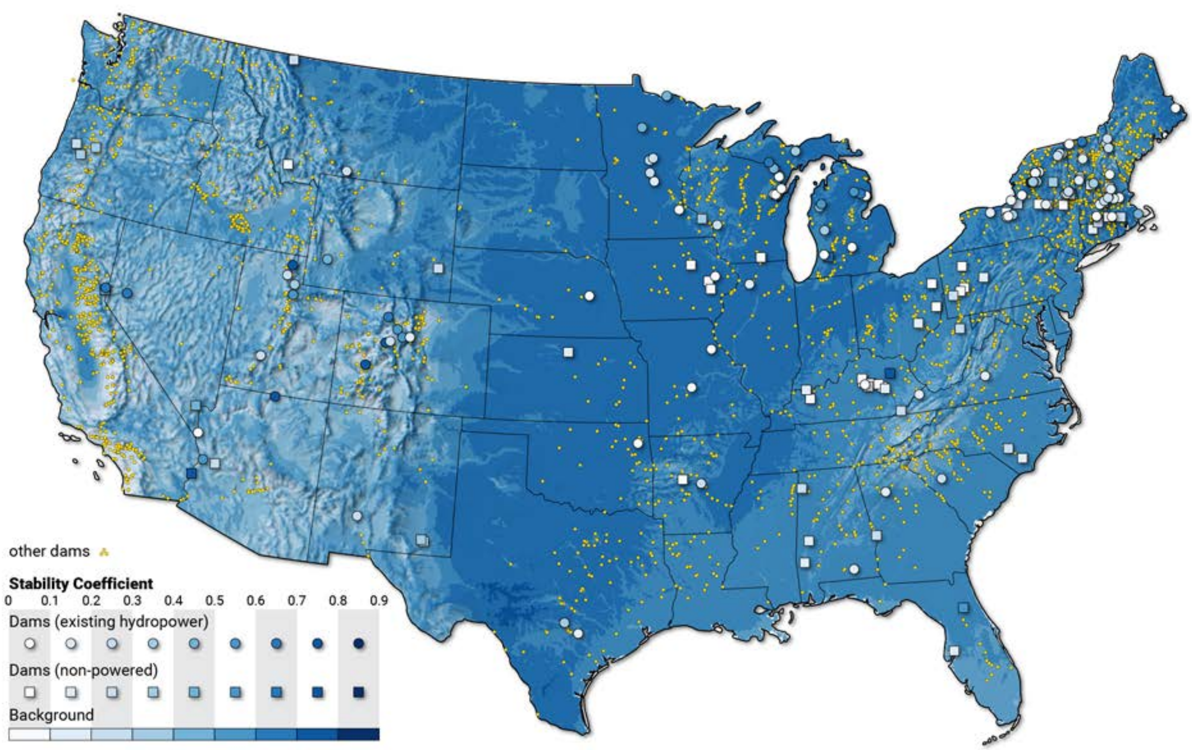

Figure 7. Stability coefficient results for wind-PV (base map), NPD-wind (square symbols), and EHD-wind (circle symbols), where darker blue shading indicates greater complementarity

The base map in Figure 7 is identical to the base map in Figure 6; it is only the hydropower symbols that differ between the two figures. Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

4 Discussion

In this section, we discuss some of the implications of our complementarity analysis. In Section 4.1, we compare the insights that can be derived from the separate metrics presented in Section 3. In Section 4.2, we present subannual results to explore seasonal aspects of complementarity. In Section 4.3, we explore regions that indicate complementarity among all evaluated resource pairs. In Section 4.4, we discuss unique considerations for hydropower-based hybrid systems. In Section 4.5, we describe additional sources of information that would be needed—together with complementarity—to derive more comprehensive insights regarding investment decisions in renewable energy-based hybrid systems.

4.1 Insights From Across Metrics and Timescales

The insights that can be derived from the daily Pearson correlation coefficient are highly nuanced. First and foremost, the Pearson correlation coefficient results depend on the timescale associated with the average capacity factors used to evaluate the metric. Indeed, the daily wind-PV Pearson correlation results presented in this report (Figure 4) involve complementarity patterns that differ from those associated with the *hourly* Pearson correlation coefficient (Harrison-Atlas et al. 2022), the latter of which more closely resemble the stability coefficient results presented in this report (Figure 6).

Regions that indicate complementarity between pairs of wind, hydropower, and PV technologies based on the daily Pearson correlation are those in which a hybrid power plant could involve more-consistent levels of generation from day to day; how meaningful (or beneficial) this is depends on many factors, including the relative strengths of each resource. However, the Pearson correlation coefficient does not take into account the relative strengths of the two resources being evaluated—so, a location with a stronger "complementarity" signal from the Pearson correlation coefficient could involve one resource producing significantly more generation than the other, as long as the generation is not overlapping in time.

By contrast, regions with positive daily Pearson correlation coefficient values indicate overlap in the days that the resources tend to have stronger output, the implications of which are not necessarily undesirable. Two resources having strong output on a given day could be beneficial, as long as (a) the *hours* of strong generation do not overlap and (b) demand for electricity is also high on that day. For example, a positive *daily* Pearson correlation would be favorable if the relatively strong wind production occurs during non-daylight hours, especially on days with higher electricity demand. This dynamic could be evaluated by combining Pearson correlation coefficient results based on daily average capacity factors (in this report) and *hourly* average capacity factors (in Harrison-Atlas et al. 2022), which would likely produce more meaningful insights, particularly for wind-PV hybrids.

For regions that indicate positive daily Pearson correlations *and* large stability coefficient values, the latter signal is likely a more meaningful indicator. In general, our analysis of the stability coefficient offers a clearer picture of complementarity, in part because it is rooted in higher temporal resolution information. Intuitively, a VRE resource with strong production during non-solar hours will likely have greater complementarity with colocated PV; however, the stability coefficient value further depends on the relative strengths of the two resources being evaluated. In other words, the stability coefficient for colocated wind and PV would be *low* if the wind resource only generated during non-solar hours but the wind output (based on the same nameplate capacity) was significantly lower or significantly higher than the PV output. This scenario may partially explain the lower wind-PV stability coefficient values in the Southwest, where the capacity factor for PV is greater than that of wind. However, the similar patterns observed for the *hourly* Pearson correlation coefficient (Harrison-Atlas et al. 2022) and the stability coefficient (Figure 6) indicate that the pattern in the Southwest is likely rooted in a lack of correlation in the timing of hourly generation from colocated wind and PV resources in this region.

4.2 Complementarity Across Seasons

To this point, our discussion has focused on complementarity evaluated over the course of one year. However, the underlying weather that drives wind, solar, and hydropower generation (and, in turn, complementarity) varies subannually. Evaluating complementarity over shorter timescales can allow for more-detailed analysis of the periods that are of greatest interest; this could correspond to the periods of the year with the highest load (or net load), a history of transmission congestion (or dynamic line ratings), or the strongest complementarity signals.

Figure 8 illustrates the seasonality of temporal complementarity by presenting the stability coefficient results for each month of the year for all resource pairs involving PV. Considering first the stability coefficient for wind and PV (base map in Figure 8), the darker shading and the greater extent of dark shaded regions in the top (January–March) and bottom (October–December) rows indicate greater wind-PV complementarity during the winter months. For most of the country, the warmer months of the year (May–August) indicate lesser wind-PV complementarity, which is likely related to both lower wind capacity factors and greater number of solar hours during the summer months; but it is interesting to note that it is in these months that the *annual* complementarity signals (Figure 6) for the Central Valley of California and southern Texas are rooted.

The temporal complementarity of hydropower and PV (symbols in Figure 8) also varies strongly across seasons, especially in regions with seasonal flows. For example, hydropower dams along the Colorado River and in northern Utah and Colorado indicate limited complementarity with colocated PV during the winter months, when water levels tend to be lower. On the other hand, the same dams indicate very strong complementarity with colocated PV during the spring and summer months, which are the months with the greatest flow rates due to snow melt and monsoon season, respectively. The timing of greater hydropower-PV complementarity (darker symbols) is especially noticeable because it corresponds to periods of lower wind-PV complementarity (lighter base map shading). Seasonality in hydropower's complementarity is similarly observed for (a) colocated PV in the Northeastern United States, albeit with stronger complementarity in the winter months (Figure 8) and (b) colocated wind (not shown), with similar regional trends.

To further visualize the subannual complementarity of hydropower-based hybrids, we rank monthly values of complementarity to find specific locations where hydropower exhibits the greatest complementarity with PV or wind generation. The annual mean of the stability coefficient for each site was considered for binning the data into deciles (0 to 9).

Figure 9 presents the results of this ranking exercise for the best site within each decile, based on the annual mean of the stability coefficient (hence, only 10 lines are shown per facet). The highlighted line with Rank 9 corresponds to the best-performing site overall, and the thin grey line for Rank 0 corresponds to the best-performing site in the lowest decile. Based on this ranking exercise, we find that sites with the "best complementarity" (Rank 9) have an almost constant stability coefficient value that exceeds 0.8 throughout the year, whereas sites with lower ranks display values close to zero for some months.

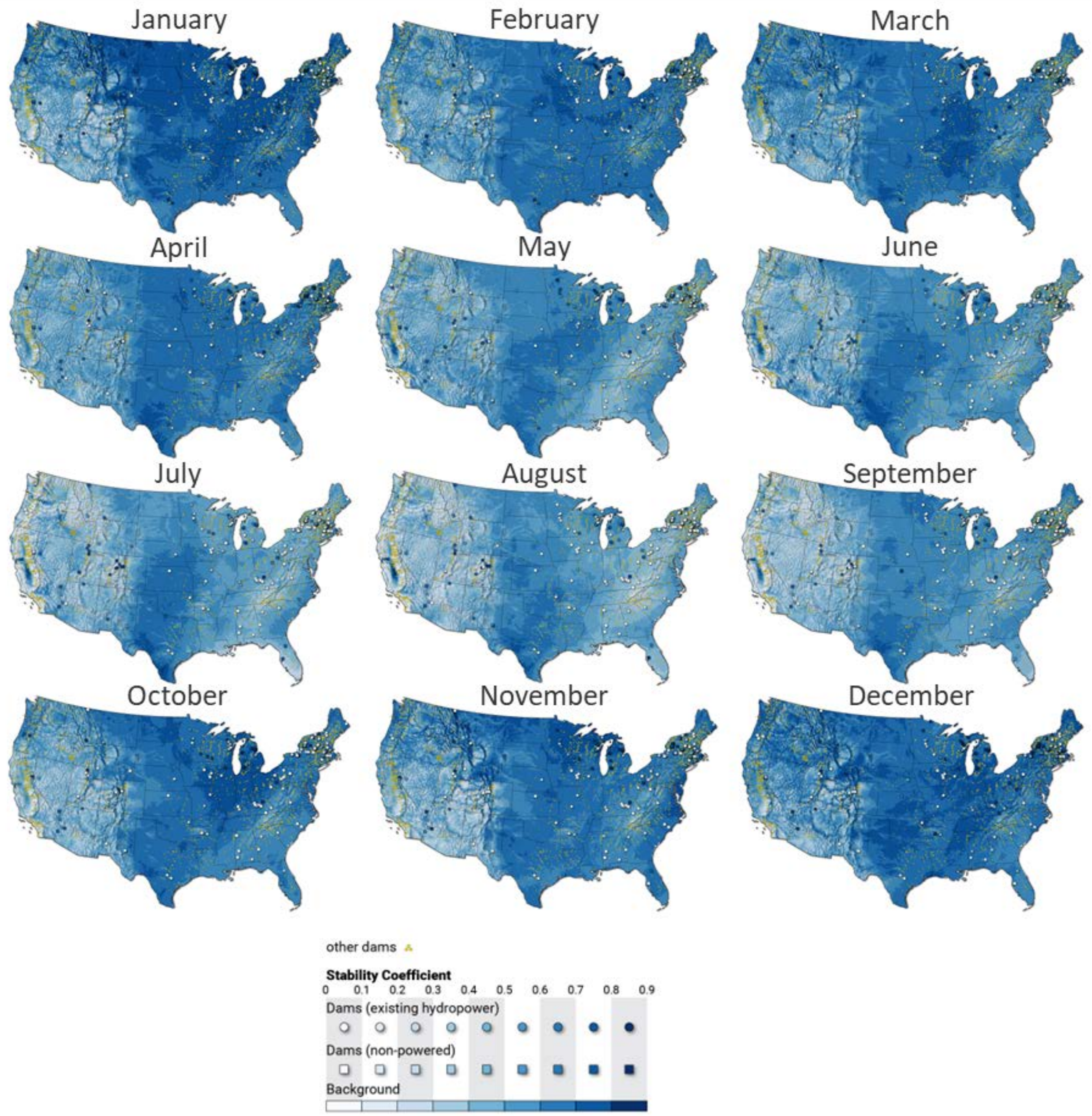

Figure 8. Stability coefficient results for wind-PV (base map), NPD-PV (square symbols), and EHD-PV (circle symbols) for each month of the year

Darker blue symbols and shading indicate greater levels of temporal complementarity as measured via the stability coefficient. Yellow circles represent dams for which flow data were unavailable or inadequate for complementarity analysis.

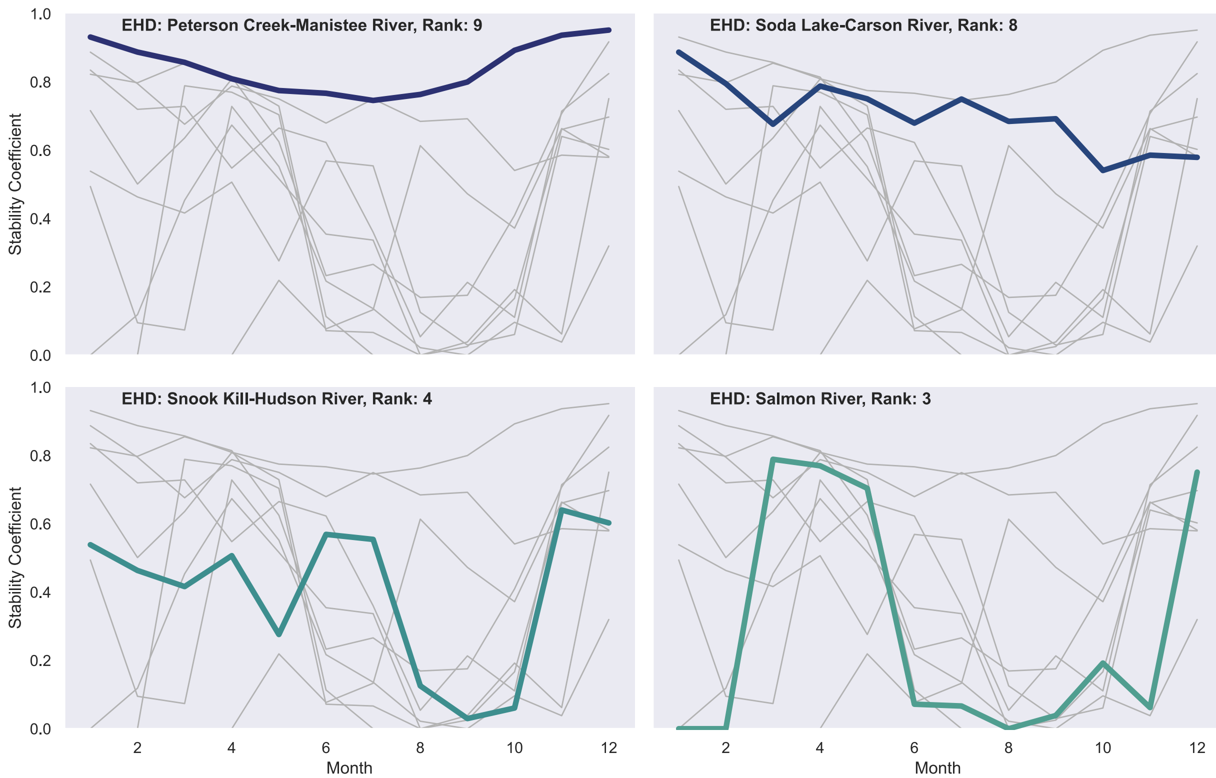

Figure 9. Example of the monthly stability coefficient between hydropower and PV for four existing sites

Each line represents the best site for each decile, based on the annual mean of the stability coefficient (hence, only 10 lines are shown per facet). The highlighted line with Rank 9 (top left) corresponds to the best-performing site overall, whereas the highlighted line with Rank 3 (bottom right) corresponds to the best-performing site in a relatively low decile.

Given these seasonal variations, it is possible that the value of hybrids may be most apparent during particular months of the year, and the resource pairs that offer the greatest complementarity may further depend on the season. There could be significant value in combining seasonal complementarity metric results with corresponding load, transmission rating, and transmission utilization data when evaluating candidate hybrid power plant locations and resource combinations, including both pairs and trios of VRE resources.

4.3 Regional Complementarity Trends Across Resource Pairs

In this section, we synthesize the stability coefficient results presented in Section 3 to identify regional characteristics of complementarity among pairs of wind, PV, and hydropower resources. The goal of this section is to describe which resource pairs could represent promising candidates for the FlexPower concept on a regional basis (and based on complementarity alone). The following discussion is presented by Census region, as illustrated in Figure 10 and summarized in Table 3.

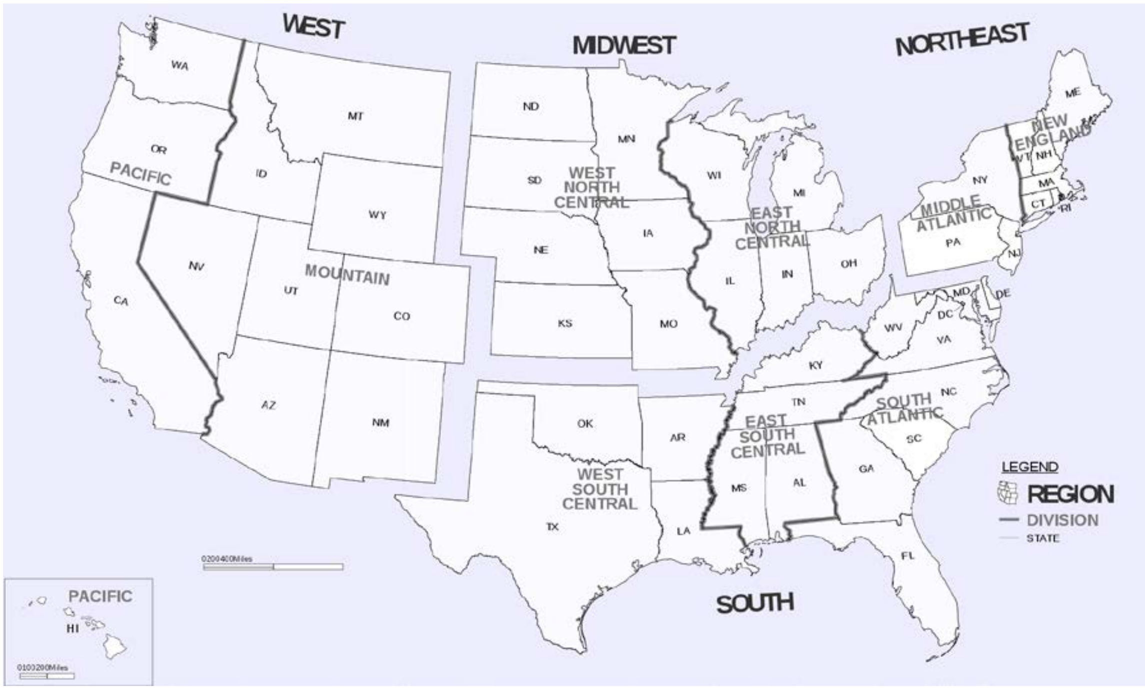

Figure 10**. We use U.S. Census regions to summarize subnational complementarity findings**

Source: (U.S. Census Bureau 2019)

Table 3. Summary of Regional Complementarity Trends

Census Region	Census Division	Regional Complementarity Findings (Annual Results)
West	Pacific	Wind and PV resources in the Central Valley of California are moderately complementary, and there are many dams for which better flow data are needed to facilitate a complementarity assessment
	Mountain	Hydropower dams along the Colorado River, near Tahoe, California, and in northern Utah indicate complementarity with colocated PV, and wind-PV resources neighboring the wind belt are highly complementary
Midwest	East-North Central	EHDs and wind both indicate complementarity with colocated PV
	West-North Central	Wind and EHDs along the Mississippi River in Minnesota both indicate complementarity with colocated PV
South	West-South Central	Colocated wind and PV resources are highly complementary
	East-South Central	Colocated wind and PV resources are highly complementary
	South Atlantic	Colocated Wind and PV resources are highly complementary
Northeast	Middle Atlantic	EHDs and wind both indicate complementarity with colocated PV
	New England	EHDs and wind both indicate complementarity with colocated PV

West Census Region

In the Pacific Census Division, the strongest (albeit complicated) complementarity signal comes from the daily Pearson correlation coefficient for colocated wind and PV resources throughout most of the northern latitudes. In the Central Valley of California, the daily Pearson correlation coefficient indicates significant overlap in the timing of solar and wind production, whereas the stability coefficient indicates that the combined output of colocated wind and PV is significantly less variable than the output of standalone PV in this region. Combining the signals from these metrics reveals that a sunny day in the Central Valley of California also tends to be windy (and a cloudy day tends to be calm), but the wind generation is concentrated in non-solar hours. Throughout the rest of the region, lower stability coefficient values suggest a general lack of wind-PV complementarity based on hourly generation.

In the Mountain Census Division, wind-PV complementarity is concentrated in the easternmost portions of the region (neighboring the wind belt). In the southern latitudes of the region, sunny days tend to be windy (and cloudy days tend to be calm), and the lower stability coefficient values suggest colocated wind does not meaningfully mitigate the variability of solar generation in the region. The relatively muted wind-PV complementarity signal highlights the role of topography in influencing weather patterns that drive the timing and strength of solar and wind resources.

More consistent complementarity signals arise from colocated hydropower and PV—for both NPDs and EHDs—with the strongest signals along the Colorado River, near Tahoe, California, and in northern Utah. The subannual analysis for hydropower complementarity (described above) explains the relatively strong complementarity between EHDs and both wind and PV resources, which is especially pronounced at Glen Canyon Dam (Figure 11). This result suggests the hydropower generation at this dam can mitigate the variability of colocated wind or PV, which represents a somewhat unique regional opportunity because wind-PV complementarity is lower in this area than in other areas of the country.

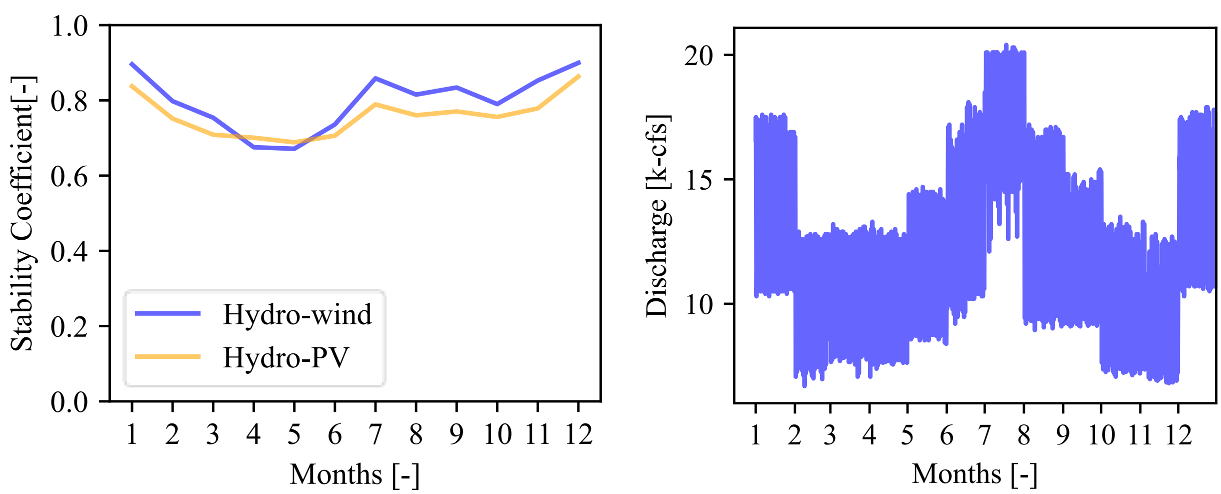

Figure 11. Monthly variation in the stability coefficient (left) and discharge (right) at Glen Canyon Dam, which falls within the top decile nationwide for the stability coefficient with wind and PV.

Finally, it is important to note the large number of dams with inadequate flow data (yellow circles) in this region, which represents the largest amount of EHD capacity (3,769 MW) and a fairly typical number[1] of NPDs (92) (Table 4). In the Pacific Census Division, we only evaluated complementarity for 10% of

[1] NPDs are reported on a counts basis because NPD *capacity* requires assumed dam characteristics.

EHDs (on a capacity basis) and 8% of NPDs (on a counts basis). This points to the need for improved flow and/or generation data to better quantify the complementarity of hydropower-based hybrid configurations. A detailed description of the challenges with hydropower data availability is presented in Appendix A.

Table 4. Summary of Dam Characteristics by Region

Census Region	Census Division	EHD		NPD	
		Total Capacity (MW)	Capacity Evaluated for Complementarity (MW)	Total Number	Number Evaluated for Complementarity
West	Pacific	1183	124	38	4
	Mountain	2586	1705	54	8
Midwest	East-North Central	245	103	43	5
	West-North Central	339	330	44	5
South	West-South Central	96	54	110	1
	East-South Central	66	5	63	15
	South Atlantic	677	37	63	5
Northeast	Middle Atlantic	546	124	80	12
	New England	341	115	19	7

Midwest Census Region

The East-North Central Census Division indicates strong complementarity among multiple resource pairs. The strongest complementarity signal exists between EHDs and PV, although these dams tend to be ≤ 20 MW. The Tippy Dam in Michigan indicates the greatest complementarity with colocated PV, and it has a very high stability coefficient value throughout the year—with a minimum value of 0.7 during the early summer as the flow decreases (Figure 12). This indicates generation from the Tippy Dam could serve to significantly reduce the variability of colocated PV. The addition of wind can also mitigate the variable output of colocated PV, accounting for both the timing and strength of wind generation in this region.

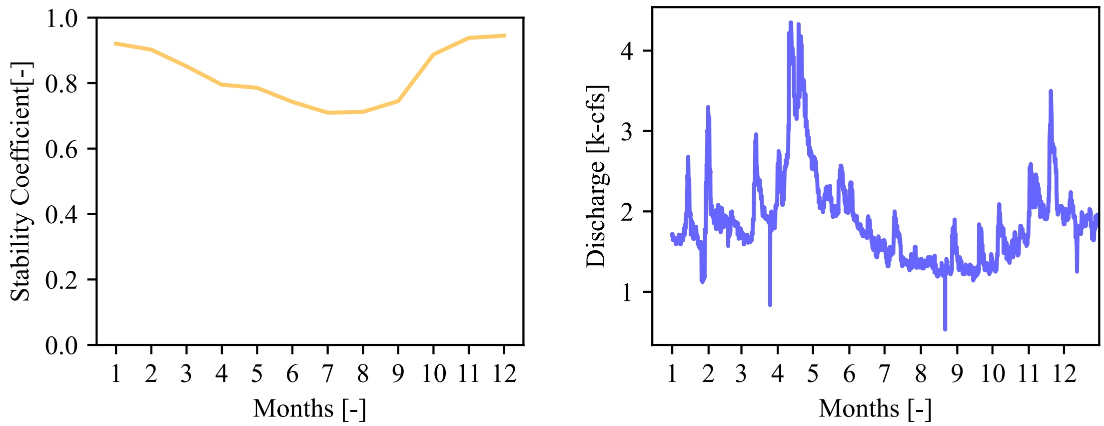

Figure 12. The stability coefficient between hydropower and PV (left) of the top ranked site and the time series for flow (right)

The West-North Central Census Division indicates strong temporal complementarity between wind and PV resources, and a windy day has similar likelihood of being sunny or overcast. Adequate flow data were available for the vast majority (97%) of EHDs in the census division (Table 4), but these dams generally indicate limited complementarity with colocated PV or wind. However, EHDs along the Mississippi River in Minnesota can help mitigate the variable output of colocated PV resources.

In terms of the broader characteristics of the U.S. bulk power system, this region is characterized as (a) straddling the boundary between the Western and the Eastern Interconnections and (b) having lower local electricity demand. The latter characteristic suggests that any candidate hybrid plants would likely require integration into the long-distance transmission network to enable the transport of generation to load centers.

South Census Region

The dominant form of complementarity in the West-South Central Census Division reflects the strong influence of colocating wind and PV, resulting in less-variable output (compared to that of standalone PV). Only five dams have adequate flow data for evaluating complementarity, and there is a significant number of NPDs (>100) for which better data are needed to understand the complementarity potential of hydropower-based hybrid systems in the West-South Central Census Division (Table 4).

In the East-South Central and South Atlantic census divisions, wind-PV complementarity is more moderate, and the number of dams with adequate flow data remains low (Table 4). For many hydropower dams, adequate flow data are unavailable, but select nearby dams (e.g., one in Kentucky and one in Florida) indicate significant complementarity with either colocated PV or wind.

Northeast Census Region

There are many hydropower dams in the Northeast Census Region, and many have adequate flow data to enable complementarity analysis. In general, hydropower is more effective at mitigating the variable output of colocated PV (compared to colocated wind), and the signal from the Pearson correlation coefficient remains muted. The most pronounced complementarity is observed for EHD-PV pairs. In terms of the broader characteristics of the U.S. bulk power system, this region is characterized by higher transmission interconnection costs, which may favor the formation of hybrid power plants at EHDs if capacity is available on their existing transmission and interconnection services.

4.4 Considerations for Hydropower-Based Hybrids

The main driver for deploying hydropower-based hybrid power plants is hydropower's inherent flexibility in operation, which translates into dispatchability and, in some cases, local grid resilience (Shafiul Alam et al. 2022). As VRE resources become more prevalent, utilities and operators are pressed to provide regulated power to ensure a stable load-generation balance. Although hydropower storage is not considered in this study, it can provide storage capabilities, as well as short-, medium-, and long-term power and energy flexibility.

The results presented in this report are limited to those NPDs or EHDs for which data quality allowed for a robust complementarity analysis. Continuous data availability was an issue for this analysis because the synchronicity with the PV and wind series was interrupted by missing values. Locations of dams that were excluded from this analysis indicate possible missed opportunities in the central United States, where the complementarity between wind and PV seems most stable (stability coefficient above 0.6).

There is an almost linear relationship between hydropower's capacity factor and the stability coefficient with either wind or PV (Figure 13), although hydropower-wind complementarity is sparser than hydropower-PV complementarity. The linear relationship between capacity factor and stability coefficient is similarly observed for colocated hydropower-wind and hydropower-PV when evaluating the stability coefficient on a monthly basis (see Appendix A), and a similar relationship is observed for colocated wind-PV as well (Harrison-Atlas et al. 2022).

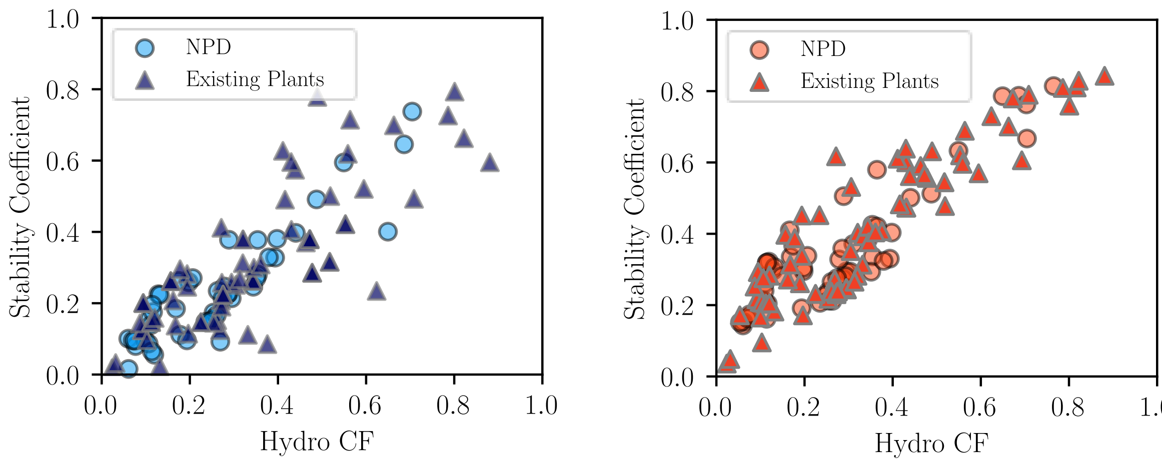

Figure 13. Annual stability coefficient versus hydropower capacity factor for NPDs and EHDs with hydropower-wind (left), and hydropower-PV (right)

No meaningful distinction is observed for NPDs versus EHDs, but results for both hydropower-wind and hydropower-PV combinations indicate significant scatter at lower capacity factors, such that we observe a wide variety of stability coefficient values at a given low-capacity factor value. This indicates the need for site-specific analysis for hydropower facilities with relatively low capacity factors, in order to better understand their potential for smoothing the output of colocated wind or PV. A similar need is implied when considering colocating wind with high-capacity factor hydropower facilities (since the significant scatter extends to high hydropower capacity factors as well), but high capacity factor hydropower plants consistently high stability coefficients with colocated PV. In particular, at least six NPDs could be retrofitted for the purpose of a hydropower-PV FlexPower plant with stability coefficients of 0.6–0.8. Take for example the Otsego Dam, an NPD in Allegan County, Michigan: this dam has a potential capacity of 2.5 MW with a capacity factor of 0.68, and the corresponding stability coefficient values with colocated wind and PV are 0.64 and 0.78, respectively.

Although these results are encouraging, they are not conclusive. In this analysis, we computed the resource complementarity for just one year, which may not be sufficiently representative, particularly given the dynamics of interannual variability in precipitation. Normally, the flow duration curves in a hydropower resource assessment are created using approximately 10 years of data. An analysis of multiple years of complementarity might present yearly variations in the stability coefficient due to the availability of the resource in "dry" or "wet" years. A multiyear analysis would also show a more complete picture of what it would look like to depend on hydropower for balancing colocated PV or wind; it would be especially valuable to include the sensitivity of the metrics to projected effects of climate change on hydropower availability and timing.

Regarding the operation of hydropower plants, we assume there is no change in the way a given plant is operated when it is (hypothetically) colocated with wind or PV. This is already the case in many parts of the United States, where VREs have been added near hydropower plants, without any coordination in the controls. Because the synchronous machines in hydropower plants tend to "follow the grid" (i.e., use the grid frequency as a reference), the operations can be impacted by the presence of colocated VRE sources, where an unexpected change in the real power has an impact on the grid frequency.

4.5 Caveats and Limitations

Though this report focuses on the daily complementarity of pairs of wind, solar, and hydropower resources, we conclude with a discussion about the additional insights and information that are needed to inform investment decisions. Complementarity provides initial insights about regions where hybridization of VRE resources could be beneficial in terms of total energy output, contributions to resource adequacy, and the potential for shared transmission costs; but many factors could prominently (or dominantly) influence investment decisions in renewable energy-based hybrid projects—compared to both standalone renewable energy projects and alternative generation sources.

This report focuses on complementarity based on average daily generation profiles and on variation in hourly generation over the course of a day (i.e., the stability coefficient), but different timescales may be relevant for informing investment decisions. Wind and PV technologies exhibit strong variability at hourly timescales, which is why dedicated wind-PV complementarity analyses typically involve finer temporal resolution (Harrison-Atlas et al. 2022). Subhourly timescales may also be needed for specific use cases, such as forecast errors and the provision of ancillary services.

Complementarity offers insights into the potential for maximizing transmission utilization, assuming a dedicated transmission line and minimal dispatchability. In reality, the transmission implications of hybridization will depend on not only short transmission spur lines and interconnection limits but also utilization patterns of the broader transmission network. Beyond complementarity, accounting for transmission congestion (and fees) along the broader transmission network will be critical for identifying regions where FlexPower could be especially important from an infrastructure perspective. The inclusion of an energy storage component could also mitigate transmission congestion issues, in addition to enabling other potential value streams.

Complementarity further depends on the chosen design and configuration of a candidate hybrid power plant; indeed, the modularity and ability to tune designs to maximize value are among the most appealing aspects of the hybrid power plant concept (Ahlstrom et al. 2021). This analysis was limited to pairs of resources with equal nameplate capacities; therefore, modest or muted complementarity could be related to strong variations in resource strengths. Such apparent limitations could be addressed through design choices, including oversizing PV relative to hydropower in New England. Related work under this project (Schleifer et al. Under Review) evaluated various wind-PV hybrid power plant configurations in Texas and found that design choices have a strong influence on complementarity and economic performance.

Complementarity is not inherently an indicator of economic value, and economic value underpins any investment decision. From a hybrid plant owner's perspective, the net-economic benefits of hybridization must consider both changes in costs and revenue. For the cost side of the equation, hybridization offers the potential for shared balance of system and operations and maintenance costs, including shared land use. On the revenue side of the equation, the potential for increased energy production will depend on the *value* of the additional energy produced through hybridization, which depends on load patterns, electricity prices, and plant design considerations. In other words, a "flat block" of generation would be suboptimal if one could avoid the deployment of PV panels or wind turbines that would primarily increase generation during very low-value periods of the day or year. Understanding this dynamic interaction requires simulating the performance of hybrid power plants within the broader grid context. This concept is especially important when considering the energy storage aspect of the FlexPower concept, which would both facilitate shifting of generation to periods with high value (or away from periods with especially low value or transmission congestion) and expand the range of reliability services that the plant could provide (and be compensated for). Additional research is also needed to understand the impacts of hybridization on additional grid services (e.g., ancillary services), such as control strategies (and/or energy storage components) to facilitate bidding and providing the highest-value services to the grid.

Finally, it is important to note that the complementarity benefits of combining multiple VRE resources does not require hybridization. Indeed, regional resource balancing has long been leveraged as a means of smoothing variability across a portfolio of generation assets, and such an approach is likely preferred in regions with vertically integrated electric utilities. Therefore, while complementarity can help inform locations where a hybrid power plant could achieve reduced plant-level variability, other strategies may be preferred or offer other benefits, depending on the generation mix, market characteristics, and perspective (e.g., system operator versus power plant owner).

5 Conclusions

In this study, we evaluate the temporal complementarity of pairs of wind, hydropower, and solar resources across the contiguous United States. We find evidence of temporal complementarity across most regions, which means combining multiple colocated VRE resources could offer integration benefits in the form of reduced plant-level variability and shared transmission and interconnection capacities (and costs). Perhaps the most important result of our study is a summary of the VRE resource pairs that indicate the greatest complementarity in each census division, which could serve as a high-level screen of the hybrid power plants that could offer integration benefits on a regional basis.

That being said, our analysis shows that complementarity between VRE resource pairs is highly nuanced, such that a single metric or timescale cannot offer all the insights needed to evaluate a candidate hybrid power plant. In addition, different metrics and timescales are designed to capture different aspects of complementarity, so care must be taken to select and evaluate the metric that most closely aligns with the sought-after-benefits of hybridization. Finally, the complementarity of a pair of resources will ultimately depend on design decisions such as the relative sizing of each generation technology and the interconnection capacity; indeed, one of the most appealing aspects of hybrid power plants is their ability to tune each of these parameters to maximize net economic benefits under current and future market conditions.

This report focuses on the temporal complementarity of pairs of wind, solar, and hydropower resources, but complementarity on its own cannot predict the competitiveness of hybrid energy systems. The economics of a power plant ultimately depend on its ability to deliver power during periods of greatest need and value, and high complementarity may not be optimal from a net economic perspective, accounting for all cost and value categories. In addition, complementarity provides initial insights into where the FlexPower concept could generate transmission and/or interconnection benefits, but the goals of FlexPower are much broader. Insights derived from this complementarity analysis can help with scenario design in operational models to provide a more complete picture of the value proposition of the FlexPower concept, including the addition of energy storage. Finally, interest in minimizing land use dedicated to renewable energy by colocating wind, hydropower, and/or PV technologies is primarily rooted in plant design decisions, and the relative weighting of complementarity versus land use impacts will depend on site-specific cost factors that are beyond the scope of this study.

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7 Appendix A
Original Hydropower Generation Profiles

This appendix details the methods implemented to obtain original hydropower generation profiles in a time series format. A high-level representation of the workflow (Figure 3 in the body of the report) can be segmented into three major steps:

1. Using the NPD (Hadjerioua, Wei, and Kao 2012) and EHD (Johnson et al. 2020) data sets from Oak Ridge National Laboratory's HydroSource, along with the United States Geological Survey (USGS) Water Services stream gage database (USGS 2016). The *USGS Preprocessing Adapter* (a) determines the IDs and head height of stream gauges located within one mile of a dam and (b) produces a database to use as an input to HydroGenerate.
2. The *Input Data Adapter* is a preprocessing module used to (a) differentiate NPDs and EHDs, (b) prepare the stream gauge IDs in a format appropriate for the application programming interface (API) call to the USGS Water Services representational state transfer (REST) service, and (c) define the data range needed.
3. Once the list of stream gauges has been curated, the API Call module inside HydroGenerate executes the request to the USGS Water Services API (Instantaneous Values service, to be exact). The data returned are preprocessed and then the hydropower potential is computed. The result is a time series that contains 15-min flow rate and estimated power. Further post-processing is conducted to resample the time series to hourly values, along with the capacity factor computation, to ensure compatibility with the PV and wind generation time series.

Additional details for select steps are provided below.

A.1 USGS Preprocessing Adapter (test)

The purpose of this process was to establish the closest USGS stream flow gauge to the dam in question. This provides proxy flow information that can be used to estimate the dam's potential power generation capacity. A key objective of this process was a low computational workload and a repeatable approach. This process takes place in two distinct steps detailed below. For this effort we examined both NPDs and EHDs.

The first step was to establish initial spatial relationships. Iterating through the dam data set, we established the hydrologic units in which each dam was located at the watershed (hydrologic unit code [HUC] 10) and sub watershed (HUC 12) levels. Simultaneously, we established the number of USGS stream flow gauges located in the same watershed. If a stream gauge was within the same watershed as the dam in question, a directed graph was created and bound to the HUC12 or HUC10 boundary (Figure 14). The directed graph was generated using the national hydrography data set (USGS 2019). A directed graph preserves the topology of the system (e.g., directionality, original latitude, and longitude) while allowing for rapid relationship assessments. Using the Momepy Urban Morphology Measuring Toolkit, endpoints were designated as nodes and lines were designated as edges within the directed graph (Fleischmann 2019). Dams with no stream gauges present in either HUC10 or HUC12 were excluded from analysis.

Figure 14. Depiction of directed graph creation

The second step was to perform a shortest-path analysis. With the directed graphs established, each dam and associated stream gauges were examined to establish (a) if a relationship between the dam and a stream gauge exists and (b) which stream gauge was closest to the dam. This subprocess involved first breaking into the graph: the closest node to each dam and stream gauge were located and their distance from the original node position was recorded. These closest nodes within the graph were used as entry points into the graph, representing the dam or stream gauge, for the shortest-path analysis. Next, the distance between each stream gauge node and the dam node were calculated following the methodology presented in Hagberg, Swart, and Chult (2008). Each calculation was weighted by the original length separating the dam node and the stream gauge. The node pair with the shortest path was recorded (Figure 15).

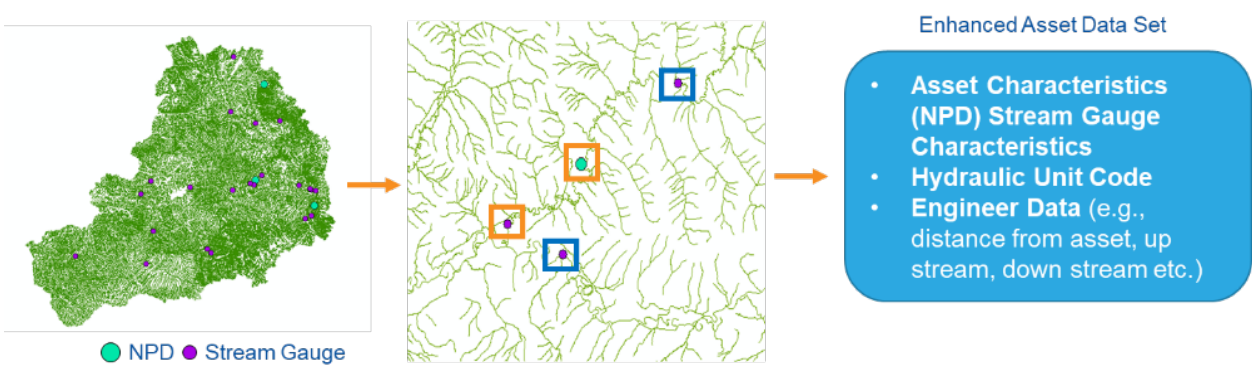

Figure 15. Geographic depiction of shortest-path analysis

This analysis takes place in graph form but for ease of explanation is represented in a geographic format here.

Next, we explore how many successful shortest paths were established between the dams and stream gauges, for both NPDs and EHDs. We successfully established shortest-path connections for 124 (or 21%) of the original 594 NPDs examined. The remaining 470 dams either had no stream gauges present in the watershed, or no shortest-path connection could be established between a dam and the stream gauges within the watershed. The 124 positive connections ranged in edge count from 0 (stream gauge and dam located together) to 210 edges (Figure 16).

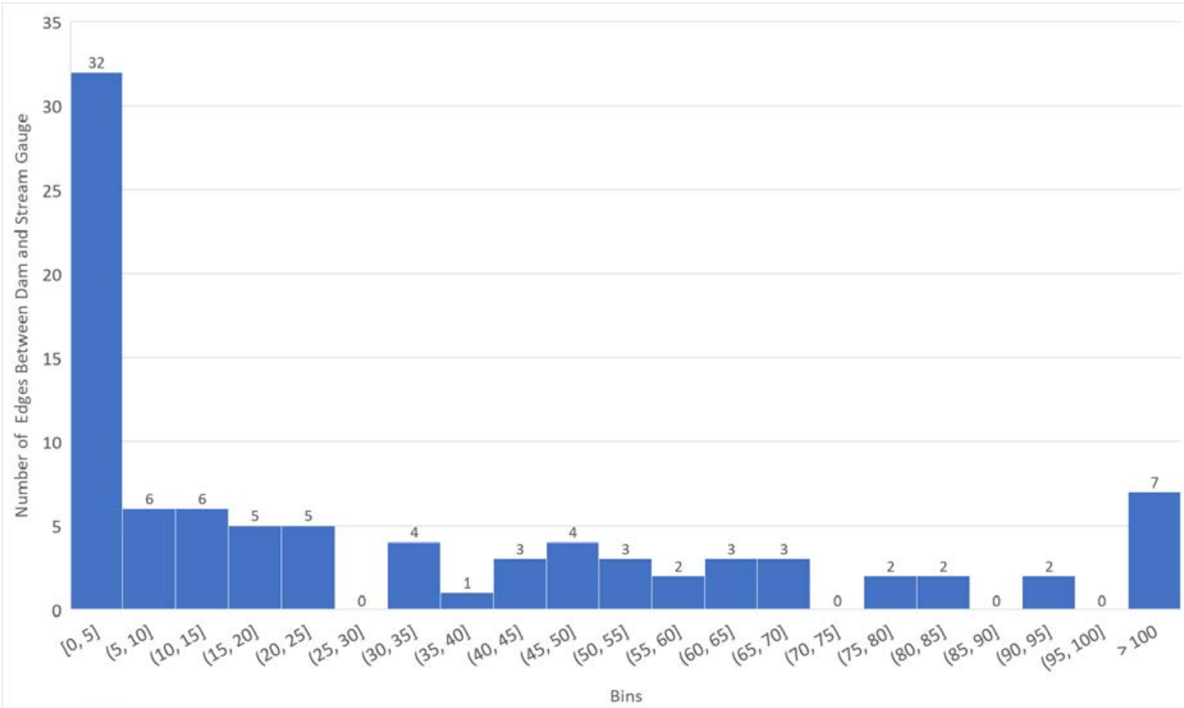

Figure 16. Histogram depicting the sum of edges between dam nodes and their associated stream gauges for NPDs

The national hydrography data set does not mandate a line length for each water feature represented within the data set, so it is not possible to determine an edge's real-world length. Real world distances were determined for the distance between stream gauges and dams to their entry nodes in the graph. Entry nodes and the physical sites they represent were within 1.2 miles of each other for both stream gauges (Figure 17) and NPDs (Figure 18). The average distance between the NPDs and their entry nodes was 0.1 miles (Figure 18), while the average distance between entry nodes and stream gauges was 0.2 miles (Figure 17). The variability in distance between physical sites and entry nodes can be attributed to discrepancies between the original dam and stream gauge point data set and the national hydrography data set.

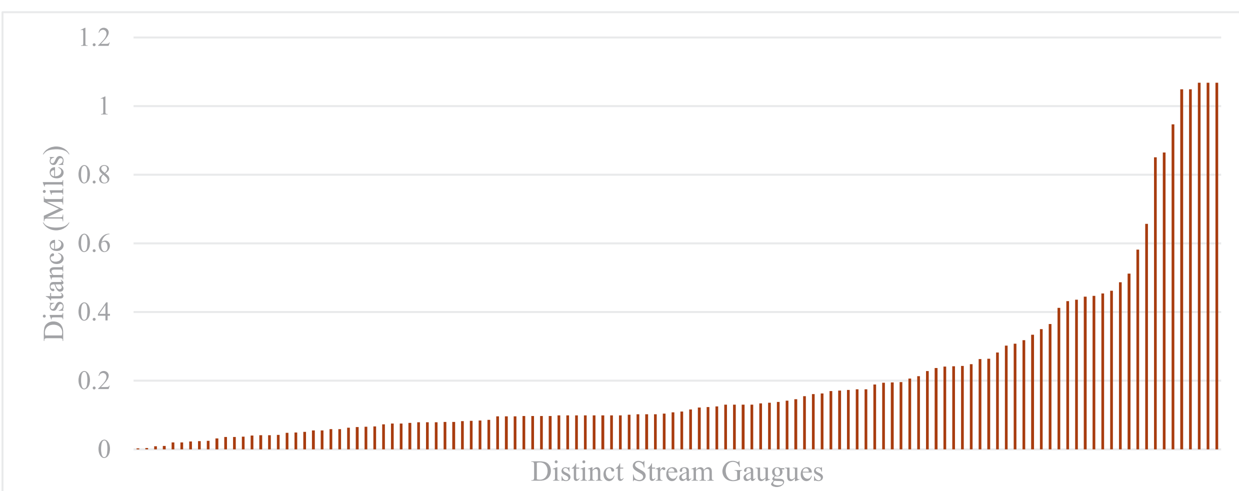

Figure 17. Accounting of the distances between physical stream gauge locations and the entry nodes used to represent the stream gauges during the shortest-path analysis

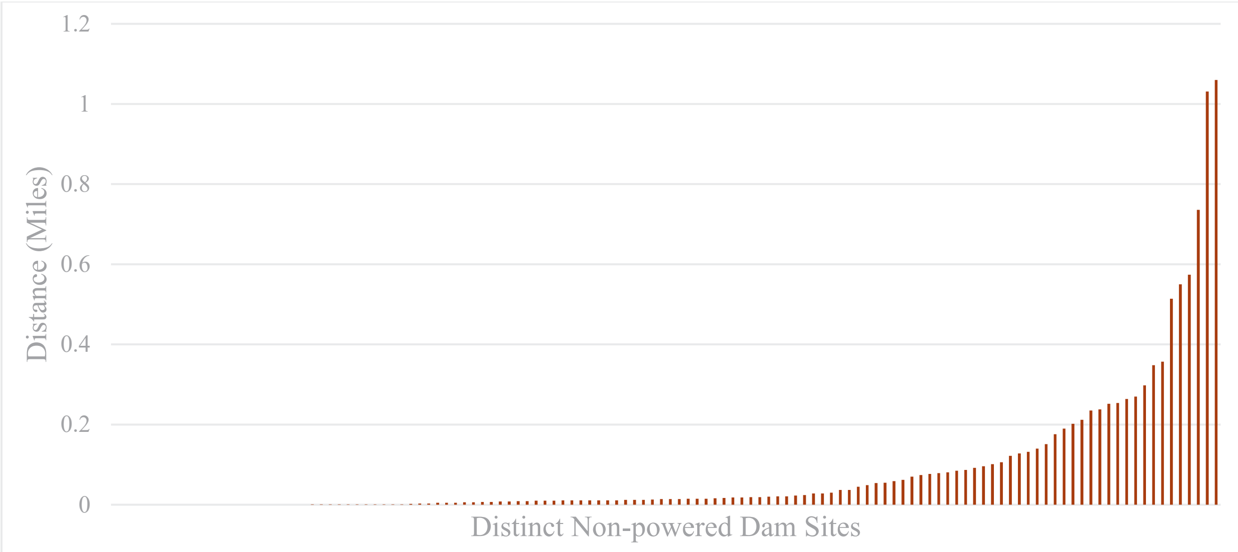

Figure 18. Accounting of the distances between physical NPD locations and the entry nodes used to represent the dams during the shortest-path analysis

Of the 2,275 EHDs analyzed, 415 dams (18%) had successful shortest-path connections. The remaining 930 dams either had no stream gauges present in the dam's watershed or no shortest path could be established. The EHD maximum edge count (245 edges) was higher than that for NPDs (210 edges). Most EHDs had edge counts ranging from 0 to 5 edges between the dam and stream gauge (Figure 19). The distance between EHDs and their entry node ranged from 0 to 2.3 miles, with an average of 0.2 miles (Figure 20). The maximum distance between stream gauges and their entry node was 1.9 miles with an average of 0.25 miles (Figure 20).

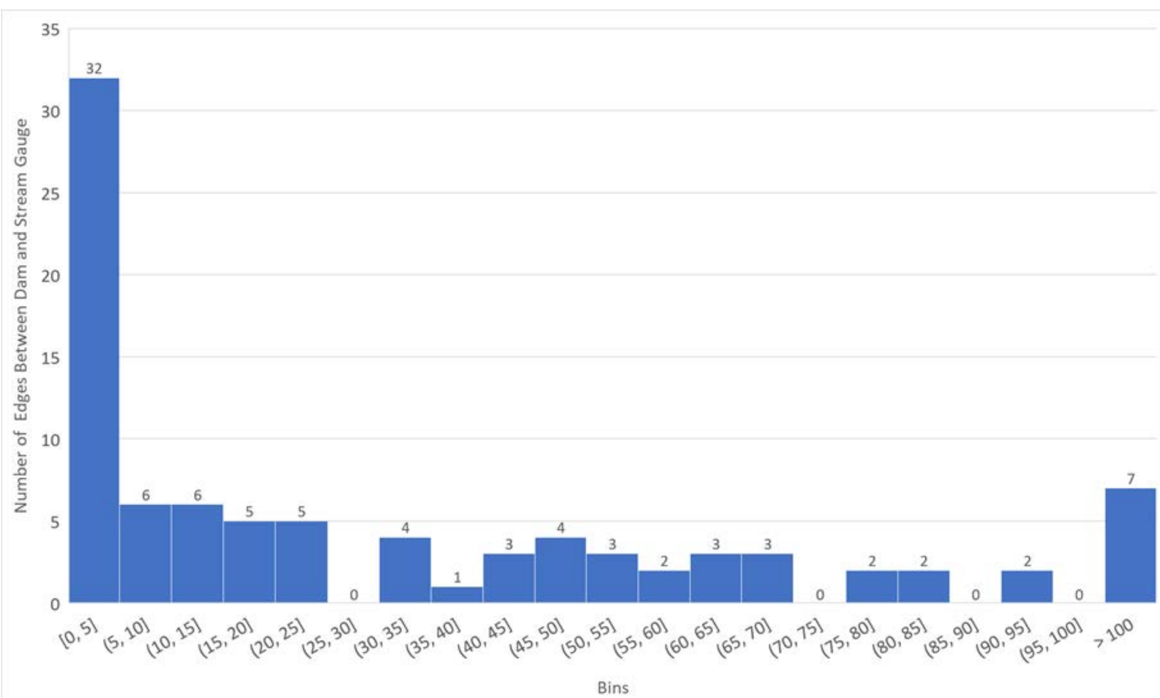

Figure 19. Histogram depicting the sum of edges between dam nodes and their associated stream gauges for EHDs

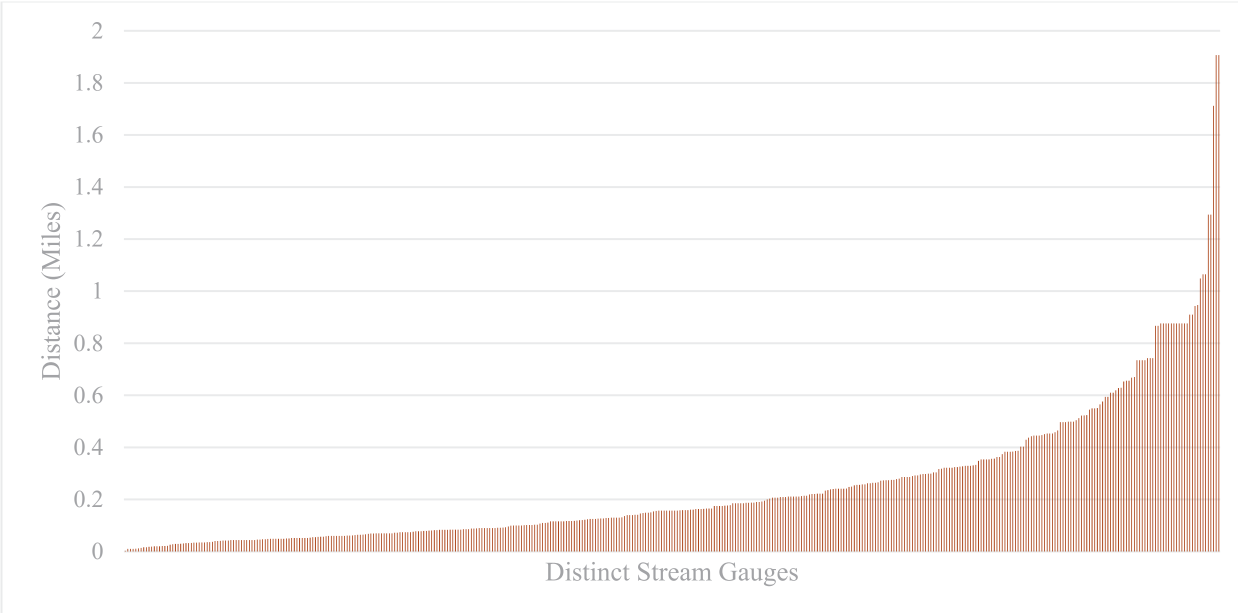

Figure 20. Distances between physical stream gauge locations and the graph nodes used to represent the stream gauges during the shortest-path analysis

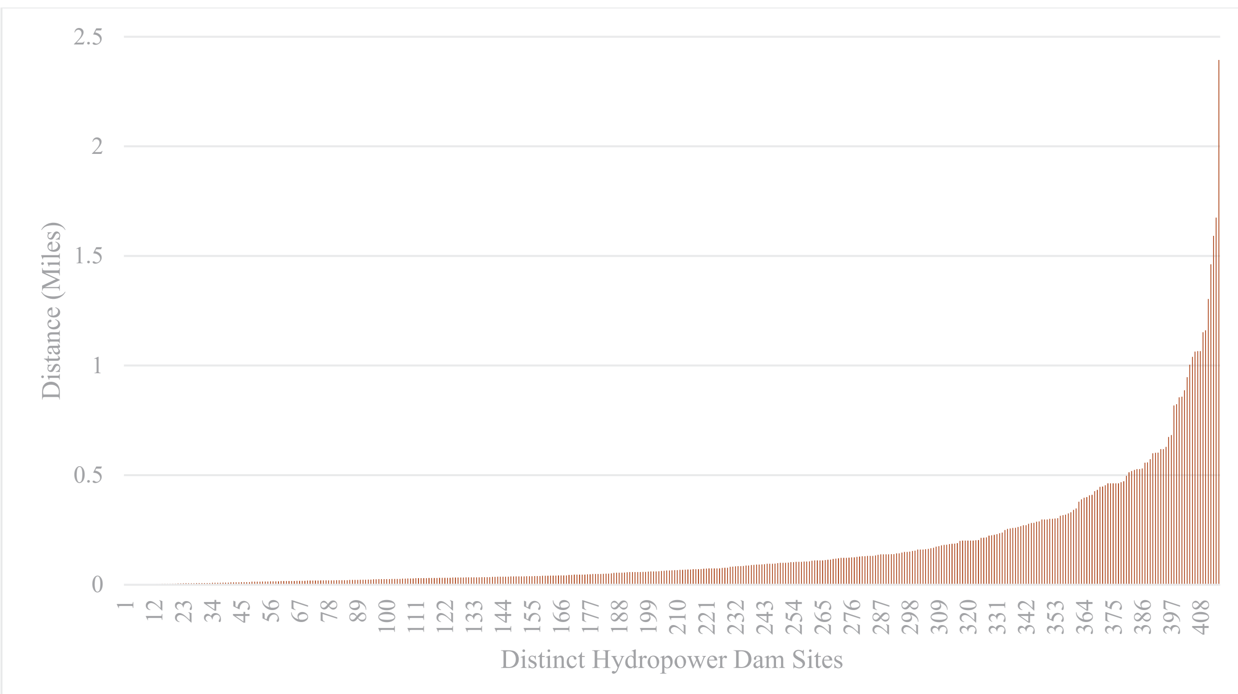

Figure 21. Distances between physical EHD locations and the graph nodes used to represent the dams during the shortest-path analysis

A.2 HydroGenerate and Capacity Factor Calculation

HydroGenerate is an open-source tool developed at Idaho National Laboratory and it implements a static computation of available power for small hydropower turbines based on stream flow. No dynamics of the electrical machine are involved, and it is based on well-known empirical equations in the literature. In essence, the tool takes two inputs: gross head and flow. Other parameters are optional such as rated flow and nameplate capacity, and these are used to estimate the head in case it is unknown. If possible, nameplate capacity should be provided to limit the potential to a reasonable maximum. Turbine type is also an optional parameter, and it overrides a feature in the tool that chooses the turbine type based on the size of the gross head of the system (Table 5). The turbine type dictates the formulation used to compute the turbine efficiency and, ultimately, the available power.

Table 5. Turbine type by head category in HydroGenerate.

Head Category	Start (m)	End (m)	Turbine Type
Very low	0.5	10	Kaplan
Low	10	60	Kaplan
Medium	60	150	Francis
High	150	350	Francis
Very High	350	700	Pelton

In general, the available power (P) of a small hydropower turbine is given by:

$$P = \rho g Q(H - h_{loss}) e_q e_{\mathrm{sys}}\,, \tag{A.2}$$

where ρ is the density of water ($1{,}000\ \mathrm{kg/m^3}$), g is the acceleration due to gravity ($9.8\ \mathrm{m/sec^2}$), Q is the flow in $\mathrm{m^3/s}$, H is the gross head in m, h_{loss} is the hydraulic loss, e_q is the turbine efficiency, and e_{sys} is the water-to-wire system efficiency (assumed as 98%).

The equations to compute the efficiency curve for a given turbine are well known in the literature and were derived based on a large number of manufacturer efficiency curves for different types of turbines, gross head, and flow conditions (RETScreen 2004). Along with the hydropower potential, the tool determines the maximum power available as the 75$^{\text{th}}$ percentile of the maximum data point, although this can be replaced by a user-defined nameplate capacity. Therefore, the capacity factor of a dam, on an hourly basis, is given by:

$$CF = \frac{P_t}{\max(P)} \tag{A.2}$$

where P_t is the hydropower potential at a given hour and the denominator is the calculated maximum potential based on the complete time-series for period T, in this case, one year. An example of the resulting capacity factor time-series data is shown in Figure 22.

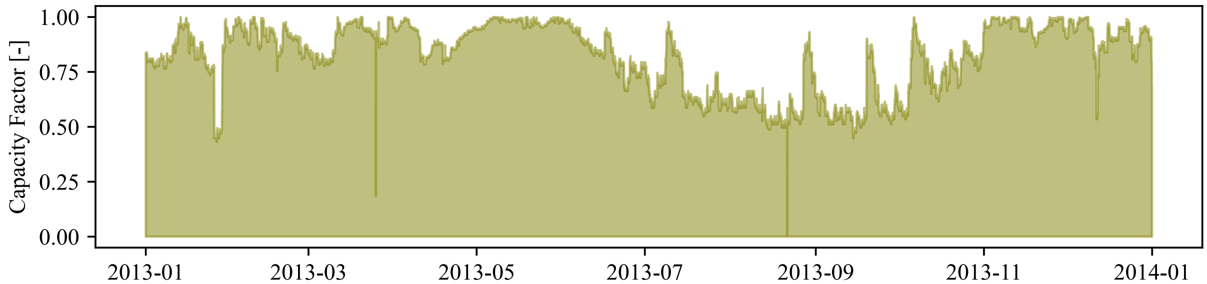

Figure 22. Capacity factor of the Glen Canyon Dam.

A.3 Data Completion and Quality Issues

The USGS Stream Gage database contains records from the 1980s for most of the stream gauges analyzed in this study. In our initial approach, we collected flow data from the year 2012 alone to compute the synthetic generation profiles, and with the purpose of matching the year of the PV and wind time-series datasets. However, this resulted in data gaps of greater than two weeks. To understand the data gaps, the missing data were quantified as monthly and annual percentages. That is, we computed the number of missing values (categorized as Nan) over the total amount of data points (N):

$$MV = \frac{N_{Nan}}{N} \times 100 \qquad (2)$$

This process was done for all stream gauges collocated with NPDs and EHDs. Figure 23 shows a heatmap with the annual missing values for EHDs. The y-axis represents the stream gauge site IDs, and the x-axis represents the years from 1980 to 2020. Note that most of the data are missing for the early years, and the best data coverage is found near 2020.

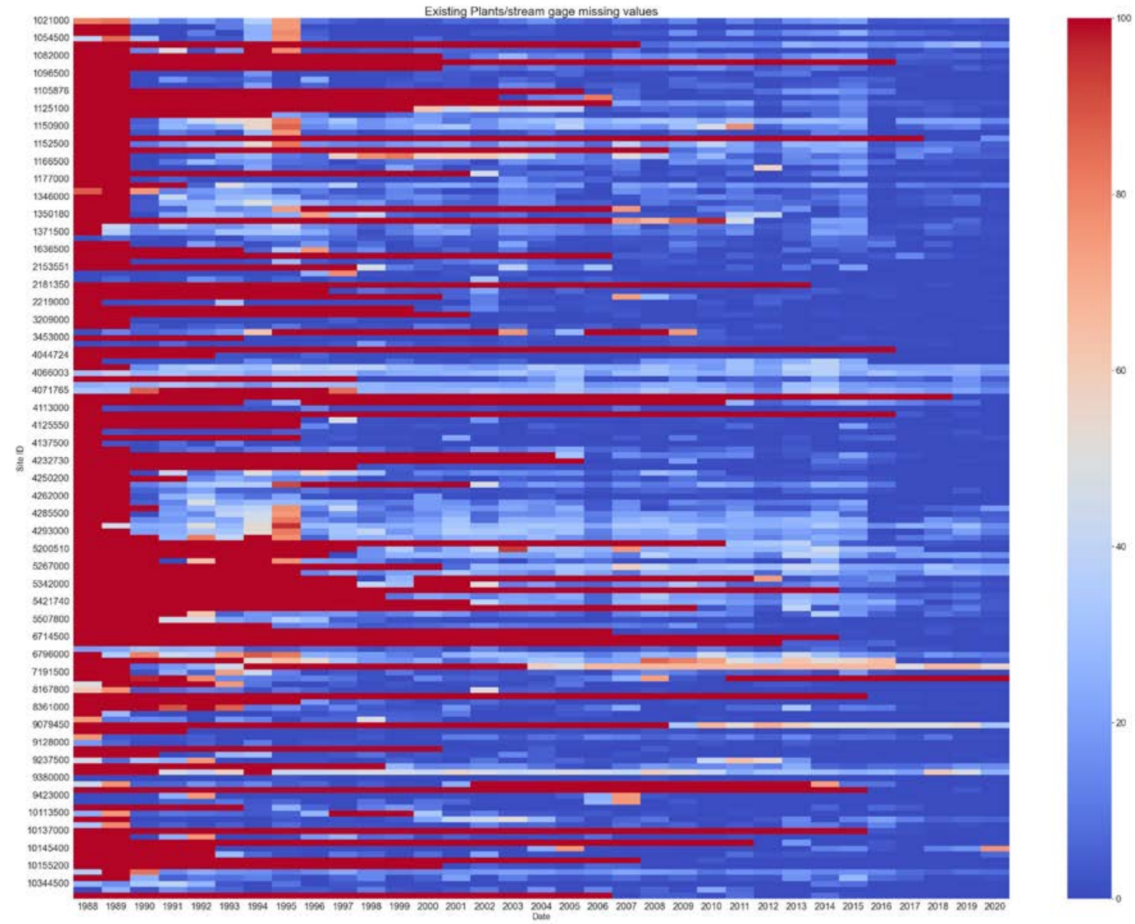

Figure 23. Yearly missing values for the stream gages colocated with EHDs.

When assessing a hydropower resource, it is common to analyze the flow data for at least 10 years. Since our complementarity analysis spans a year's worth of generation data, we determined a "representative year" for each site by computing the median flow of the available data for the years 2010-2020 and choosing the year for which the yearly mean was closest to the median value. We chose the last 10 years of data available because, in general, they contain the smaller number of missing values. A distribution of the number of sites per representative year is given in Figure 24.

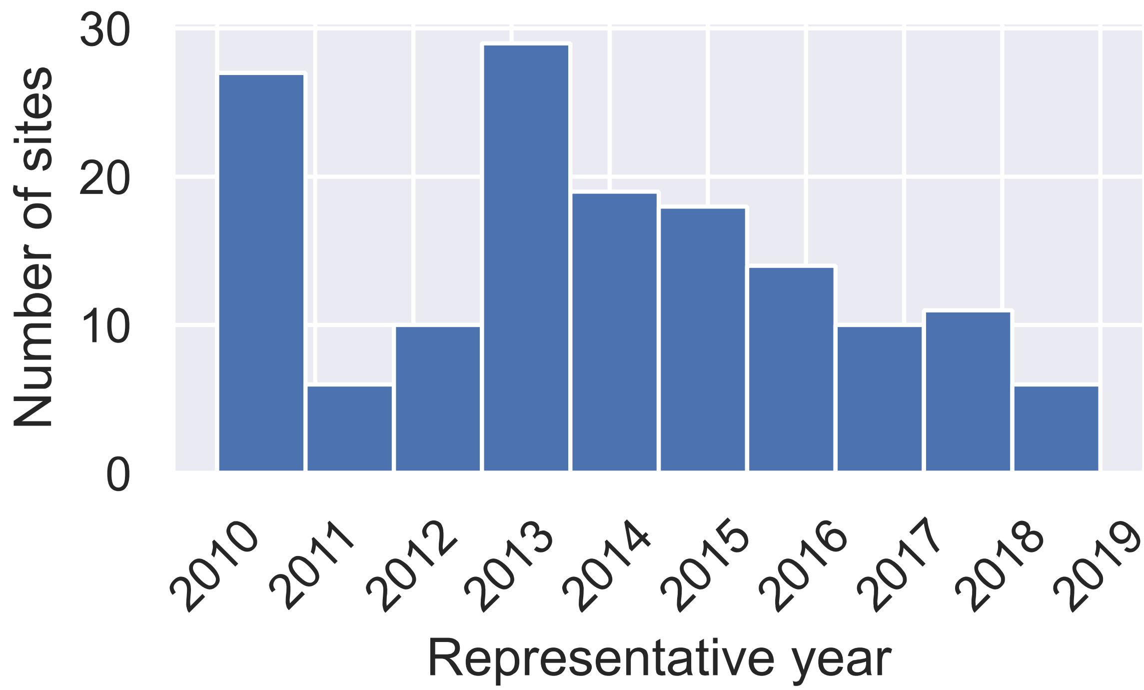

Figure 24. Histogram of the number of sites for a given representative year.

The summary in Table 6 shows high-level statistics of the percentage capacity and number of dams evaluated for EHDs and NPDs, respectively, due to either data availability or because a particular dam was not colocated with a stream gauge. The EHDs were assessed in terms of their reported nameplate capacity. By contrast, the potential power capacity of the NPDs is unknown (other than a few estimations), so we estimate the coverage of our complementarity analysis based on the *number* of dams evaluated. There is no clear indication that one region contains better data availability than others, but the average percentage of EHDs evaluated across all regions is 37%, compared to 13% for NPDs. One explanation for the greater availability of flow data associated with EHDs is that they provide additional services (other than producing power), so they might be more closely monitored than NPDs.

The highest concentrations of data available for evaluating complementarity were observed for the West-North Central (97%) and Mountain (66%) Census Divisions. In contrast, the highest concentration of NPDs evaluated was in the East-South Central Census Division (23%), in which only 7% of EHDs involved adequate flow data for complementarity analysis in this study.

Table 6. Percentage of EHDs and NPDs evaluated in the complementarity analysis.

Census Region	Census Division	EHD		NPD	
		Total Capacity (MW)	Capacity Evaluated for Complementarity (%)	Total Number	Percentage Evaluated for Complementarity (%)
West	Pacific	1183	10.4	38	7.9
	Mountain	2586	65.9	54	14.5
Midwest	East-North Central	245	40.3	43	5.7
	West-North Central	339	97.1	44	10.6
South	West-South Central	96	55.7	110	1
	East-South Central	66	6.9	63	23.4
	South Atlantic	677	5.4	63	7.9
Northeast	Middle Atlantic	546	22.6	80	12.5
	New England	341	33.7	19	31.5

A.4 Additional Stability Coefficient Results as a Function of Hydropower Capacity Factor

Finally, Figure 13 in the body of the report presents the relationship between stability coefficient and hydropower capacity factor for colocated hydropower-wind and hydropower-PV combinations. The results presented in the body of the report represent annual values, and the corresponding linear regressions for those annual values are presented in Figure 25. However, hydropower exhibits strong seasonal variation.

The results presented in Figure 26 include *monthly* stability coefficient values as a function of capacity factor for each evaluated dam. Due to the larger volume of data when presenting monthly results, we break out EHD (left) and NPD (right) results based on a wind (top) and solar (bottom) baseline. The trends observed in Figure 26 are similar to those presented in the body of the report. However, the monthly values indicate much greater outliers for hydropower-wind complementarity, including very low stability coefficient values for EHDs with very high-capacity factors. On the other hand, EHDs with very low-capacity factors can involve very high stability coefficient values as select sites, when colocated with either wind or PV. This result supports the fact that complementarity trends for hydropower-based hybrids reflect both the strength *and* timing of hydropower generation.

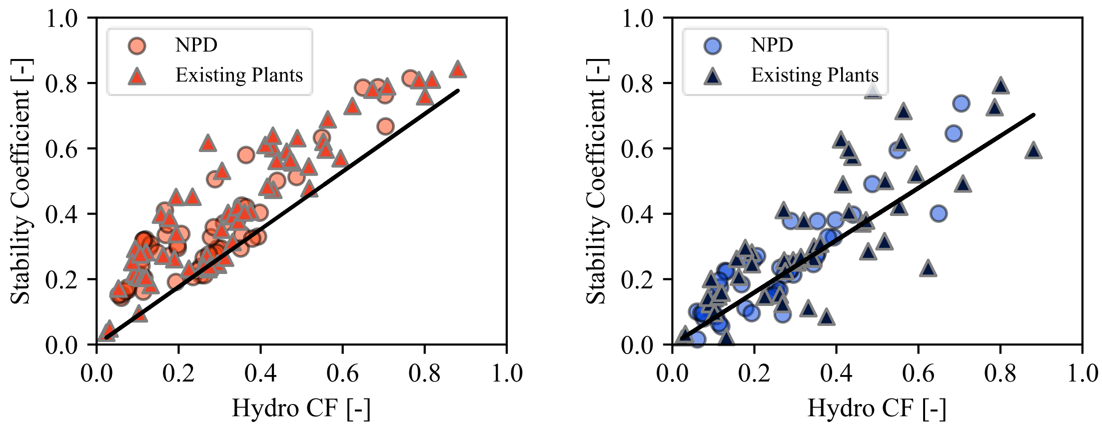

Figure 25. Linear regression between stability coefficient and hydropower capacity factor for hydropower-wind (left) and hydropower-PV (right) combinations

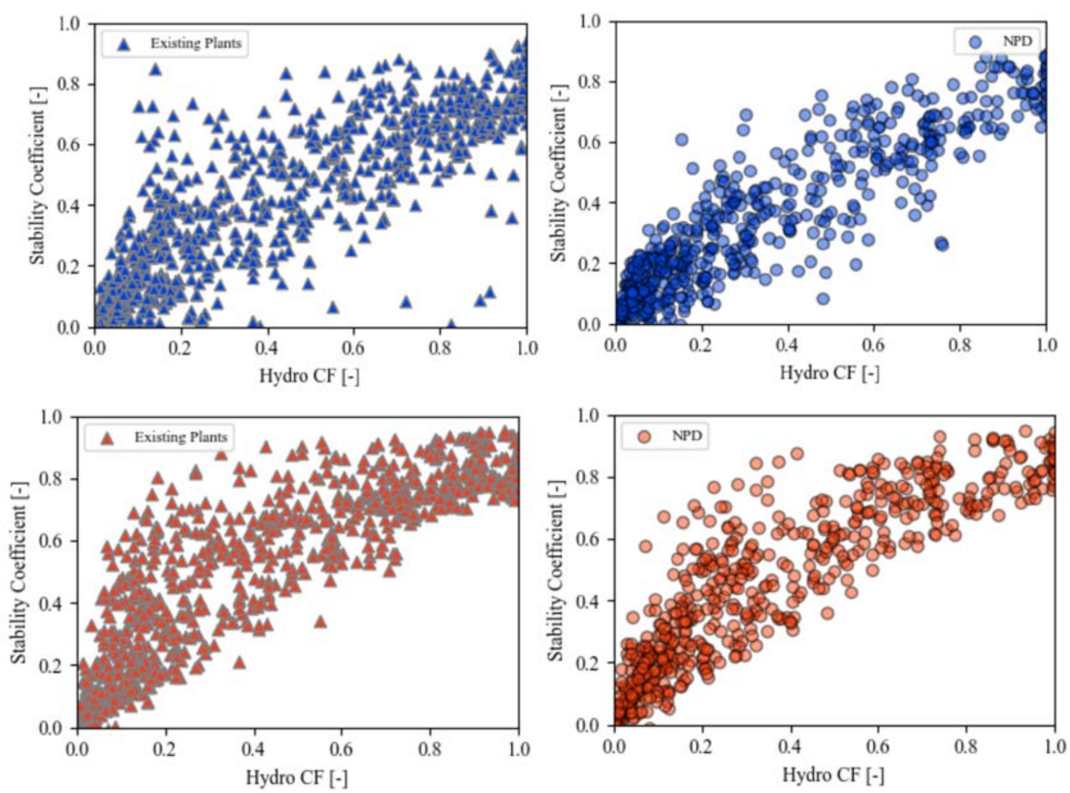

Figure 26. Monthly stability coefficient versus hydropower capacity factor for EHDs (left) and NPDs (right) with hydropower-wind (top) and hydropower-PV (bottom)

8 Appendix B
Complementarity Metrics: Formulations and Data Access

All of the complementarity calculations and results presented in this report and Harrison-Atlas et al. (2022) are publicly available and can be accessed at the following website: https://github.com/NREL/Renewable-Complementarity. The remainder of this appendix summarizes the relevant formulas for each complementarity metric discussed.

Pearson Correlation

Pearson correlation is the most commonly applied metric for assessment of complementarity (Jurasz et al. 2020). The Pearson correlation coefficient $\left(r_{g^s g^{s'}}\right)$ quantifies the strength of the linear association between two variables. It is calculated as follows:

$$r_{g^s g^{s'}} = \frac{\sum_{t=1}^{n} (g_t^s - \overline{g^s})(g_t^{s'} - \overline{g^{s'}})}{\sqrt{\sum_{t=1}^{n} \ (g_t^s - \overline{g^s})^2} \cdot \sqrt{\sum_{t=1}^{n} \ (g_t^{s'} - \overline{g^{s'}})^2}} = \frac{\mathrm{cov}(g_t^s, g_t^{s'})}{\sigma_{g_t^s} \sigma_{g_t^{s'}}}$$

where $\overline{g^s}$ and $\overline{g^{s'}}$ are the sample averages and $\sigma_{g_t^s}$ and $\sigma_{g_t^{s'}}$ are the standard deviations of PV and wind generation, respectively.

The Pearson correlation is within the range -1 <= r <=1. From a complementarity standpoint, negative correlations are a beneficial finding whereas positive correlations indicate synchrony among resources. Negative correlations imply that generation profiles are asynchronous such that increased PV generation tends to coincide with decreased wind generation and vice versa. Correlations approaching -1 indicate perfect linear complementarity. Conversely, positive correlations suggest PV and wind generation are linearly related such that increased wind generation is associated with increased PV production and that periods of low wind generation tend to be those where PV generation is also low. A correlation of zero implies that there is no association between two variables. Pearson correlation assumes variables are continuous and linearly related and that observations are paired and independent.

Stability Coefficient

The stability coefficient (C_{stab}) quantifies the reduction in the coefficient of variation for the capacity factor of a hybrid system relative to a PV-only baseline, over daily time scales (Sterl et al. 2018). The stability coefficient is computed as

$$\boldsymbol{C_{stab} = 1 - \frac{\sqrt{\sum_{t=1}^{24} \left(g_t^{hybrid} \ - \ \overline{g^{hybrid}}\right)^2}}{\sqrt{\sum_{t=1}^{24} \left(g_t^s \ - \ \overline{g^s}\right)^2}} \frac{\overline{g^s}}{\overline{g^{hybrid}}} = 1 - \frac{C_{v,\,hybrid}}{C_{v,s}}}$$

where g_t^{hybrid} is the mixed capacity factor of the hybrid system at time t, $\overline{g^s}$ is the daily average capacity factor of the base PV system, $\overline{g^{hybrid}}$ is the daily average capacity factor of the hybrid system, $C_{v,s}$ is the coefficient of variation of a PV-only system, and $C_{v,\,hybrid}$ is the coefficient of variation for the hybrid system. The stability coefficient falls within the range $0 <= C_{stab} <= 1$ with values approaching 1 indicating greater complementarity. For a wind-PV hybrid, the stability coefficient represents the added value of wind power for balancing daily electric power production relative to a solar PV system.

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