SUMMARY REPORT

Weather Dataset Needs for Planning and Analyzing Modern Power Systems

A Summary Report of the Energy Systems Integration Group's Weather Datasets Project Team

October 2023

ESIG

ENERGY SYSTEMS INTEGRATION GROUP

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The Energy Systems Integration Group is a nonprofit organization that marshals the expertise of the electricity industry's technical community to support grid transformation and energy systems integration and operation. More information is available at https://www.esig.energy.

ESIG's Publications

This summary report, the full report (and a high-resolution version for printing), "Meteorology 101: Meteorological Data Fundamentals for Power System Planning," and fact sheets are available at https://www.esig.energy/weather-data-for-power-system-planning. All ESIG publications can be found a https://www.esig.energy/reports-briefs.

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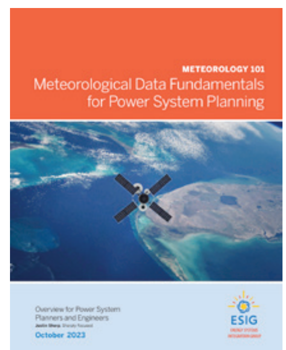
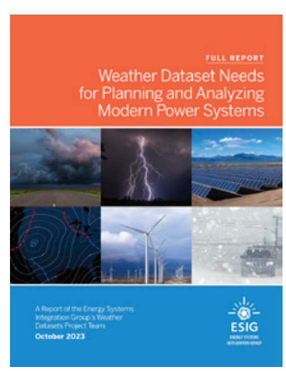
Full and Summary Versions of this Report

This summary report is a distilled version of the full report, *Weather Dataset Needs for Planning and Analyzing Modern Power Systems*. It is accompanied by an overview of meteorology, data, and modeling, "Meteorology 101: Meteorological Data Fundamentals for Power System Planning," for readers who would like to take a deeper dive into those areas. This overview also appears as Section 2 in the full report.



Weather Dataset Needs for Planning and Analyzing Modern Power Systems was produced by a project team convened by the Energy Systems Integration Group to assess the gaps in existing weather data used in power system planning, and outline a process for producing ideal weather datasets for planning studies for increasingly weather-dependent electric power systems. The report provides details on what is needed and why, outlines the status of and gaps in existing data and methods, and describes an approach to building a solid, long-term planning solution.

The full report, summary report, executive summary, and fact sheets can be found at https://www.esig.energy/weather-data-for-power-system-planning.



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Abbreviations Used

DHI	Diffuse horizontal irradiance
DNI	Direct normal irradiance
ECMWF	European Center for Medium-Range Weather Forecasting
ERA5	Fifth-Generation ECMWF Atmospheric Re-Analysis of the Global Climate
GAN	Generative adversarial network
GCM	Global climate model
GHI	Global horizontal irradiance
HRRR	High-Resolution Rapid Refresh Model
MERRA	Modern-Era Retrospective Analysis for Research and Applications
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
NWP	Numerical weather prediction
WIND	Wind Integration National Dataset
WTK-LED	WIND Toolkit Long-term Ensemble Dataset

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Introduction

The impacts of weather in the electricity sector have always been important, with weather modulating demand and affecting much of the infrastructure traditionally used to generate and deliver electricity. This relationship is growing stronger with the increase in weather-driven renewable generation and the growing electrification of the building and transportation sectors. Today and going forward, to plan and operate the electricity system reliably and cost-effectively, it is critical to gain more complete knowledge of potential weather impacts to the system. Future reliability is at risk unless we understand the range of different supply and demand balance possibilities that are driven by physically plausible weather combinations—especially combinations that drive demand, generator availability, fuel availability (both renewable resources and traditional supply), and transmission capacity in ways that stress system reliability and resilience. To ensure reliability, it is essential to have more accurate, more detailed, longer, chronological weather datasets than are available today.

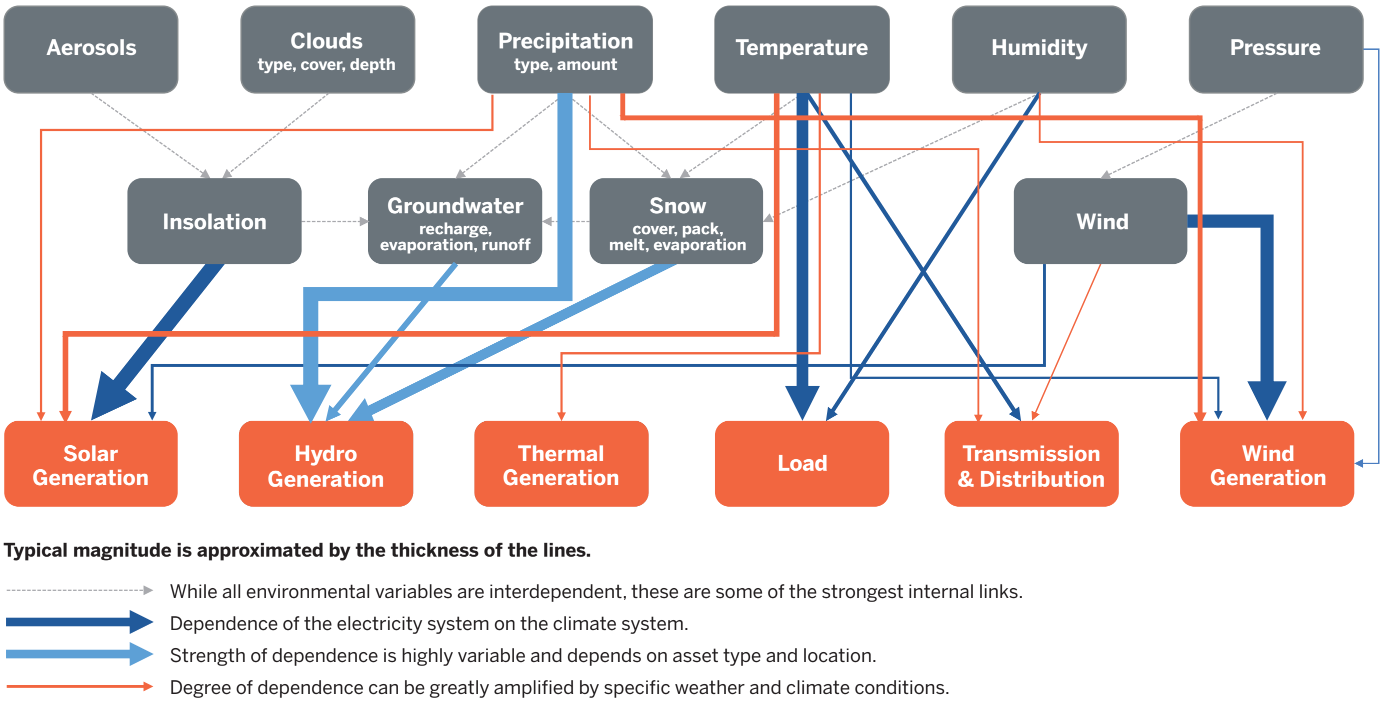
The Energy Systems Integration Group convened a project team of experts in meteorology, data analysis, and power systems. The project team produced a comprehensive report, from which this summary is distilled, that explores the linkages created by the rising weather dependence of the electricity system; describes the need for and the nature of weather data to represent these linkages; and outlines an approach to producing robust, future-proof datasets that will better serve the power system community. The full report, as well as a "Meteorology 101" brief that readers may find useful to pair with this summary report, can be found on the ESIG website.[1]

Complex Relationships Among Weather Variables

Until recently, the biggest weather impacts on electricity systems were temperature modulating load and extreme weather events driving outages of generation, transmission, and distribution. But as levels of wind and solar generation rise, the effect of temperature on demand is being surpassed by the influence of weather on wind and solar generation in some regions, and eventually will be so almost everywhere. The weather dependence of load is also increasing due to electrification of heating, cooling, and transportation. Figure 1 (p. 2) shows the web of relationships among weather variables and elements of the power system. These variables are interrelated in complex ways that vary according to the daily, seasonal, and interannual variability of weather.

1 https://www.esig.energy/weather-data-for-power-system-planning.

FIGURE 1
Electricity System Weather-Dependence



The primary linkages between variables in the weather and climate system (gray) and the electricity system (orange). There are many feedbacks between the environmental variables; the strongest links are shown in dashed gray lines. Dark blue lines indicate direct dependencies that are most important in everyday operation of the electricity system, while orange lines indicate dependencies that do not typically have a large impact on a daily basis but can have a profound impact in particular circumstances or combinations. For instance, freezing temperatures, high humidity and/or freezing rain can cause wind generation to become unavailable due to icing, and extreme winds can damage transmission and distribution infrastructure. Light blue lines denote where the strength of dependence is highly variable and depends on asset type and location.

Source: Energy Systems Integration Group.

The Use of Models

Although observations are always the most reliable representation of weather inputs at a point, given that they are far too sparse to form the basis of power system planning studies, models are used to synthesize data to fill the gaps. Weather models aim to reproduce as closely as possible the coincident observed patterns of variables impacting wind and solar generation. The weather model output can then be used to estimate the hourly generation potential at all current and possible future wind and solar facilities over a long enough period that the range of a portfolio's supply and demand possibilities is accounted for. Physics-based models are commonly used for this purpose, particularly numerical weather prediction (NWP) models, because the weather data they produce obey the physical laws interconnecting the different meteorological fields in time and space that occur in reality. Thus, the data produced are physically consistent in both their spatial distribution and their temporal evolution. However, the atmosphere and the other Earth systems it interacts with are very complex, and no model can represent all the details, no matter how much computer

Physics-based models (typically NWP models) are commonly used to reproduce the patterns of variables impacting wind and solar generation, because the weather data they produce obey the physical laws interconnecting the different meteorological fields in time and space that occur in reality.

power is used. Further, no data observation system can collect sufficient data to give the models the perfect starting point needed to produce a perfect simulation. This is why gathering and making available as many observations as possible is a crucial area of focus. More and better observations allow:

- The initial state of the atmosphere to be better represented in a modeling system
- The quality and uncertainty of the model output to be better quantified for time periods and geographies where observations and model output overlap
- The model output to be post-processed to identify and remove systematic biases

With the rapid expansion of wind and solar generation, thousands of new meteorological data observations are being made, as well as observations of concurrent power. Unfortunately, most of these observations are considered as proprietary and are not shared for the common good of improving weather inputs for power system models. A recommendation is made below to change this.

No datasets exist that meet the requirements with sufficient accuracy, spatial and temporal resolution, or record length to capture all of the possible drivers of supply and demand balance in the new paradigm.

Lack of Data of Sufficient Quality

Planning studies for power systems with high levels of renewables require correlated, time-synchronized data for wind, solar, and temperature observations.[2] While great strides have been made in the availability of high-resolution meteorological data for power system modeling studies over the past decade (especially for determining wind and solar output), no datasets exist that meet the requirements with sufficient accuracy, spatial and temporal resolution, or record length to capture all of the possible drivers of supply and demand balance in the new paradigm. In addition, the data that are available have not been sufficiently validated to assess the uncertainty of their representations of truth, and thus their appropriateness for use in power system planning. Where validation has been performed, biases and limitations have been discovered even in the current best-in-class data available (see, for example, Stenclik, Welch, and Sreedharan (2022)). Data limitations have led to gross simplifications in weather inputs even where practitioners are earnestly attempting to robustly address the added complexity. To fill data gaps, scientifically questionable "bootstrapping" methods[3] are being used to synthesize long data records from whatever limited data are available from operational projects, leading to combinations of weather variables that either are not physically plausible or occur at frequencies that are not representative of frequencies observed in reality.

Few people have more than a basic grasp of both meteorology and electricity systems, or fully understand just how much more complex a weather-driven system is than one in which weather mainly modulates demand.

2 Weather data for hydro are not considered in this report, given that the data challenges for hydro are different from those of solar, wind, and load, being multi-sectoral and significantly dependent on hydrological modeling to capture the effect of precipitation, water inflow, and surface run-off, and because historical water inflow and independent stochastic selection methods are likely sufficient for handling weather impacts on hydro power in many power system applications.

3 Bootstrapping is a statistical procedure that resamples a single dataset to create many simulated samples.

The lack of holistic understanding sometimes results in overly simple methods to synthesize longer datasets, along with several other issues.[4] For example, model data are often used as if they have the accuracy and degree of uncertainty of observations, yet their representativeness in time and space is a function of the model configuration used and model inputs. In addition, weather models can have higher accuracy for some weather conditions and lower accuracy for others: the quality of modeled weather is a function of time and place. At the other end of the spectrum, mistrust of weather model data sometimes results in useful model data being passed over in favor of inputs that are simpler and more familiar but less complete. For instance, overly simple models are often used to extrapolate data from one location to another or to estimate one weather variable using another variable. There is an urgent need for education, coordination, and cooperation between power system experts, meteorologists, and climatologists (Coughlin and Goldman, 2008; Craig et al., 2022; Bloomfield et al., 2022), in order to address:

- Misconceptions among data users about the **complex nature, limitations, and applicability of the data that are available**
- Misconceptions among meteorological data providers about **how the data they make available are applied**

These data and modeling challenges are leading to the inappropriate "black box" application of meteorological inputs, attempts to fill data gaps through using methods with many limitations, and insufficient recognition of the uncertainty in modeling results that can lead to poor decisions in power system planning. With hundreds of billions of dollars of new infrastructure being built for the energy transition, it behooves the sector to address these challenges. While the challenges are not trivial, the cost of overcoming them is trivial compared to the risks presented by the current data inadequacies.

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The Data and Modeling Challenges Addressed by the Report

This summary report aims to provide information useful to both power system planners who use weather data (particularly model-synthesized data) and the meteorologists involved in creating and providing data and advising on their use. Important gaps exist not just in the data required but in the need for more direct engagement by the meteorology community in the energy sector, with the meteorology and power systems communities working together and each learning about the needs, constraints, and capabilities of the other field.

Bridging these knowledge gaps is one of the primary goals of this report, as it:

- Describes the challenges of the evolving energy/weather nexus
- Gives a brief summary of meteorological data and modeling basics
- Outlines the weather inputs needed for power system planning
- Describes the seven attributes of an ideal weather inputs database for power system planning
- Summarizes a process of producing the necessary weather inputs data

4 A number of recent studies have recognized these needs, including the need for data to quantify the increased importance of weather dependence, including ESIG (2021), Novacheck et al. (2021), Bloomfield et al. (2021), and Dubus et al. (2022), and for improved methods for incorporating weather in power system models, including Voisin et al. (2018), Nahmacher et al. (2016), Wang et al. (2016), Dyreson et al. (2022), and Su et al. (2020).

The Challenges of the Evolving Weather/Energy Nexus

As levels of wind and solar continue to rise, the effects of temperature alone are replaced by a complex interplay among temperature, wind speed and direction, and solar irradiance on supply, load, and transmission and distribution infrastructure.

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Increasing Weather Dependence of Generation and Load

While the impact of weather on supply is still smaller than on demand today, the effects are significant and will continue to grow. Until recently, temperature was the primary weather variable impacting electricity supply in all but hydro-dominated systems. Temperature affects the efficiency of thermal plants and the reliability of thermal and renewable generators, with periods outside of typical ranges more likely to see forced outages (Murphy, Sowell, and Apt, 2019). Cold temperatures can affect the availability of the natural gas supply for gas-fired generation through conflicts with residential heating, decreased pipeline pressure, and increased failures of gas transportation infrastructure.

With rising levels of wind and solar generation, supply-side weather dependence is increasing rapidly. Wind power output is very sensitive to small changes in wind conditions, because the power density in wind is proportional to the third power of wind speed. Solar

generation is sensitive to irradiance, and both wind and solar generation are impacted by temperature, humidity, and precipitation. Solar and (to a lesser extent) wind generation are affected by smoke and other atmospheric aerosol loads, which are strongly influenced by weather patterns.

The magnitude of weather impacts on renewables today and going forward is greater than the chiefly temperature-driven weather impacts on the electricity system seen in the past. Wind and solar resources can go to zero for periods of time, and changes in weather at the location of wind and solar generators affect their output immediately. Weather impacts on variable renewables are also more complex. Wind and solar generators are located in a wide range of locations, and resource conditions can vary considerably across short distances and change rapidly in time.

The sensitivity of load to weather is also increasing and becoming more complex, with the electrification and decarbonization of transportation and the built environment—namely, the electrification of heating, increasing use of air conditioning, and electric vehicle adoption. And the impact of weather on demand shape and amplitude is changing with the continued deployment of behind-the-meter generation—mostly rooftop solar.

Increasingly Vulnerable Transmission and Distribution Infrastructure

The vulnerability of transmission and distribution systems is rising due to changes in extreme events and their frequency, especially region-wide heat and cold waves. Temperature and wind can affect transmission line ratings, and drought increases the likelihood of wildfires that can impact the transmission system. Transmission and distribution systems are both vulnerable to weather extremes involving lightning, icing, snow, and high winds.

The transmission of power will play an important role in the adoption and integration of variable renewable resources, and some weather events will concurrently stress every part of the power system. The planning of mitigation and response strategies thus requires a better understanding of the interplay of weather impacts across supply, demand, transmission, and distribution.

Conditions that drive system stress are becoming much more complex, driven by coincident weather impacts on generation, load, transmission, and distribution. Data defining these variables are not collected or modeled at anything close to the required fidelity if we are to assess system reliability across the range of expected weather conditions.

Complexity and Interdependence of Weather Impacts

Concurrent with the increase in weather dependence across supply, demand, transmission, and distribution is an increase in the complexity and interdependence of these weather impacts. In the past, relatively simple relationships could be developed between: (1) the temperature at a small number of weather observation sites within population centers and the load expected within a balancing area, and (2) the temperature measurements near thermal generating facilities and the probability of outage. However, it is much less common to see simple relationships between individual observational data points and wind and solar resource production within a region. In addition, wind and solar generation facilities are widely distributed, with significant variability in weather-driven resources between sites, and located in

rural areas where weather observations are sparse. Thus, multiple weather variables are driving both supply and demand in ways that range from strongly synergistic to strongly antagonistic. The nature and diversity of system stress is becoming much more complex, driven by coincident weather impacts on renewable supply, hydro generation, load, generator availability, transmission, and distribution. Data defining the distribution of these variables in time and space are not collected—or modeled—at anything close to the required fidelity. It is crucial to have data that can allow the envelope of possible supply and demand combinations to be quantified across the range of expected weather conditions, for use in assessing the reliability of increasingly weather-dependent systems.

Complexity Posed by Climate Change

Climate change poses an additional layer of complexity and uncertainty in power systems' weather dependence, as weather increasingly deviates from historical norms. The impacts of climate change on wind and solar resources are only just beginning to be examined at scales necessary to model its impact on supply and assess how these effects correlate to temperature and precipitation changes. Current global climate models generally cannot predict changes in wind and solar resources at sufficient spatio-temporal resolution for use in system planning models.

However, large changes are generally not expected in the overall spatio-temporal wind and solar resource distributions over the coming decade. For this reason, and because, at least in the short term, it is more urgent to quantify the impact of weather variables on rapidly expanding renewables and rapidly changing demand, this report does not attempt to provide definitive recommendations around producing and using weather inputs that incorporate climate change projections into resource adequacy and other system planning studies. A deeper treatment of this topic is recommended for a future task force.

Resulting Data Needs for System Planning

Because the impact of weather on the electricity system has broadened, it is no longer sufficient to simply ensure there is enough generation to meet the peak loads for the climatologically hottest and/or coldest days. While in the future the overall electricity consumption will still peak on the hottest and coldest days, demand will no longer be primarily described as a function of time of year, day of the week, time of day, and temperature, and utility-scale generation will no longer be simply a function of available capacity and outage rates.

The increase in the number of weather variables—and the number of locations at which these variables have an impact—means that much more weather data are needed to estimate the weather impact on the electricity system at any given moment.

Both demand and supply have large, rapidly growing components that are influenced in numerous ways by different weather variables—all of which vary in time and space and in interrelated ways. This increase in the number of weather variables—and the number of locations at which these variables have an impact—means that much more weather data are needed to estimate the weather impact on the electricity system at any given moment. Further, weather data spanning many years are needed to determine the range of possible outcomes of these variables and the likelihood they will occur. And the weather variables in these datasets must coincide in time and represent a realistic chronology of weather patterns.

Brief Overview of Meteorological Data and Modeling for Power System Planning

When available, direct observations are the most accurate way to characterize atmospheric variables. However, the necessary observing network does not exist and would be impractical to build; therefore, models are used to fill in the temporal and spatial gaps. Models that synthesize weather data for use in power system analysis should ideally capture the physical and dynamical relationships between weather variables and produce weather states that are physically plausible, evolve realistically in time and space, and produce distributions of conditions like those that are observed in reality.

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Currently, the models range from simple models, often developed by power systems engineers with little meteorological training, to highly sophisticated physics-based weather models. Some of the latest artificial intelligence methods are also starting to be deployed in conjunction with physics-based models, to reduce the enormous computational requirements of running the physical models at high spatial resolution.[5]

Simple Models

Simple models are easy to understand, but because of the complex nature of the atmosphere, they are often inaccurate. Simple statistical models develop relationships between two or more variables at a site or, in some cases, across several locations. A category of methods often used in integrated resource plans and similar planning studies is to use actual historical generation data or loads for a region, and develop empirical relationships between these data and a longer time series of weather observations from one or more nearby sites. These methods are easy to understand, are simple to implement, and use standard meteorological observations, which are relatively easy to acquire for long time periods. It is possible to create useful relationships between variables like temperature observed within a load center and the concurrent load. Similar relationships are used to link wind speed at an offsite location to wind speed at a generating site in order to predict a longer time series of monthly and annual output expectations during renewable development resource assessment—a process usually called measure, correlate, and predict (MCP). The simplicity of these methods and their successful use in load estimation and long-term generation output makes their use appealing.

However, it is much more difficult to use this type of statistical relationship to estimate hourly or more granular wind and solar generation, because the relationships between quantities cannot be described with linear or even multivariate relationships. For instance, wind and solar observations at one location are often used to estimate wind and solar generation at other locations.

5 "Meteorology 101: Meteorological Data Fundamentals for Power System Planning" provides a longer, more in-depth version of this overview and can be found at https://www.esig.energy/weather-data-for-power-system-planning.

Sometimes, even more indirect connections are attempted; for instance, a relationship may be created between temperature at a site and the expected wind generation at that location (or even some other location). Attempts to fit data in this way rarely produce accurate time series data at the granularity needed for power system analysis. Any suggestion that such modeling is possible should be viewed with deep skepticism in all but the simplest cases. Because they are not physics-based, these methods typically exhibit large errors when used to produce hourly (or more frequent) time series even if the average bias is low, and they usually do not correctly reflect the dependence of each weather input on the others, and thus on different components of the electricity system. Where data are derived in this way, it is important that they be validated, not just to verify that the overall distribution of outcomes for wind or solar generation looks realistic, but to confirm that the data produced are representative of actual concurrent and chronological measurements—otherwise, the data will not represent the overall balance of supply and demand situations that actually occur.

Physics-Based Models

Physics-based models solve mathematical equations that represent physical laws describing atmospheric processes and the connections between atmospheric quantities. They can be diagnostic, in which case they relate one quantity to another, or prognostic in which case they can predict the evolution of the atmosphere in time and space. NWP models are a class of prognostic model that mathematically represents the physical laws governing the weather and can be used together with observations to estimate the conditions at a later time. Not only are these models able to predict future conditions but, when used together with past observations, they can estimate a denser array of historical meteorological data than is available from observations alone. NWP models produce data that are usually much more accurate than non-physics-based methods, but synthetic data produced this way can still contain large errors even when appearing to be realistic. The errors are related to the data used as inputs to the NWP process and to unavoidable imperfections specific to the model configuration used.

The NWP Modeling Process

NWP models can be used to forecast weather conditions in the future or to create historical datasets by "forecasting" weather conditions in the past. In either case, NWP modeling starts with an initial condition produced by taking a "first guess" of the atmospheric state from a prior model run (usually a short-range prediction of 1, 3, or 6 hours) and adjusting it using as many sources of observational weather data as possible, including surface observations, balloon soundings, radar data, ground- and space-based remote-sensed information, and aircraft data. This complex process incorporates the observations into the model in a way that considers both model and observational uncertainty. This becomes the new initial condition for the next time step of the model.

The same weather model can produce vastly different output depending on how it is configured and initialized. Atmospheric processes are highly non-linear; small changes in one variable can result in large changes in another. This means that even a slight difference in the initial condition and/or the model representation of atmospheric processes, or even just the level of computer rounding, may amplify and change a weather pattern's evolution. This is the so-called butterfly effect, where the pressure change produced by the flapping of a butterfly's wings may later affect the course of a hurricane thousands of miles away.[6]

Figure 2 illustrates the typical cyclical NWP process where weather observations and the first guess field are melded in the data assimilation process to produce the model initial condition. The NWP model then iteratively solves equations that are mathematical representations of the laws governing atmospheric evolution until the desired forecast horizon is reached. This process is called model integration. The weather forecast data that are generated are then post-processed to produce useful products for specific end users, and one of the short range forecasts (usually 1, 3, or 6 hours beyond the initial condition time) is fed back to the assimilation step to produce the initial condition for the next cycle. When carried out to forecast future weather, the collection

FIGURE 2

The NWP Cycle and Representation of Atmospheric Data on a Model Grid

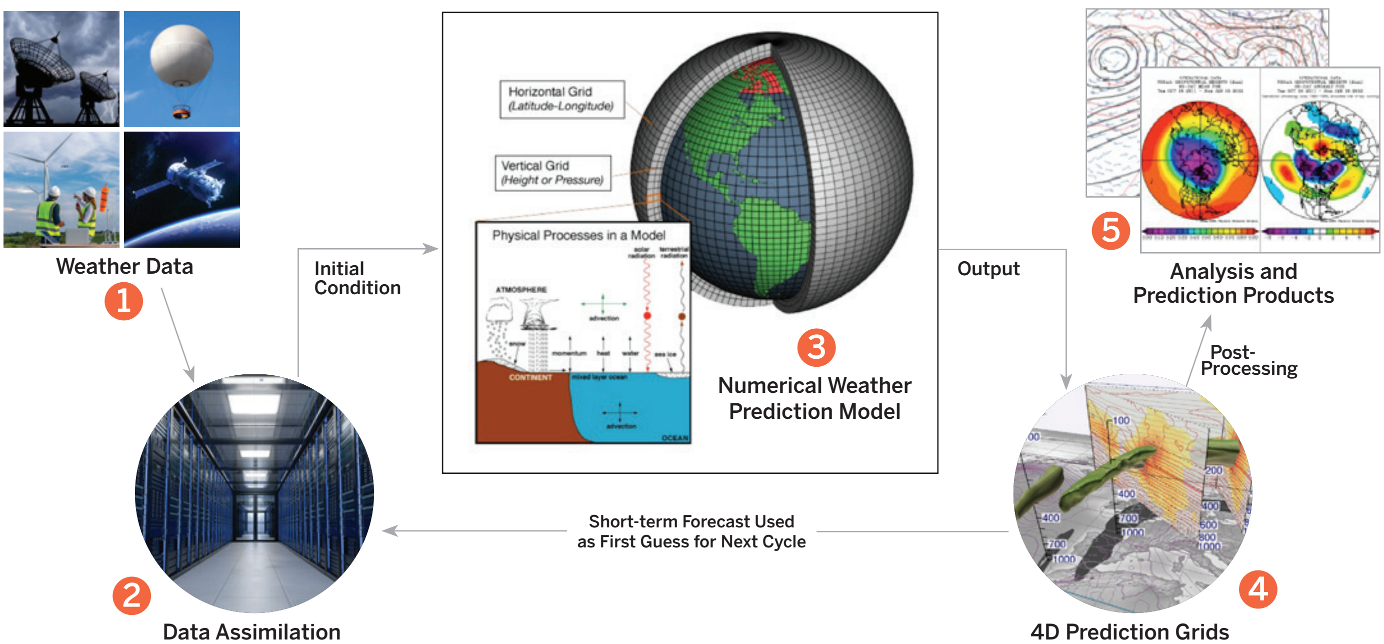


Illustration of the cyclical NWP process. Gridded weather data output from a prior NWP iteration becomes the background field (or first guess) to the next iteration. This first guess is then nudged toward observations, while keeping it consistent with differences between how the model configuration represents the physical world. The NWP calculations are then performed and the result post-processed according to the use case, while a short-range forecast feeds the next cycle.

Source: Justin Sharp.

6 See Lorenz (1972), and https://science.howstuffworks.com/math-concepts/butterfly-effect.htm.

and processing of weather data, the assimilation process, and integration must be done as quickly as possible so that the data are a forecast of the future state of the atmosphere. However, the same NWP process can also be used on historical observational to synthesize a higher-fidelity (in time and space) estimate of the state of the atmosphere than is possible with the available observations alone. In this case, more observations are usually available, and the assimilation and integration processes can be configured to prioritize accuracy over timeliness by, for example, using smaller grid spacing and more sophisticated representations of physical processes.

It is often mistakenly believed that lower-resolution models will predict the broad features of air flow in complex topography and that this output can then be statistically corrected. However, if the model topography cannot properly support conditions that cause a phenomenon, the phenomenon may be absent altogether from model output.

Resolution

Processes used to produce datasets for use in power system planning must provide sufficient spatial resolution to accurately resolve the phenomena impacting supply and demand. This means:

- Knowing temperature in enough detail to accurately predict its impact on load
- Specifying variables driving wind and solar in enough detail to quantify the generating potential at every plausible generation site
- Having information about weather phenomena at a scale that can be used to estimate their impact on thermal generation derates and outages, transmission, and distribution

Wind resource is the limiting factor in determining how to use models to fill in gaps in observations, because the wind field is heavily influenced by topography and near land and water interfaces. To estimate the output from wind plants at the granularity needed for system planning will require that the data points are no more than 2 km from the point of interest, and ideally much closer.

NWP models can be run at different grid spacing in both the horizontal and the vertical, which determines the granularity of the geography and attendant physical processes that the model can simulate. Model resolution is crucial, as small-scale features can strongly affect weather; the effects of topographical features that occur at scales smaller than the grid spacing will be represented inaccurately in the model or not at all (Figure 3, p. 12). Discrepancies between model data and reality are particularly important to consider in regions with hilly or mountainous topography. Where model topography differs significantly from actual topography, even if a large-scale weather pattern is correctly modeled, the projection of it onto a smaller scale will be consistently incorrect, and modeled values may be very different from those of reality.

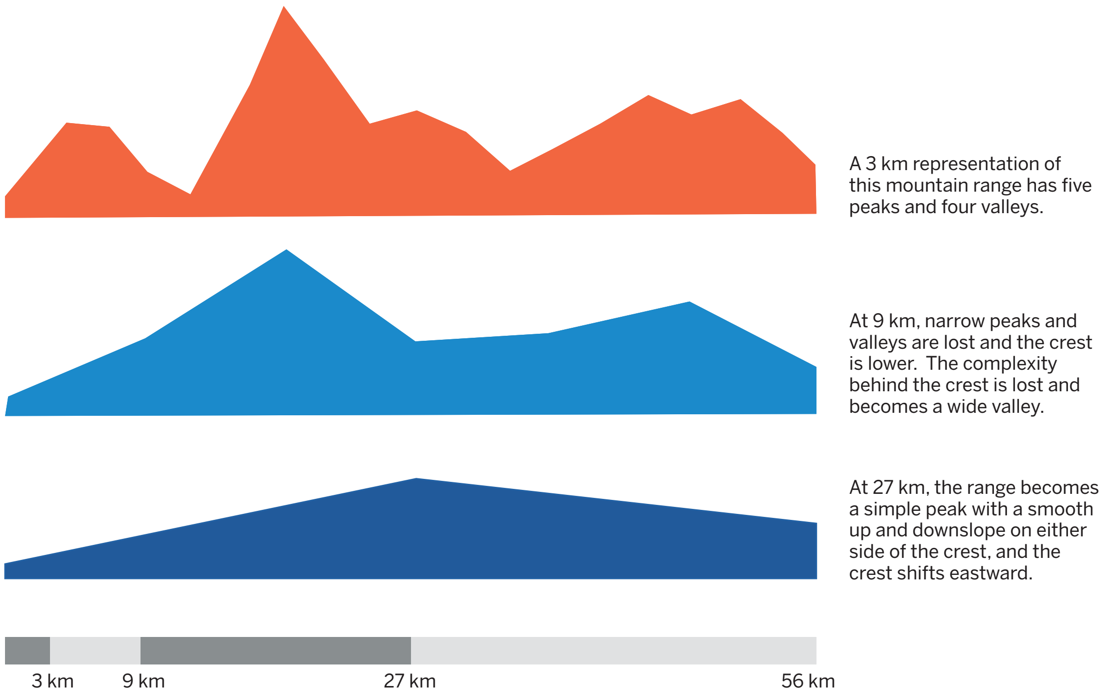
While it is generally understood that lower-resolution models will not properly predict the details of air flow in complex topography, it is often mistakenly believed that these models will predict the broad features of the flow and that this output can then be statistically corrected. However, if the model topography cannot properly support conditions that cause a phenomenon, the phenomenon may be absent altogether from model output.

Limitations of Model-Synthesized Weather Data

The same physics-based weather model can produce vastly different output depending on how it is configured. While physics-based methods produce detailed outputs with realistic weather patterns that reflect the input observations, the uncertainty of the model output is vastly greater than that of direct meteorological observations. The model output uncertainty is also not uniform in time and space or between different weather regimes and geographies. And it is a function of model configuration and model parameterizations—settings that allow models to simulate phenomena that cannot be explicitly modeled because they are too small, are too poorly understood, occur too rapidly, or are too complex to model explicitly.

FIGURE 3

Hypothetical Cross Sections Showing Model Representations of a Complex Topography at Different Grid Spacing



The top plot shows a cross-section of hypothetical complex topography represented at 3 km grid spacing. The middle plot uses the average of sets of three 3 km points for each 9 km point. In the bottom plot, three 9 km points were averaged to get to each 27 km point.

Source: Justin Sharp.

Given that synthetic weather data have much more inherent uncertainty than data coming from weather observations, validation and uncertainty quantification are essential to prevent invalid conclusions from being drawn from studies utilizing synthetic weather inputs. Few synthetic model data have been robustly validated against observations, largely because in many cases such validation is not possible because the modeling was performed specifically to fill gaps where observations were unavailable.

NWP is a complex subject with many nuances. It requires expert knowledge to understand the inherent uncertainties in the modeling process, and it changes for particular locations, weather variables, and weather regimes. Expert knowledge is required to determine what model resolution, parameterizations, and parameter settings are best for the problem being solved and/or determine the best compromise between accuracy and computational burden. When performing long simulations across broad regions, configurations that work well in one region or season may perform poorly in others. And even with well-chosen selections of resolution, parameterizations, and other configurable options, NWP models can sometimes be inconsistent. Differences in performance are not random and are often related to specific atmospheric conditions and/or geographies. When factors adversely affecting model performance align with weather situations that stress the electricity system, the weather inputs going into power system models may compromise the downstream results.

It is crucial, for any study using NWP data as a proxy for observations, that the data not be utilized as a black box dataset as if it contained quality-controlled observations. Users need to have at least a basic understanding of how

> **Even with well-chosen configurations, NWP models can sometimes be inconsistent. Differences in performance are not random and are often related to specific atmospheric conditions and/or geographies. When factors adversely affecting model performance align with weather situations that stress the electricity system, the weather inputs going into power system models may compromise the downstream results.**

the data were produced or engage with a meteorologist who has an NWP background—and ideally an understanding of how weather data are used in power system models—who can guide them in whether the data are appropriate for the application at hand. As part of this process, to ensure the appropriateness and accuracy of a modeled dataset for power system planning, users should review a comprehensive validation report for NWP data being used that has been performed within the context of the power system modeling use case. If a comprehensive validation report is not available, such a validation should be performed.

Some meteorologists without deep NWP backgrounds are not fully aware of these limitations and may recommend inappropriate usage of these models in power system planning. Even meteorologists *with* NWP backgrounds are sometimes not aware of how the data are being utilized and might recommend different approaches if they were. It is essential to have a feedback loop between power system modelers and NWP experts when NWP data are being used for weather inputs into power system analysis.

Estimating Generation: Extrapolation Versus Synthesis

Ideally, a planning study will have high-quality, clean generation data (free from contamination from curtailment or other effects impacting output in ways we don't want to incorporate into the study) covering the period

of interest. However, it is very rare that quality generation data will exist for a long enough period and/or at all sites of interest to use on its own. Therefore, once weather data have been identified that describe the resource (the fuel) available at a current or planned renewable energy facility, the next step is to convert that resource weather data into a generation estimate. The options are to extrapolate an existing generation dataset to a longer record or produce a completely synthetic estimate of output. Both methods have advantages and disadvantages, but it is worth noting that while the use of empirical correlations to extrapolate longer generation time series for renewable resources is intuitively easy to grasp for non-meteorologists, it should be regarded with skepticism even if other options seem limited.

Extrapolation methods relate the observed generation to meteorological variables to create an empirical power curve in a similar fashion to creating the relationship between temperature and load. If done at the level of an individual wind or solar facility, this will implicitly account for loss factors like wind plant wakes, inverter losses and clipping,[7] collector system losses, and substation losses. However, unless the data used to create the empirical power curve are carefully prepared, the function will also implicitly account for the average effects of other loss factors like output curtailment, equipment availability, icing, snow on panels, or high wind cut-out. These are factors that it would be best not to include in an extrapolation because they lower the output across all time periods, instead of just specific times.

Synthesizing generation estimates without reference to actual generation data uses power curves specific to the installed equipment (for example, model specification for the wind turbine, PV panel, and inverter). The advantage of this is that it is more generic and can be used for hypothetical future plants, but the disadvantage is that loss factors are not based on actual power plant configurations in the field. Thus, factors we do want to consider, like location-specific wake losses, are not included.

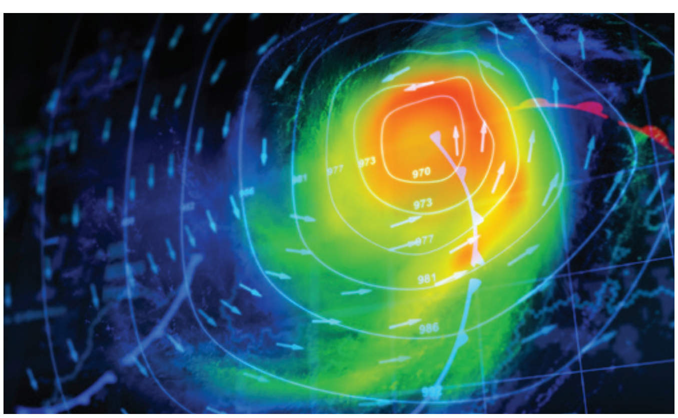
Whether extrapolation or synthesis methods are used, if aggregated estimates of output for an area are needed, the aggregation usually needs to be done by estimating the output at each facility and summing the results, to recognize the fact that the resource changes over short times and distances and different technologies may be used at different plants. Some current practices attempt to extrapolate production at a regional level, but at best this produces a coarse relationship between regional meteorological conditions and renewable output and is generally not recommended.

7 Because of the variable shape of solar output through the day and year, and because inverter capacity is very expensive, solar facility inverters are often sized smaller than the installed capacity of solar panels, because the energy lost during the relatively limited times that output exceeds the inverter sizing is worth less than the cost of a larger inverter. The resultant effect is called clipping.

Weather Inputs Needed for System Planning

Weather data are put to many uses in power system studies. This is discussed here together with how the data have typically been sourced and used, how the data needs are changing in more weather-dependent systems, and what the ramifications of this shift are for the applicability of currently available data.

Power system modeling applications—renewable integration studies, integrated resource plans and similar planning studies, and resource adequacy studies—evaluate load, resource mix, and transmission scenarios. In addition to the broad categories of system operations and system planning, weather data are also needed for a range of renewable resource development activities, including identification of prospective sites, evaluation of projects' generation expectations and variability, generator placement (especially for wind turbines), and optimal sizing and siting of battery storage. These activities require the same data and a similar temporal length as those needed for power system planning, but they focus on small geographical areas and the specific variables associated with the resource type. At the same time, they often require more detailed spatial resolution. Weather data are also vital for renewable resource project operations and maintenance, and power scheduling and participation in market processes handled by renewable facility operators. Lastly, weather data are used in performance analysis of renewable resource projects to determine the fuel (renewable resource) availability and other environmental conditions and compare them to generator output.



While the goal is typically to represent future scenarios, the data used, including the weather inputs, are usually based on conditions in the past for which measurements are available, and used either directly or as inputs for data synthesis using models.

Because the elements of the electricity system are becoming increasingly interwoven—with weather conditions being the consistent linkage—modeling efforts require quality weather data to obtain quality results. Databases are needed that include the concurrent weather variables that will impact load, wind, solar, hydro, and thermal generation, and that are long enough to capture weather variability and infrequent severe weather events (weather records at least 10 years, and ideally 40 or more, are needed to capture the variability, especially of tail events). They need to be of high enough resolution to get a reasonable assessment of generation at any current or future renewable generation facility; most power system modeling requires hourly or better granularity of these data, with 5-minute intervals preferred for some production cost modeling applications to assess ramping capability and reserve needs. And they need to be physically consistent, so that the estimates for all resource types are based on the same underlying weather conditions and thus able to capture weather periods that will lead to grid stress.

Box 1 (p. 16) describes the weather data needs for the main types of power system studies.

BOX 1

Power System Modeling Categories and Their Respective Data Needs

Weather data inputs are used extensively in power system planning, modeling, and operations. Although there are many different types of power system models, the most relevant for our purposes here are those used in the following three planning activities. At the heart of all planning, operational, and resource adequacy modeling is the requirement for the various simulations to proceed chronologically through one or more years. Planning models typically require hourly data, and operational models often use a five-minute time scale. Therefore, all renewable energy datasets need to faithfully preserve the chronology throughout the entire time period on either an hourly or five-minute time scale.

Renewable integration studies typically use models that simulate power system operations with various levels of renewable resources. As more renewable resources have been added to the power system and more regions in the U.S. have adopted ambitious renewable energy targets, these studies are evolving to incorporate very high levels of renewable resources and focus on how the power system could be operated—specifically to balance short-term fluctuations and uncertainty in wind and solar production—under these scenarios.

Integrated resource plans (IRPs) or similar planning studies are used in many state jurisdictions. The models used for this type of study can vary to some degree, but they most often include some type of planning/optimization model that can evaluate long-term costs and benefits of alternative resource mixes. These planning studies are sometimes augmented by more detailed operational models that require higher time resolution and more accurately simulate power system operations. Planning studies, and some operational modeling, often also include a resource adequacy assessment.

Planning models require a very large input dataset that can be used to choose the most effective combination and location of wind, solar, and other resources that are consistent with the planning objectives (optimized capacity expansion). Planning models used in renewable energy studies evaluate many alternative renewable resource build-out scenarios, performing what can be thought of as a "search" function to find the best combination of resources. This means that data for many renewable resources will be evaluated as candidate sites; hence, data for a very large number of renewable resource locations must be available for the planning models. The time resolution needed for renewable resource data for these models is hourly, and for as many years as possible (ideally three or more decades, though this is not always feasible), so as to guide the selection of the best long-term locations for renewable resource development.

Resource adequacy studies can be part of an IRP or carried out separately. Resource adequacy analysis typically requires hourly data and is an investigation of the ability of the power supply to reliably meet demand across a range of uncertainties. Resource availability, the probability of generators being out of service, and other factors are used to calculate one or more reliability metrics, which may include loss-of-load expectation, expected unserved energy, or heat maps that show times of expected supply risk. These studies are used to determine the total amount of resources that are needed to ensure reliability. The results of resource adequacy studies are being increasingly driven by the changing resource mix that includes more renewable resources and fewer traditional resources.

An Ideal Weather Inputs Database for Power System Planning

The Data and Attributes of Ideal System Planning Weather Inputs

The main attributes of time series data necessary to meet general power system modeling needs are that they need to include the necessary variables (described below), cover multiple decades, and be coincident and physically consistent, validated, documented, periodically refreshed, publicly available, and easily accessible (Table 1).

The production of one or more datasets to meet these needs will likely need to use NWP modeling approaches to either produce an original high-resolution reanalysis dataset for a limited domain, or to downscale an existing reanalysis dataset like the Fifth-Generation ECMWF (European Center for Medium-Range Weather Forecasting) Atmospheric Re-Analysis of the Global Climate (ERA5). It may be possible to combine the NWP approach with generative adversarial network (GAN) machine learning methods, which show promise

TABLE 1

The Main Attributes of Time Series Data Necessary to Meet General Power System Modeling Needs

Including the necessary variables	Include the necessary variables at sufficient spatio-temporal resolution and accuracy to reflect actual conditions that define the generation potential at current and future wind/solar sites and temperature at load centers
Covering multiple decades with ongoing extension	Cover multiple decades with consistent methodology and be extended on an ongoing basis to capture the most recent conditions and allow climate trends to be identified
Coincident and physically consistent	Are coincident and physically consistent, in space and time, across weather variables
Validated	Are validated against real conditions with uncertainty quantified
Documented	Are documented transparently and in detail, including limitations and a guide for usage
Periodically refreshed	Are periodically refreshed to account for scientific and technological advancements
Available and accessible	Publicly available, expertly curated, and easily accessible

Source: Energy Systems Integration Group.

for producing sufficient spatio-temporal resolution at lower overall computational cost than using only high-resolution NWP modeling. Other statistical post-processing methods could also be applied to correct known NWP model biases.[8]

The use of NWP modeling allows the resultant dataset to be anchored on as many observations as possible, while at the same time the full dynamics and physics of the NWP system can produce dynamically consistent and realistic fields where observations are not available, especially in complex topography. The ideal weather dataset for power system planning should have the following seven attributes.

ATTRIBUTE 1: Includes the Necessary Variables Across Required Regions with Sufficient Spatial and Temporal Resolution to Meet Power System Modeling Study Needs

Data for Wind Generation Estimation

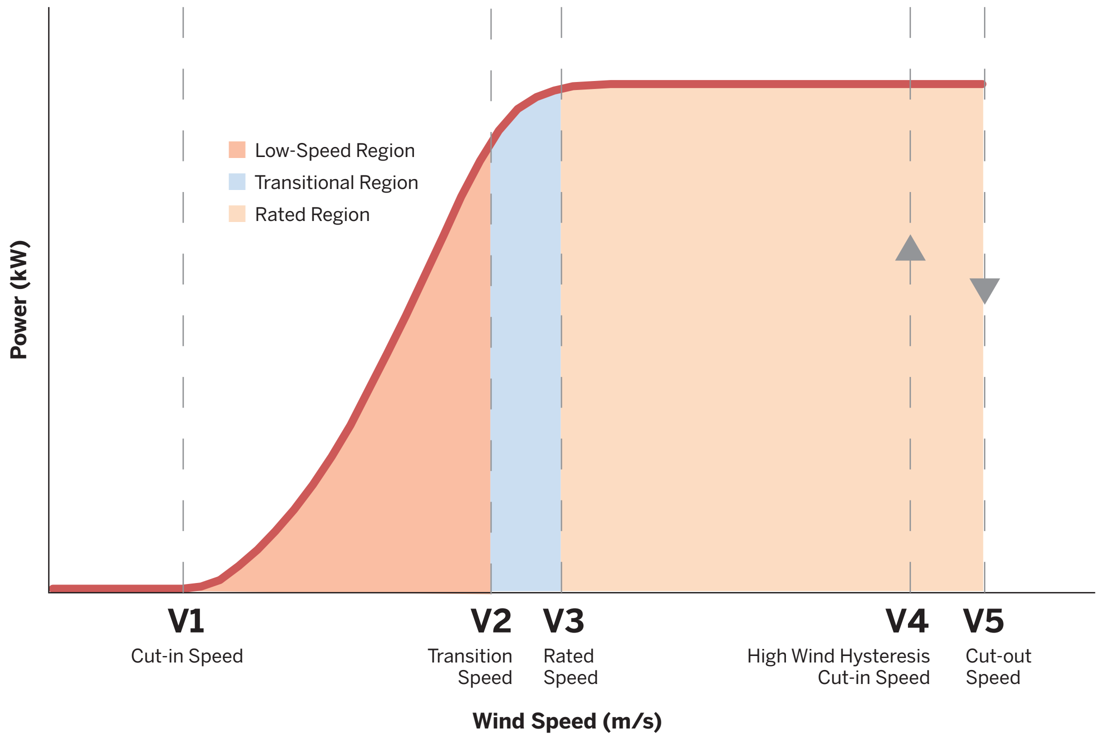
While it is not necessary to resolve the wind speed at every turbine in a power systems dataset, it is important for the dataset to estimate the impacts of features in complex terrain at least to a level where the regional wind generation can be accurately modeled. If an NWP system is used at a resolution that does not resolve the existence of features in complex terrain—if it cannot "see" them—it will not be able to produce wind fields that correctly estimate the hourly output from these facilities.

Deriving wind data also requires sufficient vertical resolution. Near the surface, the vertical structure of the atmosphere across the rotor layer needs to be realistically captured as it evolves through the diurnal cycle. In addition, the strength of the wind resource is often heavily influenced by regions of strong atmospheric stability near the surface, and good vertical resolution will allow the sharp vertical gradients in fields like wind and temperature to be sufficiently resolved.

To make an approximation of wind generation, wind speed near hub-height is needed. Wind speed accuracy is a major factor in reducing uncertainty in the generation estimate, primarily because generation scales with the

8 See "Meteorology 101: Meteorological Data Fundamentals for Power System Planning" for more detail about each of these methods, at https://www.esig.energy/weather-data-for-power-system-planning.

FIGURE 4
Wind Turbine Power Curve



Wind turbines are sensitive to small changes in wind conditions. V1 is the cut-in wind speed, the speed above which a turbine begins generating power. V3 is the rated wind speed, the speed at which the turbine reaches its rated power output; at speeds higher than this, no additional power available in the wind is captured, as the generator cannot further increase its output. V5 is the cut-out wind speed, the speed at which the pitch of the turbine blades reduces the output to 0 to protect the turbine. Operation of the turbine is suspended until the wind speed has slowed to V4 before it goes back up again, cycling between V4 and V5.

Source: Energy Systems Integration Group.

third power of wind speed in the part of a wind turbine power curve between cut-in and the knee of the power curve (Figure 4).

Wind data are needed at several levels from the surface through to 300 meters to provide wind speed throughout the rotor layer for many different possible hub heights, including those of the tallest offshore turbines. It is crucial *not* to extrapolate near-surface (10 m) winds to hub height, because at night the surface decouples from the free atmosphere above so that hub-height winds increase while surface winds decrease.

Temperature data are also useful—ideally at regular intervals from the surface to the top of the blade-swept area, although a single value somewhere between 50 m and 100 m will suffice. These are used to determine air density, which is a secondary variable in calculating power generation and can be important when building time series for prospective sites that do not have any generation data that can be utilized to create a plant power curve.

Temperature at multiple levels through to the top of the blade-swept area is useful as well, indicating the presence of strong surface stability, which itself is an indicator that the model winds might be less accurate than usual, because NWP models are notoriously poor at handling stable boundary layers and mix them out too quickly. Hub-height temperature can also be used to determine whether cold or hot weather shutdown is likely. And relative humidity is a useful variable, as the combination of temperature and relative humidity can predict icing. NWP models can produce the required spatial and temporal resolution needed for wind generation predictions. However, it should be understood that no model can consistently predict wind speeds to within the 1–2 m/s accuracy range that is needed. Thus, model data must be validated against wind observations wherever possible to develop insight into the skill and uncertainty of the model and the resultant impacts on generation estimates. If possible, some form of bias correction should be applied if model distributions are found to deviate considerably from observations. The model grid spacing required varies according to the complexity of the topography and weather phenomena in the region of interest; this is something an NWP expert should opine on. Where only output from NWP modeling performed at a lower resolution is available, a statistical correction trained with actual observed data may be possible, but generally refinement by downscaling with higher-resolution NWP or methods like the GAN machine learning technique will be necessary.

Data for Solar Generation Estimation

Producing a first-order estimate of solar photovoltaic production requires global horizontal irradiance (GHI), while estimation of concentrated solar power production requires direct normal irradiance (DNI), variables that must be modeled using NWP models or models that derive these variables directly from satellite observations.[9]

For solar, resolution is also important in some regions for defining the complexity of fields impacting solar generation potential, especially if NWP output is being used instead of model-processed satellite data to predict clouds and aerosol components.

Solar generation is also impacted by panel backplane temperature, which is largely a function of ambient temperature and wind speed. Measurements of temperature on the panels would be ideal, but having somewhat accurate near-surface wind and temperature data in a convenient dataset is helpful in adjusting the output expectations. For existing

plants, long NWP-based records can be tuned against actual observations.

Weather data indicating the presence of weather impacts that can dramatically impact generation estimates are also valuable, such as indications of snow, ice, and wildfire risk based on temperature, relative humidity, and wind speed. Including diagnostics based on these variables would allow users of power system modeling to determine periods where modified inputs could be used to stress-test high-risk periods.

Data to Estimate Gross Demand

Temperature is the driving weather variable for demand, with humidity, cloud cover, solar angle, and wind speed also contributing. These variables are measured at many surface observing sites and tend to be of higher quality and density in highly populated areas, where they have the most impact on demand. The data are also available in datasets derived from NWP as required variables in atmospheric modeling. It is important to note that raw NWP temperature data, even from reanalysis datasets, may differ from actual measured surface temperature observations. Given that they represent the average of the grid cell, they may deviate due to differences in model elevation and land surface characteristics relative to actual observations, especially if the grid cell is quite large.

9 The data assimilation process in NWP performs a similar task of deriving irradiance data from observational satellite measurement for the NWP initial condition.

Data to Estimate Outage and Derate Probabilities and Other Weather Influences

To capture the weather affecting outages and derates of all electricity system assets requires near-surface variables for fields such as temperature, wind speed, and frozen precipitation. Weather observations probably provide enough coverage of the extent and duration of frozen precipitation to allow the impacts to be handled in power system models that are sophisticated enough to include it now or in the future, but NWP methods will produce an estimate of frozen precipitation in a convenient, easy-to-process gridded format, so it is recommended that these data be archived when produced as part of synthesis of other weather inputs.

Other Meteorological Data

General Meteorological Data Defining Atmospheric State

Output from NWP models contains data that are not immediately of value to power system modeling but that can be used to restart the NWP process with another model (or the same model with a different configuration), to perform advanced post-processing, or for research and data-mining tasks that could inform power system modelers of trends and uncertainties in a model dataset. If considerable investment is made to synthesize weather inputs datasets, it makes sense to retain some of these data not immediately of value to power system modeling. However, high-resolution models spanning continental-sized domains can contain tens of millions (possibly hundreds of millions) of grid points, each with a suite of variables, for every output interval. Thus, choices need to be made about which data to keep. It is recommended to archive as much near-surface information as possible, as well as data from levels typically used to analyze and characterize meteorological regimes.

Recommendations

For wind generation, datasets should have horizontal resolution sufficient to resolve the wind field and vertical resolution sufficient to resolve surface inversions, several levels within the rotor plane, and sharp inversions capping flows driven by phenomena such as sea breezes and topography. Meeting these requirements for wind will usually provide for improved representativeness of solar and temperature data as well when the same source of model data is used. Vertical resolution is variable in NWP models; the selection of levels needs careful consideration by experts based on the application. Grid spacing of 2 km or better is required if complex topography is present.

For some applications, power system modelers would like data that have a 5-minute time resolution to align with typical dispatch intervals. This would allow the intra-hour variability of load and renewable resources to be assessed in production cost models. However, many power system modeling efforts utilize hourly data to reduce computation time and make problems more tractable.

Assuming that NWP is used as part of the process to produce the necessary data, it is technically feasible to produce data at 5-minute intervals. The higher the resolution, the shorter the time step needed to maintain numerical stability, but even at a relatively low resolution like 10 km grid spacing, most NWP models use a time step of one minute or less. There are some caveats for outputting this frequently, however. Most intuitively, outputting high-resolution gridded data at 5-minute intervals dramatically increases the volume of data created and can create processing bottlenecks as data are written to storage. Second, data users should realize that NWP models represent average changes over grid cells and will not capture all the variability that exists regardless of the output time step. Third, if a reanalysis method is used for data synthesis, a 5-minute assimilation interval is likely not computationally tractable, and the frequency is higher than that of many of the observations being assimilated. Lastly, shortwave and longwave radiation parameterizations in NWP models are performed less frequently than the dynamical time step, as they are computationally expensive, although newer schemes allow for fast radiation calculations every model time step with minimal degradation in accuracy.

The summary below reconciles these trade-offs and provides recommended specifications of dataset variables and spatial and temporal requirements.

Required data at a time interval of no less than 15 minutes, and horizontal grid spacing of 2 km or better:

- Wind speed and direction at 10 m, 25 m, 75 m, 100 m, 125 m, 150 m, 200 m, 300 m

- Temperature at 2 m, 10 m, 25 m, 75 m, 100 m, 125 m, 150 m, 200 m, 300 m
- Relative humidity at 2 m, 100 m, 300 m, or alternatively a post-processed icing risk field
- GHI, DNI, and diffuse horizontal irradiance (DHI)

Recommended data at an interval of no less than hourly, with a grid spacing of 2 km or better:

- Accumulated rainfall and snowfall, and precipitation type (hourly)
- All other model surface data and 2D fields
- All data from native model levels below 1 km above ground level. This will be useful for academic and applied research.
- Primary prognostic data (air temperature, pressure, water vapor mixing ratio, horizontal and vertical wind components) interpolated to standard meteorological pressure levels from the surface to 300 hPa (1000, 925, 850, 700, 500, and 300 hPa)[10]

ATTRIBUTE 2: Covers Multiple Decades with Consistent Methodology and Is Continuously Extended

Weather input datasets need to cover a climatologically valid time span if they are to capture the inherent variability in the atmosphere. Typically, atmospheric scientists have considered a 30-year period as sufficient to capture most of the variability that is expected. However, even longer periods are required to capture the distribution tails including extreme weather events that are critical when assessing power system reliability. Ideally the longest datasets possible are desired to capture as much variability as possible and derive information about events in the tails of the distribution.

The other side of the coin is the impact of climate change. While datasets going back 60 years or more probably reflect the variability of wind and solar resources in the future better than datasets covering only the last 10 years, there is no question that overall temperature distributions have changed and that these changes are likely beginning to impact other weather fields. Longer datasets are more likely to reveal climate change signals, and datasets that are continuously extended in the future are the best way to ensure that trends can be detected and evaluated as they develop.

Datasets covering large areas for long durations are essential to capture the full range of possible conditions and long-term trends. NWP methods are core to producing these. Importantly, the data availability to produce high-quality initial conditions for NWP modeling has been enabled by weather satellites which began to become prevalent in the late 1970s. This is important to recognize when deciding how far into the past to develop power system weather inputs using NWP modeling techniques. While we want the longest dataset possible, we do not want to utilize lower-quality data—which generally means being cautious with records going back further than 1990. When using datasets created with NWP methodologies, it should be recognized that the quality of the data is a function of the observations going into them, as well as the model resolution. Even when using modern models to assimilate data, earlier periods, especially before the satellite era, contain higher biases

10 Prognostic variables provide information about atmospheric state that can be used to both describe the state and predict the future state. These are the most useful variables that meteorologists can use to understand how the atmosphere is evolving and are the basis for performing forecasting tasks.

Extreme caution should be exercised if using NWP data archived from operational forecasting as weather inputs to energy system modeling. The model configuration used to generate the operational forecast data is unlikely to be consistent throughout the entire period of interest. In addition, operational models prioritize timeliness over producing the best possible initial condition and predictions.

and deficiencies because of this. These issues may be difficult to detect because the observing network contained much less detailed information than the grid data.

Another possible source of inconsistency in a multi-decadal dataset is the use of non-standardized model set-ups. As noted earlier, NWP model data archived from operational forecasting are sometimes used as weather inputs to energy system modeling.[11] However, this should be done with extreme caution. First, the model configuration used to generate the operational forecast data is unlikely to be consistent throughout the period of interest, as operational models are regularly updated to incorporate new developments from the research community or to increase resolution or size of the region being modeled as computational power increases. Each time an update is made, model biases and error levels may change. Second, data assimilation in operational models is optimized to starting model integration at the earliest possible moment so that the forecast is timely, rather than produce the best possible initial condition. Thus, operational model output is generally inferior to output from the same NWP configuration performed retrospectively with no time constraints.

Recommendation

Datasets produced as weather inputs to system planning models should extend back to at least 1990 and should use a consistent methodology throughout. Ideally, datasets should go back as far as possible, but documentation should be clear about the increased uncertainty in earlier years, especially prior to 1978. Longer datasets also require more computational resources, and if trade-offs need to be made between producing data prior to 1990 and other attributes like resolution, future-proofing, and continuous extension, then limiting the historical duration is preferred.

Datasets aimed at power system modeling users should be extended in an ongoing fashion using a consistent methodology. Continuous extension is essential and is far more important than extending the record back many decades. This will ensure that the latest gridded data are always available for power system modeling and to compare against new observations (particularly at renewable resource sites) that can be used to validate the model performance. Continuous extension of the dataset will also allow any trends in climate to be observed and will provide accurate, easily accessible weather information to analyze outages and future extreme events.

Datasets aimed at power system modeling users should be extended in an ongoing fashion using a consistent methodology. Continuous extension is essential and is far more important than extending the record back many decades.

ATTRIBUTE 3: Coincident and Physically Consistent Across Weather Variables

Given the increasingly weather-correlated behavior of supply and demand, time series variables must be coincident in time to maintain correlations between related phenomena that impact supply, demand, and infrastructure risks. Given the insufficient density of observational data to meet power system modeling needs, data must be synthesized with models, and the output variables must be physically consistent. It is vital to realize that if different weather variables that are used as inputs for power system modeling are sourced from different meteorological models, or if the models are not physics-based, it is unlikely that the time-coincident data will be physically consistent *even if* the inputs to

11 This practice of using data archived from operational forecasting to analyze past weather conditions was common practice prior to the widespread production of reanalysis data. This is because the forecast model initial conditions combined with short range forecast data provided the best 4D representation of historical atmospheric conditions, as their resolution in the horizontal and vertical is far higher than any observing network.s

the meteorological models are the same consistent set of weather observations. The inconsistency can lead to combinations of weather variables that are not physically reasonable and combinations that have a different likelihood of occurrence in the synthesized time series than in reality.

Incorrect distributions of net load and non-plausible outcomes can produce resource adequacy findings that are inconsistent with reality.

This data incongruency must be minimized because it will produce incorrect distributions of net load and may result in non-plausible outcomes. This in turn can lead, for example, to suboptimal portfolio optimizations in capacity expansion models or, in the case of tails in the distribution events, can produce resource adequacy findings that are inconsistent with reality.

When the same physics-based model configuration is used for all required variables, these incongruencies will not occur, though of course the model data themselves can differ from reality. However, if the meteorological models are statistical in nature, or even if two different physics-based models are used to source different variables, inconsistencies will occur. For statistical models the inconsistencies are likely to be profound. If two different physics-based models are used, the incongruency will be smaller but may still be significant, especially if output, while time-coincident, comes from models that have simulated different lengths of time from their starting point or have significantly different resolution. See Box 2.

Recommendation

Observations or physics-based models, as opposed to statistical models, should be used wherever possible. When combinations of observations and one or more physics-based models are used, even though the times are coincident, some validation must be performed to ensure that the resultant combinations of variables produce physically reasonable outcomes and that the differences between these outcomes and those seen in reality are understood and quantified.

BOX 2

Example of Incongruencies That Can Occur When Data from Different Datasets Are Used Together

One example of inconsistencies that can result from combining different datasets is the common combination of data from the National Renewable Energy Laboratory (NREL) Wind Integration National Dataset (WIND) Toolkit with the NREL National Solar Radiation Database (NSRDB). The WIND Toolkit data come from a model that runs multi-day NWP simulations. That is, using an initial condition and physics-based equations, the model predicts several days' worth of data. Meanwhile, the NSRDB data are created using a different model (the Physical Solar Model). This is still physics-based, but uses a diagnostic process to convert current satellite data into surface irradiance estimates. Although the large-scale weather pattern present in the simulations used to produce the WIND Toolkit is nudged back toward observations throughout the prediction period, it is possible for local-scale wind (and cloud) structures that the model develops in response to topography to become inconsistent with the cloud fields in NSRDB. This incongruency is probably nowhere near as serious as that which could arise from using different statistical models; however, no literature could be found by the ESIG project team that explores its magnitude. Since these two sources of data are frequently used together by power system modelers, the impact on the balance of supply and demand should be investigated if the datasets are to continue to be used together. This serves as a cautionary example of how even apparently coincident datasets that are commonly used together might not be physically consistent.

ATTRIBUTE 4: Validated with Uncertainty Quantified

Output data produced by any type of model, even if the model inputs are well quality-controlled observations, must be robustly validated and the uncertainty must be quantified. The data should not be expected to perfectly match actual observations, but the degree to which they do not needs to be known for each variable of interest—in the case of power system modeling, this is primarily

Datasets produced for power system analysis should include validation as a core part of the project to create them. This validation should pay particular attention to high-risk scenarios such as weather regimes yielding resource adequacy concerns, where biases and errors could lead to incorrect conclusions.

wind, irradiance, and temperature—and as a function of location, elevation, time of day, and time of year. In addition, it is important to pay particular attention to errors and biases that occur in weather regimes where the combination of moderate to high load and low wind and/or solar resource produces high net loads. If these scenarios coincide in a systematic fashion with significant errors or biases in the modeled variables contributing to supply and demand, then this must be considered when stating confidence in study results using the weather inputs. The issue should then become part of a feedback process to improve the weather inputs either through post-processing or improvement of the underlying model.

Aside from validating the data and quantifying the possible magnitude of errors, if using NWP, it is worthwhile to create ensemble datasets.[12] This produces multiple potential realizations of the atmospheric state, forming an envelope of "truth." Even where ground truth observations are not available for validation, the spread of the data within the different ensemble members provides a measure of the uncertainty of the model data and can also be used downstream to run several instances of a power system analysis and examine the spread of outcomes.

Recommendation

Datasets produced for the purposes of power system analysis should include validation as a core part of the project to create them. This validation should pay particular attention to high-risk scenarios, for example, weather regimes yielding resource adequacy concerns, where biases and errors could lead to incorrect conclusions. For example, a resource adequacy study is less concerned about the accuracy of average annual capacity factor of wind and solar resources, and more concerned about the accuracy—and associated probabilities—of sustained low-wind and low-solar periods. While a dataset that accurately predicts annual capacity factors but not outlier

12 In ensemble datasets, the same initial data are passed through different models or the same model with different configurations, or slightly perturbed versions of the initial data are run through the same model (or some combination of the two).

Documentation should transparently highlight the strengths and weaknesses of the methodology employed and provide guidance on how weaknesses may impact power system modeling efforts.

events may be appropriate for a solar or wind plant developer, it is insufficient for power system reliability analysis. In addition, new model datasets should use ensemble techniques to produce more than one estimate of weather inputs so that sensitivity of the power system models to weather inputs can be evaluated.

ATTRIBUTE 5: Documented in Detail and Transparently

Documentation of weather datasets used as inputs for power system studies is critical. It must be detailed and cover the items identified below. It should also transparently highlight the strengths and weaknesses of the methodology employed and provide guidance regarding how weaknesses may impact power system modeling efforts.

Recommendations

Documentation should include:

- Everything needed for an independent entity to recreate the data, including model configuration and input data sources. This also allows outside entities to test and critique the methodologies used.
- Validation results and measures of uncertainty, including ongoing validation as the dataset is extended.
- An accessible tutorial that educates non-meteorologist users in how the data were produced. The tutorial should help users understand the differences they should expect between the dataset and the actual truth that could theoretically be measured if a microscale observing network was possible. It should make it clear that any gridded dataset will be imperfect, and describe the dataset's limitations and possible flaws.
- A clear description of the format of the dataset so that the necessary information can easily be parsed by end users.
- Descriptions of each variable provided along with advice about the known issues regarding the modeling of each variable that might be relevant to power system modeling. For example, for data that have been produced by regional downscaling using an NWP model, during cold periods with strong surface inversions the inversions tend to be eroded faster than in reality. This results in time series data of temperature, wind speed, and low-lying cloud/fog (and thus irradiance) that progressively drift away from reality until the model initial condition is refreshed. This will obviously impact estimates of wind and solar generation and load that are derived from the data.

Plans should be made to ensure datasets are refreshed when they no longer represent the state of the art.

ATTRIBUTE 6: Future-Proofed

Plans should be made at the beginning of any project producing power system planning weather inputs to make sure that, within reason, it continues to represent the state of the art.

Recommendation

Aside from continuously extending any dataset produced for power system modeling, plans should be made—and budget assigned—to update the entire database at the point where improved science and methods can produce a materially more useful dataset. For example, the output from the existing method could be compared to that of the very latest methods each year for a sample of the dataset. When output from a test run shows 10 percent improvement of core metrics, the entire dataset would be recreated using the latest methods.

ATTRIBUTE 7: Publicly Available, Easily Accessible, and Standardized

To move toward the next generation of power system modeling techniques, quality weather inputs are essential. As we have seen, producing such datasets, while possible, is no small task. The data volume will also be very large. Therefore, those datasets that are produced should be

While several datasets meet some of the requirements, all of them fall short, largely because they either are too low in resolution, do not have a long enough time history, are antiquated, or do not capture all necessary weather variables in a physically consistent fashion.

broadly available, easy to access, and provided in a standardized manner.

Recommendations

- Create a data standard for weather inputs. The standard should define the format of the data and indicate which data are mandatory and which are optional.
- Divide the data into buckets as follows:
  - Data that will be routinely used by power system modelers. This should include everything that is needed, but no more, in order to minimize complexity and data volume. This will largely be fields on geometric height levels above ground level and will include wind, temperature, relative humidity, solar irradiance, and precipitation (amount and phase).
  - Data that may be needed for more in-depth analysis of the power system as a function of meteorological conditions likely to be of interest to those doing a deeper dive. This will be a more complete set of meteorological variables available on pressure levels and/or the native NWP model vertical coordinate. The recommendations for Attribute 1 provide a possible list for a technical review committee to consider as a starting point.
  - All other output deemed worth keeping relative to the cost of archiving it.

How Existing Datasets Compare Across the Attributes of an Ideal Dataset

Aside from the uncertainties of using model-based weather inputs, no datasets are available at this time that meet the requirements of (a) providing all the necessary weather data for a long enough time period, and (b) having sufficient resolution to properly estimate the necessary variables, to estimate generation across a long enough time period, especially in locations other than flat plains. Table 2 (p. 28) assesses existing datasets relative to the attributes of an ideal dataset. For example, the WIND Toolkit provides enough resolution to capture most features driving wind resources but currently does not cover a long enough period, while the ECMWF's ERA5 dataset covers a long enough temporal period and is regularly extended, but does not have sufficient resolution to capture many regional or local weather features driving renewable resources (Molina, Gutierrez, and Sanchez, 2021). The NSRDB provides good overall estimates of solar irradiance, but validation suggests it may not capture some of the short-term variability sufficiently for power system studies (Habte, Sengupta, and Lopez, 2017). It is regularly extended, but its 23-year length is not quite long enough to use concurrently with wind and load data to capture the full envelope of concurrent variability.

Table 2 summarizes some of the most useful available datasets, including ones recently introduced or currently in development, and indicates where they do and do not have the required attributes. (Descriptions of the main datasets currently used in power system planning can be found in the appendix.) Using the United States as the area of interest, if we apply the seven attributes to the datasets in Table 2, most datasets are eliminated, because the complex topography from the Rocky Mountains westward and the Appalachian Mountains eastward requires geographical spacing of 4 km or less to represent many of the phenomena driving renewable resources. While meeting the length requirements, the currently available global reanalysis datasets are nowhere close to providing the required spatial resolution. The highest-resolution option is ERA5, which has approximately 30 km grid spacing. Likewise, data from observations are far too sparse.

Thus, while several datasets meet some of the requirements for power system modeling, all of them fall short, largely because they either are too low in resolution, do not have a long enough time history, are antiquated, or do not capture all necessary weather variables in a physically consistent fashion.

TABLE 2

Summary of Current Power System Modeling Weather Input Data Sources

	Spatial Resolution	Temporal Resolution	Length	Continuously Extended	Correct Variables/ Levels	Coincident and Coherent	Validated/Uncertainty Quantified for Power System Use	Detailed Documentation	Future-Proofed	Availability/ Ease of Access	Curation and Advice	Region Covered
MERRA-2[a]	~60 km	60 min	1980–present	Yes	Yes/No	Yes	No		Probably		Basic	Global
ERA5[b]	~30 km	60 min	1940–present	Yes	Yes/No	Yes	Some		Yes		Good	Global
HRRR[c]	3 km	15 min	2014–present	Yes	Yes/No	Yes/No	No		Unideal		Basic	U.S.
WIND Toolkit[d]	2 km	5 min	2007–2014	No	Yes/Yes	Yes	Yes		No		Basic	Various
WTK-LED[e]	2 km/4 km	5 min	3 year/ 20 year	No	Yes/Yes	Yes	Not yet	Not yet	No	Unknown, dataset not yet available		Various
NSRDB[f]	4 km/ 60 km	30 min	1998–present	Yes	Yes/No	Solar only	Yes		Yes		Basic	Most of globe
CERRA[g]	11 km/5.5 km	60 min	1980–present		No/Yes	No solar	Yes		Possibly		Basic	Europe
CONUS404[h]	4 km	60 min/ 15 min (precip)	1980–2020	No	Unknown/ Probably	Yes	Not the intended use					Continental U.S.
BARRA[i]	12 km/ 1.5 km	60 min	1990–2019	No	Yes/ Probably	Yes				Fee-based		Australia/ New Zealand
Public Observing Networks[j]	Non-uniform, variable density	1 hr or less	Variable	Yes	Yes/No	Mostly	Varies. Not for power systems	Varies	Usually	Usually easy	Varies	Global
Renewable Energy Project Data[k]	Non-uniform, variable density	Usually minutes	Variable but rarely more than 10 years	Varies	Yes/ Usually	Yes	Usually	Varies, but usually poor	Varies	Usually poor	Usually none	Very limited
Proprietary Statistically Derived VRE Shapes[l]	Non-uniform, variable density	Usually hourly	Variable. Rarely reliable long records.	Varies	Usually incomplete	No	Partial	See note	No		None	Very limited

■ Fully Met ■ Close to Being Met ■ Partially Met ■ Met in a Very Limited Way ■ Not Met at All ■ Not Enough Info. for Determination

Summary of the most applicable datasets globally that are (or can be) used to provide weather inputs for power system analysis tasks, especially for providing estimate of site-level generation, and concurrent weather-driven load and generation outage risks. The degree to which the needs of each column heading are met is estimated with color coding. See documentation for each dataset for all details.

Source: Energy Systems Integration Group.

See the figure footnotes on the following page.

Table 2 Footnotes

a MERRA-2. The resolution of MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications) is typically insufficient for weather input use in power system analysis.

b ECMWF (European Center for Medium-Range Weather Forecasting) Reanalysis v5. ERA5 has insufficient resolution to diagnose regional or local weather, yet it is widely used for power system analysis.

c High-Resolution Rapid Refresh (HRRR). The HRRR is an operational model and therefore configured to balance accuracy with speed. It undergoes regular configuration updates, so model skill is changing in time. Occasionally, major updates may occur that can create step changes in model biases.

d Wind Integration National Dataset Toolkit. The years 2007 through 2013 cover the U.S., and 2014 uses a different configuration that includes Mexico and Canada.

e WTK-LED (WIND (Wind Integration National Dataset) Toolkit Long-term Ensemble Dataset) is still in production, and there is little current documentation. There are three years at 2 km, and 20 years at 4 km that are downscaled to 2 km with the machine learning GAN (generative adversarial network) approach. In addition, one year of ensemble data is being produced to aid in quantifying uncertainty.

f NSRDB (National Solar Radiation Database). Irradiance resolution is 4 km. Other variables are interpolated from MERRA-2 data using an unvalidated method. These data are generally not appropriate as weather inputs to power system analysis, forcing NSRDB to be used in combination with other datasets, which creates consistency issues.

g CERRA (Copernicus Regional Reanalysis for Europe). Ensembles at 11 km. Does not include all weather variables.

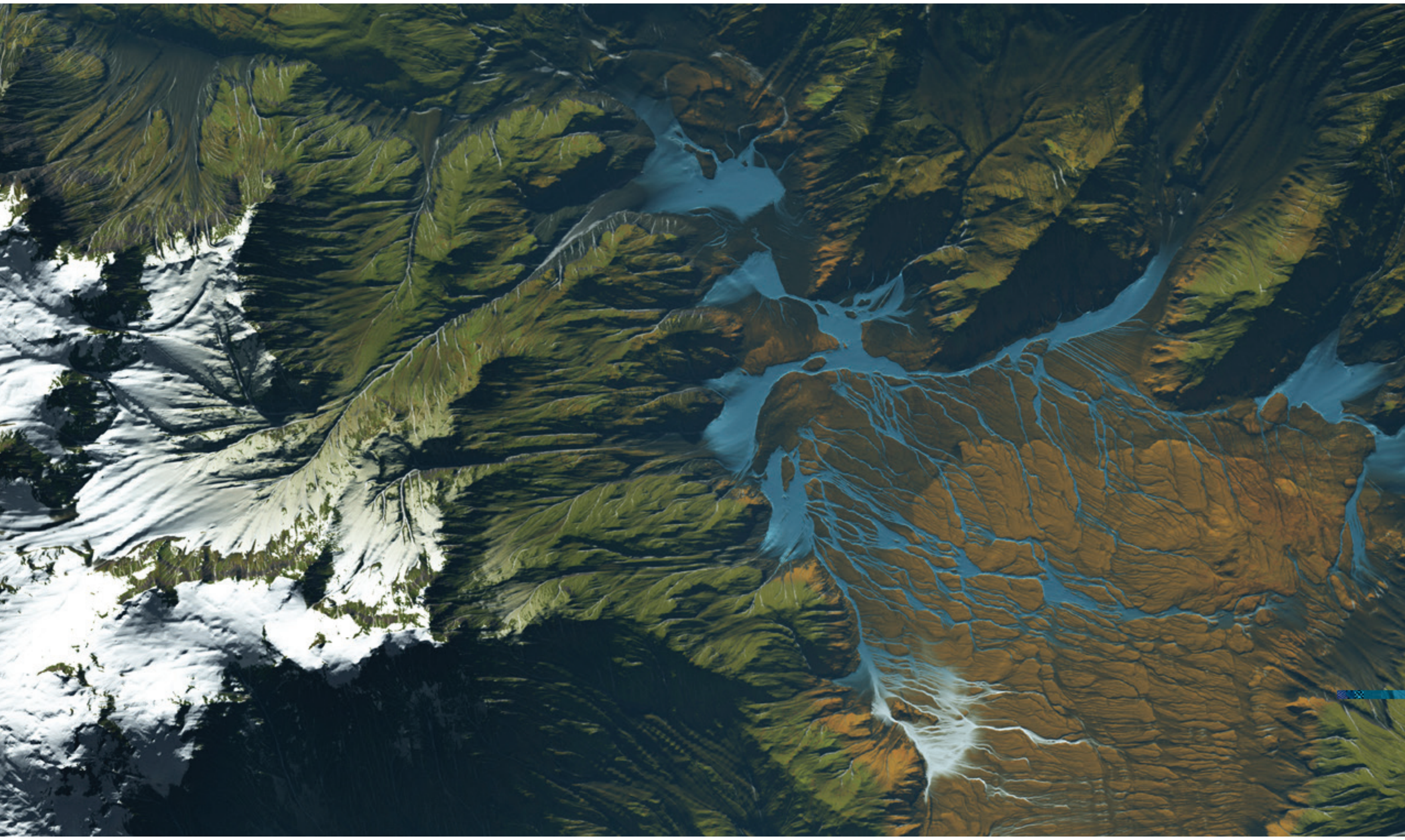
h CONUS404. A 4 km, long-term regional hydroclimate reanalysis over the conterminous United States (CONUS), 1979–2020. Developed by the U.S. Geological Survey to assess hydrological climatology, but may be useful to repurpose for power system analysis.

i Bureau's Atmospheric High-Resolution Regional Reanalysis for Australia. A 12 km reanalysis with 1.5 km domains over four cities in Australia.

j Many public observing networks exist with variable density, quality, and applicability.

k Observed data from renewable energy facilities is of course applicable to variable renewable energy, but quality varies from site to site and is typically proprietary. Data across the upper portion of the rotor sweep is often not measured.

l Often used proprietary data. The same shape is often assumed across broad areas. Validations are not rigorous, and methodologies are usually not fully documented in a transparent way. Output usually includes only a single weather variable.



Project Description for Producing Robust Weather Inputs Data

There can be no reliable energy transition without broadly available, consistent, weather datasets for power system analyses that meet the seven criteria outlined in this report. Given public policies that promote or require increases in renewable resources, these data should be considered a public good—one that is government funded, publicly available, and routinely maintained.

While the proposed effort is not trivial, the computer power needed is considerably less than that currently used by the National Oceanic and Atmospheric Administration (NOAA) for its operational forecasting efforts, and it is inexpensive compared to its value: providing accurate information guiding the deployment of trillions of dollars of renewable assets, specifically, where to locate and how to interconnect them in order to minimize cost and maximize reliability. It would be ideal for an entity with sufficient resources to have responsibility for curating the data, performing ongoing validation, flagging issues, and advising on the dataset's use.

The project would likely use either a high-resolution reanalysis or reforecast method, or a hybrid of high- and moderate-resolution solutions with one of these methods plus downscaling using machine learning methods. It would proceed in two stages. First, a technical review committee would refine the dataset requirements, assess methods for creating a sample dataset, and preside over a request for proposals to create one or more sample datasets that are thoroughly evaluated to assess accuracy expectations for the second phase. Second, a high-fidelity archive would be built using the selected methodology, and ongoing extension would be implemented.

The computer power needed is considerably less than that currently used by NOAA for its operational forecasting and is inexpensive compared to its value: providing accurate information guiding the deployment of trillions of dollars of renewable assets, locating and interconnecting them to minimize cost and maximize reliability.

STAGE 1: Validate and Refine Requirements and Confirm Need and Fitness

The initial stage of building an ideal weather dataset would convene a technical review committee including:

- Expert power system stakeholders
- One or two experienced energy meteorologists who are familiar with the big picture of how power system modeling is performed for both hypothetical studies and actual utility or system planning

- Experienced NWP modelers whose experience covers high-resolution modeling and data assimilation
- Experts in NWP post-processing methodologies including bias correction and downscaling techniques employing machine learning techniques

The technical review committee would perform the following steps:

1. **Vet and refine the dataset requirements.**
2. **Determine possible methods to create the sample datasets:**
   a. Select a period for which data will be produced. This may be a period of a year or a selection of dates intentionally chosen to cover different regimes that are important to system modeling. A recent year and/or a period that overlaps with that of past observational campaigns like the jointly sponsored NOAA/U.S. Department of Energy Wind Forecast Improvement Projects should be used in order to aid validation.[13] The period chosen should be one where as many quality observations as possible can be obtained to validate the fields that impact wind and solar generation across a broad range of geographies and weather regimes.
   b. Select candidate methods for dataset production. Ideally, candidate methods would be selected in an open and transparent competitive process. For example, a request for proposals could be broadcast, allowing interested parties to submit proposals describing the methodology they believe will best fulfill the requirements. Submissions would then be reviewed, and the most promising ones invited to produce sample datasets. This would ensure the maximum likelihood that candidate methods would include the latest innovations to maximize accuracy and provide a range of options and price points. Another avenue could be a cooperative agreement with NOAA to produce a high-resolution reanalysis dataset based on the current High-Resolution Rapid Refresh Model (HRRR) configuration. This would have the advantage of largely mimicking the current operational set-up and would be highly synergistic and useful to other sectors. Incorporating both approaches would provide the optimal information with which to determine the source(s) that provide the most effective and efficient pathway to producing the full historical and ongoing dataset(s).
   c. Using three to seven candidate methods, produce sample datasets.
3. **Compare the candidate methods and determine their value relative to using continuously extended datasets that exist today.** Datasets that could be

13 See https://psl.noaa.gov/renewable_energy/wfip/ and https://psl.noaa.gov/renewable_energy/wfip2/.

compared to the sample dataset include the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) and ERA5 reanalysis datasets and the NOAA HRRR operational forecast archive. NSRDB solar irradiance data could also be compared.

a. Obtain as much observational validation data as possible, with a focus on meteorological observations relevant to power system modeling. If possible, use industry outreach to obtain the most relevant observation data.

b. Rigorously validate the sample datasets and the control datasets against observations.

c. If quality power-output data can be obtained from a representative set of renewable resource facilities, create a post-processing model and train it to predict power based on the candidate and control model output to determine whether the new datasets better predict the overall characteristics of generation than the controls. This is important, because while it is certain that low-resolution datasets like MERRA-2 and ERA5 will not accurately predict the wind features present in complex terrain, it is still important to determine how accurately low-resolution output might predict power by statistical means (e.g., building a relationship between site generation and model wind speed/irradiance). It is unlikely that they will more accurately predict power output, but the experience of operational wind power forecasters has been that statistical models relating NWP output to project power can be as valuable as improved wind speed predictions. If such statistical processing of low-resolution model data can yield power predictions on par with those from high-resolution models, it may be worth spending effort looking at ways to utilize existing data.

   Of course, using a method like this would not be possible where no generation history exists, and it is likely that we need the large modeling effort that is being proposed. However, since most new renewable generation is now built near currently operational plants, if such a method works for existing sites using existing low-resolution, easy-to-obtain data from datasets like ERA5, and if operational output data can be obtained from sufficient numbers of existing projects, then developing methods of estimating generation at locations with no history using the existing reanalysis and generation history from existing nearby plants would be a much simpler, cheaper, and quicker solution.

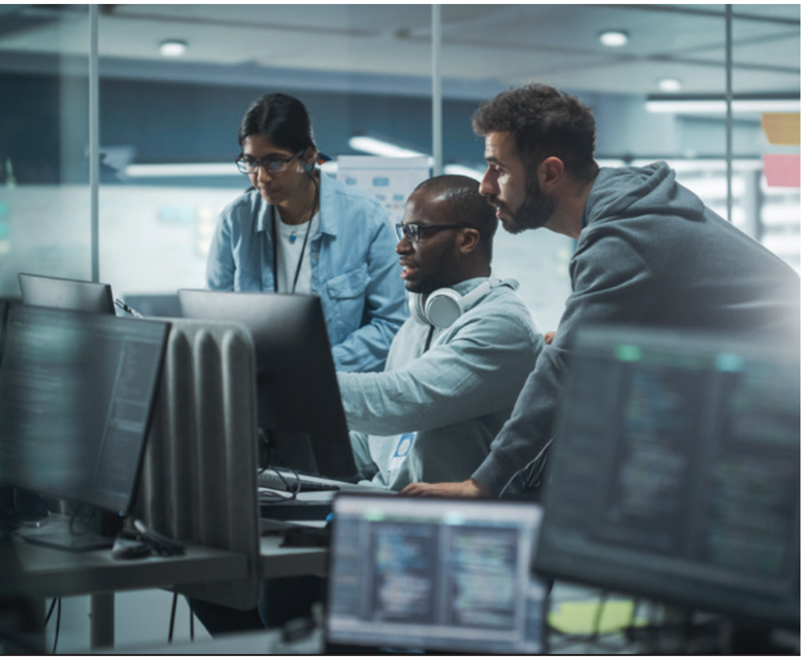
4. Determine whether the candidate datasets add value over the controls. Assuming they do, select the method with the best combination of cost and accuracy and move to Stage 2.

STAGE 2: Produce Historical Archive and Ongoing Process

Once the value of a dedicated process to produce a high-fidelity archive is established, the next step is to build the archive and operationalize the process of ongoing extension using the method selected in Stage 1. The main decisions at this point would be how far the archive will go back and when operational extension would be performed (for instance, are data for January 5, 2023, produced on January 10, 2023; are data for January 2023 produced in March 2023; or are data for all of 2023 produced sometime in 2024). The rest of the process of developing the data should be relatively straightforward and automated.

At this stage, curation of the data will be key to its usability and to understanding its limitations and uncertainty. The following issues would need to be thought through:

- **Data access:** Data volumes will be very large (many petabytes), and users will need a way to efficiently access the data they need.
- **Observation network:** A broad observation network is needed. This could be achieved by constructing new observing stations, but these are expensive to build and maintain. Obtaining meteorological data from existing renewable plants is a far more efficient approach, but there is currently substantial resistance to data sharing from renewable asset owners. Regardless of their source, more observations will be needed to properly validate high-resolution output. These observations will also be valuable in data assimilation where NWP-based solutions are deployed, and in post-processing to reduce systematic errors.



– Regions where wind and solar plants exist or may be built should be targeted, as these are often regions with no currently available public measurements. Where there are public data, these rarely measure wind at the elevations required, and almost never record solar radiation. To obtain the required density of observations will require educating renewable resource project owners on the value of (confidentially) sharing observations to improve ground truth data and getting the renewable energy sector to understand that improved meteorological datasets are in the interest of the entire sector.

– Interaction with system operators and regulators may also be needed to help secure meteorological data.

– In a limited number of cases, new observing networks may need to be deployed, either temporarily or permanently, to assess the quality of the data being produced in important data voids.

- **Ongoing validation:**
  – The data are only valuable if there is confidence in their accuracy. While no dataset will ever be perfect, understanding and communicating the flaws can prevent incorrect downstream conclusions from being drawn, as well as lead to methods to improve it.
  – Low-frequency, high-impact events should be identified and differences between available observations and the model data for these events analyzed in detail to determine how well tail events are captured. Sufficient human resources should be deployed so that high-impact events can be documented in detail to produce a library of such events for future stress-testing of the power system.
- **User education:** Providing insight into how and why the data might differ from ground truth will help to ensure that they are applied correctly. This will also reduce the misuse of existing weather datasets, because users will become more informed about the nuances and limitations of physical model–based datasets and learn best practices for their use. There should also be outreach efforts to promote the use of the data and report back on findings when they are used in important research.
- **Documentation of alternative data sources:** It may be helpful for the project to produce a central knowledge repository describing other energy meteorology datasets and their uses and limitations. This would be valuable for users and would provide insight into ways that data in any dataset can be improved by being refreshed. It is possible that the project could be further expanded to become a repository for the actual data from other efforts as well, allowing it to become a one-stop shop and promoting ongoing innovation.

The Importance of Cross-Disciplinary Cooperation

The weather is complex, as is the electricity system. Few people have more than a basic grasp of both fields. The lack of holistic understanding is leading to the misapplication of data that can result in invalid power system modeling results and poor decision-making. There is an urgent need for coordination, cooperation, and education between power system experts, meteorologists, and climatologists. It is crucial that power system modelers clearly articulate their data needs, and just as important that the providers of weather and climate data understand how the data are being applied in power system modeling and engage with power system planners to ensure they understand the limitations of the data that are being provided.

With rising levels of wind, solar, and storage and increased electrification, power system planning is becoming more complex and more weather-dependent—with a greater need to accurately model the impacts of weather variables on resource adequacy and system reliability. Accurate modeling requires a validated, high-resolution dataset with a long time series for key weather variables. The availability of such an ideal weather dataset, together with education and coordination between the meteorology and power system communities, will equip system planners to guide future resource siting and build-out for a reliable, high-renewables grid.

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This bibliography contains selected references for additional reading that are pertinent to this summary report. A complete reference list can be found in the full report.

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Appendix: Comparison of Data Requirements and Currently Available Datasets

The section, "An Ideal Weather Inputs Database for Power System Planning," describes seven attributes required of weather data for power systems analysis. Table 2 (p. 28) summarizes the most pertinent weather data currently available for power system analysis, including some that have recently been introduced or are currently in development. Below, selected datasets are compared against the seven attributes to indicate where they do and do not have the required attributes. A full comparison of all the datasets can be found in the full report.

ERA5 and Other Global Reanalysis Datasets

There are several global reanalysis datasets. (See "Meteorology 101: Meteorological Data Fundamentals for Power System Planning" for a detailed description of this type of dataset.) The most well known are the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis,[14] the National Aeronautics and Space Administration's Modern-Era Retrospective Analysis for Research and Applications (MERRA), MERRA-2 (an update of MERRA),[15] the Interim ECMWF (European Center for Medium-Range Weather Forecasting) Atmospheric Re-Analysis of the Global Climate (ERA-Interim),[16] and the Fifth-Generation ECMWF Atmospheric Re-Analysis of the Global Climate (ERA5).[17] These datasets provide an estimate of all the main variables that define the state of the atmosphere, as well as the state of the interface with the land and ocean surface on easy-to-use three-dimensional grids for every time interval in the dataset. Data include latitudinal and longitudinal wind components, temperature, humidity, liquid and frozen water content, and geopotential height in three dimensions; two-dimensional fields like irradiance, accumulated precipitation and snowfall, soil and water temperature, and model topography and land use; and often many other derived fields. The datasets span multiple decades and have a temporal resolution between one and six hours. Each is or was regularly extended with the latest weather data until deprecated by a subsequent improved dataset designed to take its place.

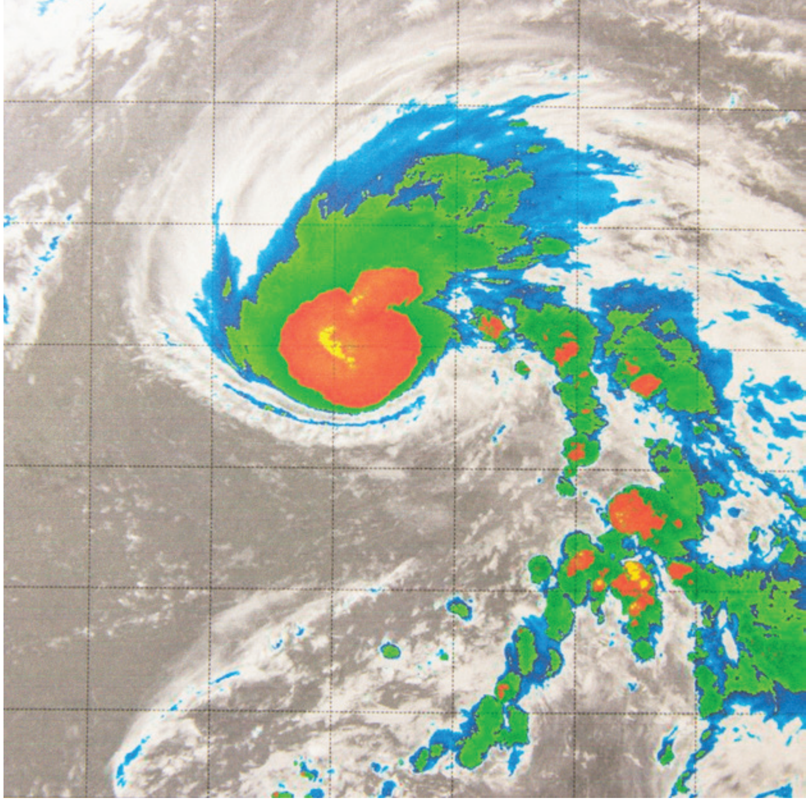
The focus here is on ERA5 (which was preceded by ERA-Interim), since for the purpose of weather inputs to the energy sector, it is far superior to the others. The NCEP/NCAR reanalysis was one of the earliest available global reanalysis datasets and is still being regularly extended, but its resolution is far too coarse for the needs of power system modeling. MERRA-2, which replaced MERRA, has a finer resolution than either MERRA or the NCAR/NCEP reanalysis, but is still much too coarse to use in any capacity for power system modeling without downscaling first. (Note that MERRA-2 provides the meteorological companion dataset to the National Solar Radiation Database, discussed below.)

14 https://www.ncei.noaa.gov/products/weather-climate-models/reanalysis-1-2

15 https://gmao.gsfc.nasa.gov/reanalysis/MERRA/ and https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/

16 https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-interim

17 The landing page for ERA5 information is https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5. From here there are links to detailed documentation. Documentation for the other reanalysis datasets can also be found online.



ERA5 is a global reanalysis dataset on which important meteorological fields defining the state of the atmosphere are represented on a 0.25°x0.25° grid, with 137 terrain-following vertical levels. (See "Meteorology 101: Meteorological Data Fundamentals for Power System Planning" for an explanation of terrain-following coordinates.) The data that are typically served to users are interpolated onto a regular Cartesian grid with regular 30 km spacing. The reanalysis is performed using the ECMWF Integrated Forecasting System (IFS) model and its 4D-Var data assimilation system, which are widely considered best in class. The output has been broadly validated and is found to produce meteorological fields that are representative of observations, especially in simple terrain. The archive extends back several decades and is regularly updated. ECMWF commits significant resources to quality-controlling the output. The modeling system is clearly documented, and the data are easy to access for any region of interest on the planet. For these reasons, ERA5 is an attractive dataset that is widely used, including for power system planning studies.

However, while ERA5 is unquestionably the best global reanalysis dataset currently available, it is not a panacea. Average validation statistics are very good, but the horizontal grid spacing of 30 km is insufficient to produce detailed meteorological fields present in complex topography, fields that are crucial to resolve for estimating renewable generation in these areas. As an example, a validation study including complex topography in southern Europe showed that variables like wind speed can exhibit average correlation coefficients in the range of 0.5 when compared to observations.[18] Poor correlations between the reanalysis data and observations are also found for other important variables such as temperature and precipitation when the combination of weather and terrain produces phenomena like valley cold pools, and large deviations from reality have been observed west of the Rocky Mountains in the United States.[19]

The main way in which ERA5 fails to meet the criteria for a long-term historical dataset for use in power system planning is its horizontal grid spacing (see Table 2, p. 28). Other, less serious limitations are that (a) the output is only available at hourly intervals, and (b) easily accessible data for near-surface levels are only available at 10 m and 100 m. Because of ERA5's low resolution, using it to estimate renewable generation for power system modeling can produce large errors, especially in regions of complex terrain, which are often good locations for renewables development. However, because ERA5 is such a good dataset overall, it is possible that it might be used as the input to downscaling methodologies, and it is valuable in regions with simple topography.

The High-Resolution Rapid Refresh Model (HRRR)

The National Oceanic and Atmospheric Administration's (NOAA's) HRRR is an operational limited-area model that runs on a rapid update cycle and covers the continental United States. New observational data are assimilated every hour, followed by a short forecast run (currently either 18 or 48 hours ahead, depending on the time of day), meaning that a new analysis is available every hour. Because the model is high resolution (currently 3 km grid spacing) and tethered to reality with frequent data assimilation, it offers many of the benefits of reanalysis but with high resolution. However, the fact that it is an operational model is a major drawback. To get the model refreshed with new observations and update the

18 Molina, Gutiérrez, and Sánchez (2021).

19 As seen in unpublished client work performed by Justin Sharp of Sharply Focused contrasting reanalysis datasets with observations.

short-term forecast, strict data cut-off times need to be enforced. (See the discussion of data assimilation in "Meteorology 101: Meteorological Data Fundamentals for Power System Planning.") Thus, many fewer observations will make it into the analysis than in the case of, for example, ERA5.

In addition, the HRRR model configuration and code are updated quite frequently, which might seem like a good thing, but it introduces changing biases into the time series data. At some point a major model change is likely to happen, such as an increase in horizontal resolution or a change in dynamical core, and this will create a data discontinuity. Lastly, the model has only been running since 2014, so the time series is too short for use in power system modeling.

Despite these flaws, the HRRR may be a good choice to provide weather inputs for some modeling exercises in which it is not essential to have a long time history to cover all possible conditions. Possible examples are renewable integration studies within the continental U.S. that aim to study periods since 2014, capacity expansion studies, and perhaps production cost modeling studies focused on reserve and flexibility needs. However, resource adequacy studies will require longer and more consistent time series data than are provided by this dataset.

The WIND Toolkit

The National Renewable Energy Laboratory's (NREL's) Wind Integration National Dataset (WIND) Toolkit dataset was produced specifically to provide weather inputs to wind integration studies.[20] The team that created it went to significant lengths to tune the model configuration so that wind speed autocorrelation and spatial covariance accurately represented the scales being examined. They also chose a 2 km grid spacing to ensure that most weather features important to wind generation were resolved. Data are output at 5-minute intervals to provide the granularity needed to resolve wind ramping events. The WIND Toolkit is unique in that a companion dataset containing "forecasts" was also created. For each hour in the WIND Toolkit output, there is an accompanying set of values that represents what forecasts of the weather at that hour would be for different lead times that correspond to power systems' operational gate closure times. The weather forecasts were then used to produce power forecasts at thousands of possible wind generation sites. The forecasts were tuned to have a similar skill to state-of-the-art forecasts. Of course, forecasting has improved since 2014, so the skill of these forecasts is lower than is possible today.

In one validation study the dataset was compared to wind observations located on tall meteorological towers at 13 sites around the U.S.[21] The comparisons were reasonably good but by no means perfect. The daily shapes of the wind averages showed some differences between the model and observational data, as did the distributions of wind speeds. The skill of the model is good relative to what can be expected from numerical weather prediction (NWP), but the differences are large enough to matter in power system applications. The most significant issue is an overall high bias in the wind speed. In another validation,[22] wind speeds from the WIND Toolkit at the locations around 284 real and hypothetical wind plants were used to calculate wind power at each plant. The "plants" were designed to represent either existing wind generation facilities or places throughout the country that were reasonable possibilities for future wind plants. Among other comparisons, the aggregate capacity factor for existing plants in the Midcontinent Independent System Operator (MISO) and Electric Reliability Council of Texas (ERCOT) territories was compared to power data derived from the WIND Toolkit. The simulated aggregate output was found to be reasonably consistent with reality, but again, there were significant differences in daily output shape and in energy volume. Of most concern was a tendency to over-predict the wind speed, yielding capacity factors that were 5 to 10 percentage points too high when aggregated across broad U.S. regions like ERCOT and MISO.

This finding underscores how critical it is not only to produce an easy-to-use dataset, but also to ensure that

20 https://www.nrel.gov/grid/wind-toolkit.html.

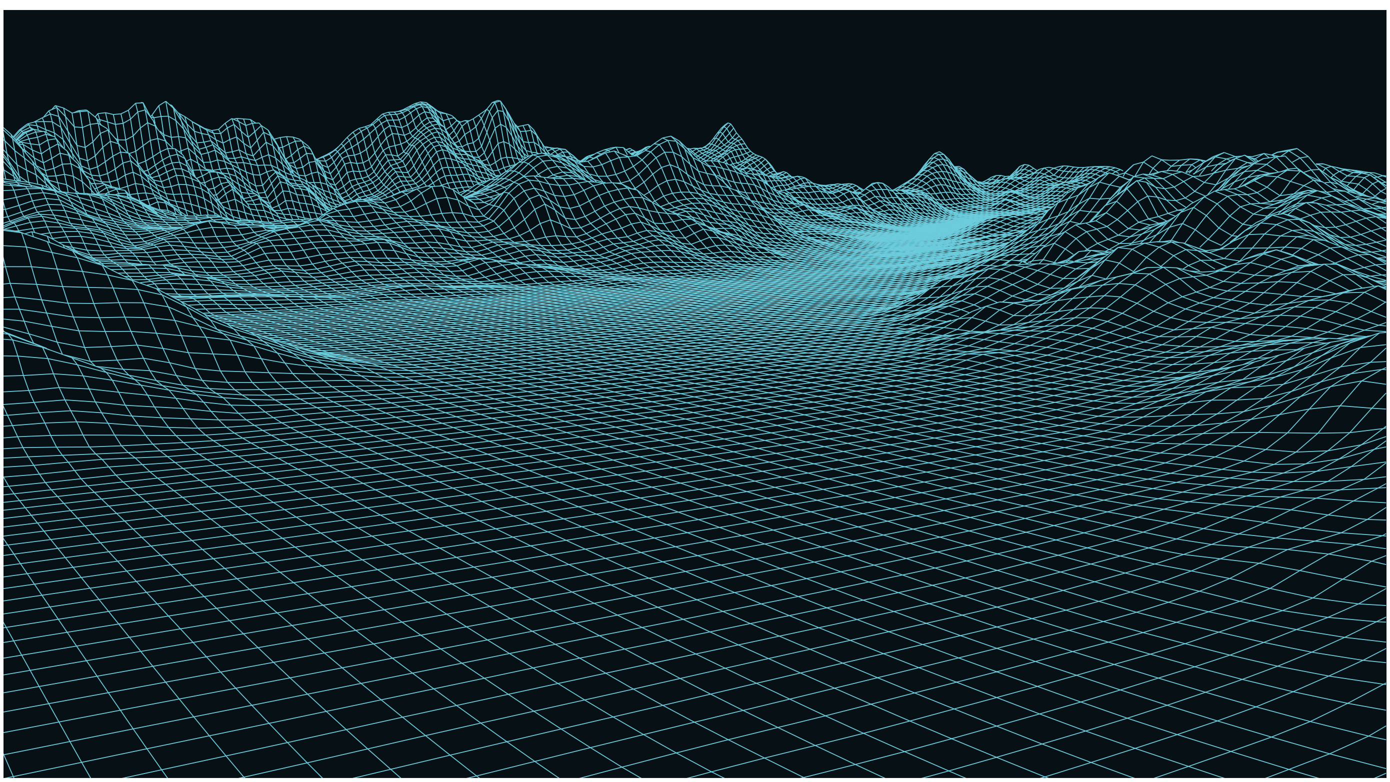
21 Draxl et al. (2015).

22 King, Clifton, and Hodge (2014).

it is validated in detail. While it would be desirable for the WIND Toolkit data not to exhibit this bias, at least the bias is documented, which is not the case for many other datasets. It is also important to make sure that inaccuracies are communicated. While the over-prediction has been noted by several users of the dataset, it is perhaps not as widely broadcast as it should be. The WIND Toolkit data contain significant errors during some critical weather regimes. For instance, it was found that during periods of low wind resource across the entire western U.S., the WIND Toolkit often greatly over-predicted the wind speed in the Pacific Northwest, yielding generation estimates for the large amount of wind in the Bonneville Power Administration balancing area that were much too high.[23] These errors are due to NWP models often struggling to represent stable boundary layers and mixing momentum to the surface from aloft too quickly during cold stable weather.

The output of the original WIND Toolkit covers the period from 2007 through 2013. An additional year, 2014, was added later but used a different model set up, and the 2014 data have different biases. Thus, the dataset clearly does not meet the multi-decadal requirement, the requirement for regular extension, or the requirement for consistent model configuration.

The objective when the WIND Toolkit was produced was to provide the best wind inputs to integration models, and the NWP model used was tuned to do this. At the time it was produced, solar predictions from the model used were not particularly good. Therefore, when using the WIND Toolkit data, a companion needs to be found for solar data. Usually the National Solar Radiation Database (NSRDB) is used, but this brings up some of the issues mentioned above for Attribute 3 (coincident and physically consistent across weather variables). Despite its flaws, the WIND Toolkit is still one of the best available datasets for providing wind inputs to power system models and is widely used. However, the flaws highlight the importance of validating data before use, and of taking the findings into account so as not to draw erroneous conclusions. In addition, its limited length means that users will often seek to extend the dataset using statistical methods. This needs to be done with great care (see Section 6 of the full report, "Guidance for Using Existing Weather Inputs," for details).



23 Sharp (2022).

The WIND Toolkit is now rather antiquated, and NWP modeling has advanced considerably since the Toolkit was produced because of general advancements and targeted programs like the Wind Forecast Improvement Projects and the Solar Forecast Improvement Projects funded by the U.S. Department of Energy. Subsequent projects have extended the geographical scope of the WIND Toolkit data to Canada and Mexico as well as several Asian locations using a similar methodology. New projects are now underway to create the WIND Toolkit Long-term Ensemble Dataset (WTK-LED) using updated models. This will feature three years of 2 km grid spacing simulations over the continental U.S. and Alaska with 5-minute output, and 20 years over North America at an hourly output. The longer time series will then be downscaled using a generative adversarial network (GAN) machine learning approach to ultimately provide 20 years of 2 km output with 5-minute temporal resolution. In addition, an ensemble of model runs was generated for 2018, and this is used to provide uncertainty quantification. A limited validation has been performed that compares the WTK-LED wind speeds to lidar observations taken at a wind plant in flat terrain in Oklahoma and two lidars offshore from the East Coast.[24] The validation also compares these observations to the ERA5 dataset in order to assess the value of the WTK-LED relative to existing data. The validation indicates that WTK-LED-predicted wind speed profiles show a limited negative bias offshore (~ -0.5 m/s) and a slight positive bias at the land-based site (~ +0.5 m/s). ERA5 shows a significant negative bias at both locations (~ -1 m/s), with a larger bias at the land-based site, but ERA5 outperformed the WTK-LED in terms of the centered root-mean-square error (cRMSE) and correlation coefficient, for both the land-based and offshore cases, in all atmospheric stability conditions.

Work on the WTK-LED is ongoing, so there are few published results at this time. It will be particularly interesting to see how well data from the GAN downscaling approach compare to corresponding raw NWP output and how both compare to actual field observations. If the project is successful and the validation shows accurate results, the new dataset would meet most, though not all, of the criteria for power system weather inputs. The main issues would be a lack of ongoing extension, lack of future-proofing, and lack of dedicated curation. In addition, the project is designed explicitly to produce wind data, so it is unclear whether it will produce useful concurrent solar irradiance data or whether a different dataset will need to be used for this, potentially yielding physical consistency issues.

The National Solar Radiation Database (NSRDB)

NREL's NSRDB is a database of solar irradiance that covers the period 1998–2021 (as of July 2023).[25] It is extended annually to cover the previous year. The data currently use the Physical Satellite Model (PSM) to derive historical global horizontal, direct normal, and diffuse horizontal irradiance.[26] At the time of writing, the data for the U.S. are available for 4 km x 4 km grid cells for the period 1998–2021 and for 2 km x 2 km grid cells for the period 2019–2021. Output is available at 30-minute intervals throughout the period of record and at 5-minute intervals from 2019 onward. In addition to the United States, the NSRDB has been extended for several other countries.[27] The geographical and temporal resolution of these extensions varies depending on the available satellite data in each area.

Research and development to further improve the data accuracy and usefulness is ongoing. Satellite observations are also improving as more advanced instruments are deployed. Thus, in addition to being regularly extended, the NSRDB data are periodically refreshed throughout the entire period of record to incorporate new methodologies and improved inputs. This is the type of future-proofing that is needed for weather inputs to be most useful to power system models. The one drawback of updates to NSRDB is that new instruments have only limited value for periods prior to their deployment. However, to ensure a consistent record, when the entire record cannot be refactored as a result of an update, the

24 Pronk et al. (2022).

25 https://nsrdb.nrel.gov/data-sets/us-data.

26 See Sengupta et al. (2015a) for a description of the Physical Satellite Model.

27 https://nsrdb.nrel.gov/data-sets/international-data

old version is still provided. For instance, 2 km data have been available since 2019, but 4 km data are still provided as well so that they are consistent with the rest of the dataset.

The NSRDB data have been validated against surface observations,[28] but there is a lack of publicly available, high-quality surface solar radiation measurements in the U.S., and only seven sites were compared in the 2015 study and nine in the 2017 study. In addition, comparisons of point measurements at surface stations to the 4 km pixels in the NSRDB is not really an apples-to-apples comparison. Long-term biases at the seven stations compared in the validation study were relatively small, so there is reasonable confidence that the overall values derived with the method are relatively accurate for monthly and annual averages. However, correlation between the 30-minute observations and NSRDB data is not very good, especially on cloudy days. For example, the root-mean-square error of hourly-averaged DNI was found to be as high as 40 percent compared to the surface measurements.[29] This level of error might have a significant impact in power system modeling. As with the discussion of the WIND Toolkit above, it is very positive that these types of validations have been carried out, but it is unclear whether users of the data are aware how large the errors might nonetheless be.

The NSRDB also contains time series data of wind and temperature and some other commonly used meteorological fields on the same 4 km grid, *data that should under no circumstances be used in power system modeling.* These fields come from the MERRA-2 reanalysis and are interpolated from the 60 km data. They absolutely should not be used in power system modeling because the source modeling system is too coarse to correctly model any of the fields required to calculate weather impacts on loads or wind generation. The interpolation process does little to improve this and adds confusion because it makes the data appear to have higher resolution than they really do. The wind speed is simply a linear casting of the wind data from 60 km model output to a 4 km grid, while temperature is interpolated and then adjusted to the altitude of the high-resolution grid using a simplistic lapse rate correction that will not, in most cases, represent real atmospheric conditions.

NSRDB appears to meet many of the criteria described above for use in power system modeling. There are decades of observations, the resolution is acceptable, it is continuously extended, and it has been validated and is documented. However, only the irradiance components have an appropriate resolution for power system modeling, and validation reports raise questions as to the applicability of the irradiance data, too. Careful validation of power estimates against observed output is required.

Public Weather Observations

There is a huge number of public weather stations located throughout the world, and when they provide the right data, with the right attributes for use in power system modeling, they should always be preferred, as observations are always better than model data. Observed temperature data are often available for long enough periods, at high enough density for use in determining the weather impact on load. However, weather observations are typically much denser and higher quality in urban areas; in less densely populated areas where wind and solar generators tend to be located, observations are sparse. In addition, publicly available weather data are not designed to capture the information needed to

28 Habte, Sengupta, and Lopez (2017); Sengupta et al. (2015b).

29 Habte, Sengupta, and Lopez (2017).

estimate variable renewable generation. For instance, public stations *very* rarely measure solar irradiance, and the wind is measured at a height of 10 m and not within the rotor plane of wind turbines. This is a significant issue because 10 m wind and hub-height wind follow opposite diurnal profiles, with 10 m wind peaking during the afternoon and hub-height wind peaking at night. There are some quasi-public high-density observation networks, such as the New York State Mesonet,[30] which do have pyranometers that measure global horizontal irradiance (GHI) at all 126 standard sites statewide and higher-quality radiation flux sensors at 17 enhanced sites, but gradual degradation, and occasional recalibration or outright replacement, of some of the radiation sensors can lead to changing and/or inconsistent observation error characteristics across a network. Particularly for solar radiation observations, users must be aware of instrument quality and calibration issues that can affect measurement uncertainty.

Proprietary Time Series

As wind and solar capacity has increased, private consultancies that perform tasks such as resource adequacy studies using power system models have had to begin to consider the impact of wind and solar generation. As should be abundantly clear by now, doing so is no simple task, especially since the data needed are not readily available. To their credit, these companies have tried to make do with what data they have and have developed some innovative approaches to estimate renewables generation. However, because filling wind and solar data voids is complex, it behooves downstream consumers of these data or of products derived from them to ask questions. Consumers of the data need to ensure that the methodology is scientifically defensible and that any limitations and their impacts on power system study outcomes are well understood. See Table 2 (p. 28). Ideally, methods should be peer reviewed.

A Summary of Current Weather Data Coverage Level and Gaps

Datasets available today for power system modeling have significant shortcomings. If we apply the attributes of an ideal weather inputs dataset to the datasets listed in Table 2 (p. 28), none fully meet all the requirements. Using the United States as the area of interest, the complex topography from the Rocky Mountains westward and the Appalachian Mountains eastward requires geographical spacing of 4 km or less to represent many of the phenomena driving renewable resources, which eliminates all of the datasets other than the NREL WIND Toolkit, the NREL NSRDB, and the operational forecast archive of NOAA's HRRR model. Of these datasets, only NSRDB is longer than a decade and regularly updated. Unfortunately, the global reanalysis datasets, with their benefit of a long time history and regular extension, do not provide the required fidelity in much of the country. This includes the frequently used ERA5 dataset, which, despite being the highest-resolution global reanalysis dataset, has a grid spacing of approximately 30 km.

At the time of writing, NREL's WIND Toolkit best fits the overall needs for public weather datasets in the United States, especially for any studies within complex terrain, and these data are often augmented with data from the NSRDB for estimating solar generation. For studies in simple, relatively flat terrain, ERA5 can be considered because its longer history and regular updates may outweigh the issue of low resolution in these regions.

Table 3 (p. 46) distills the current state of weather input options, looking at how well the combination of the WIND Toolkit and NSRDB datasets, and the stand-alone ERA5 dataset, currently meet power system modeling needs and highlighting the gaps and weaknesses of each dataset. While these datasets are currently the best in class, the full report notes that several new datasets are in the works, including extensions to the WIND Toolkit. However, none of these new datasets meet all of the required criteria for power system modeling either. This highlights that even when looking at the best and most recent options available, considerable improvement is urgently needed, including a coordinated plan to address the current deficiencies in future datasets' definition and production.

30 Brotzge et al. (2020).

TABLE 3

Summary of Best Available Public Datasets to Estimate Site-Level Generation at All Current and Future Wind and Solar Assets in All Regions of the United States

Attribute	WIND Toolkit/NSRDB Combination		ERA5
	For Wind/Load	For Solar	Wind/Solar/Load
Has required temporal resolution[a]	5-min produced	5-min since 2019	Hourly
Has required spatial resolution	2 km	4 km; 2 km since 2019	30 km
Includes multiple heights above the surface		N/A	
Available for several decades	8 years[b]	Since 1998	Yes
Has regular updates	Nothing formal	Annual	Daily (7-day lag)
Is future-proofed	Ad hoc	Yes	Yes
Is long enough to detect climate signals	Unlikely	Possibly	Yes
Models are adequately validated			
Accuracy assessed, including for risk periods	Against tall meteorology towers	Limited	Limited
Variability assessed, against reality	Limited	Limited	Several studies
Assessed power system modeling applicability?	Designed for this	No studies found	No studies found
Provides companion "forecasts"[c]	Produced	No, but possible	No
Is based on consistent input observations and/or models	Yes, except 2014	Yes	Yes (single modeling system)
Physical consistency between wind/solar	No; impact should be investigated		
Well documented and easy to use			
Limitations are clearly specified			

Fully Met · Close to Being Met · Partially Met · Met in a Very Limited Way · Not Met at All

This summarizes key attributes of the three best available public datasets that can provide a reasonable estimate of site-level generation at all current and future wind and solar assets in all regions of the United States. The WIND Toolkit and NSRDB are typically used in tandem, with the WIND Toolkit providing data for estimating wind generation (and possibly loads) and NSRDB being used for estimating solar generation, because neither provides acceptable accuracy for both variables. This introduces physical consistency issues.

a All datasets have hourly data. Five-minute data were produced for the WIND Toolkit, but NREL reports that they are no longer available.

b Data from the years 2007 through 2013 use a different configuration compared to 2014. An extension is being produced for the whole dataset.

c NREL reports that the forecast dataset is no longer available but other sources may have an archive.

Notes: WIND = Wind Integration National Dataset; NSRDB = National Solar Radiation Database; ERA5 = Fifth-Generation ECMWF Atmospheric Re-Analysis of the Global Climate. Climate; N/A = not applicable.

Source: Energy Systems Integration Group.

SUMMARY REPORT

Weather Dataset Needs for Planning and Analyzing Modern Power Systems

A Summary Report of the Energy Systems Integration Group's Weather Datasets Project Team

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This summary report, the full report (and a high-resolution version for printing), "Meteorology 101: Meteorological Data Fundamentals for Power System Planning," and fact sheets are available at https://www.esig.energy/weather-data-for-power-system-planning.

To learn more about ESIG's work on this topic, please send an email to info@esig.energy.

The Energy Systems Integration Group is a nonprofit organization that marshals the expertise of the electricity industry's technical community to support grid transformation and energy systems integration and operation, particularly with respect to clean energy. More information is available at https://www.esig.energy.

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