METEOROLOGY 101

Meteorological Data Fundamentals for Power System Planning

Overview for Power System Planners and Engineers

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October 2023

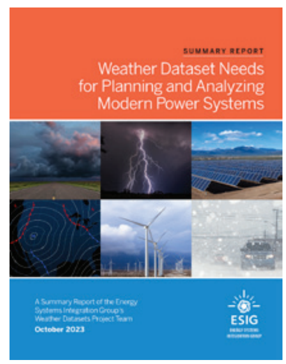
ESIG
ENERGY SYSTEMS INTEGRATION GROUP

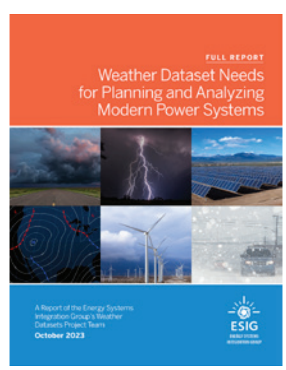
Full and Summary Versions of the Weather Dataset Report

This overview of meteorology fundamentals for power system planners, modelers, and others is Section 2 in the report *Weather Dataset Needs for Planning and Analyzing Modern Power Systems*. We have published it as a stand-alone document to accompany the summary version of the report, for readers of the summary who wish to delve more deeply into datasets and models used in power system planning studies.

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





About ESIG

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 Publications Available Online

This meteorology overview, together with the full report, summary report, and other related materials, is available at https://www.esig.energy/weather-data-for-power-system-planning. All ESIG publications can be found at https://www.esig.energy/reports-briefs.

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Acknowledgments

Grant Buster and Irene Schicker provided important contributions with respect to machine learning techniques. Valuable reviews and editorial feedback were provided by Jim Wilczak, Julia Matevosyan, Karin Matchett, Jared Lee, Priya Sreedharan, Hannah Bloomfield, Erik Smith, Andrea Staid, and Derek Stenclik.

Suggested Citation

Sharp, Justin. 2023. "Meteorology 101: Meteorological Data Fundamentals for Power System Planning." Reston, VA: Energy Systems Integration Group. https://www.esig.energy/weather-data-for-power-system-planning.

PHOTOS

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Abbreviations Used

BTM	Behind the meter
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
IRP	Integrated resource plan
MCP	Measure, correlate, and predict
MERRA	Modern-Era Retrospective Analysis for Research and Applications
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
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

Need for Accurate, Long-Duration, Chronological Weather Datasets for Power System Studies

This document originates from the ESIG report *Weather Dataset Needs for Planning and Analyzing Modern Power Systems* and is meant to accompany the summary version of that report, providing an overview of the nature of meteorological data available for use in power system planning.

It is important for users to be aware of the challenges when applying weather data to power system planning studies. Today's available observations are generally too sparse to be used for renewable generation estimates, and data from weather models often used as a proxy for observations have limitations that need to be understood to estimate their impact on the results of power system modeling. Further, simple models that are sometimes used to synthesize the wind and solar profiles for a given day based on observed predictors like temperature may appear to produce a long time series that looks as though it reflects reality quite well; however, careful validation will usually reveal a poor match with reality, especially when one looks at coincident combinations of different variables across a region. There is an urgent need for accurate, long-duration, chronological weather datasets for use in power system analyses.

Power systems span continents, with weather events in one corner of the grid having an impact on operations hundreds of miles away. Therefore, analyzing how weather will impact the electricity system means knowing,

with a reasonable degree of certainty, the evolution of weather in time and space that impacts electricity system supply (generation), demand (load), transmission, and distribution.

Accurately representing the state of a modern electricity system, where wind and solar generation are distributed over wide areas and often far from load centers, requires:

- Knowledge of the weather variables driving the generation potential at the location of every weather-driven generator, as well as every potential generation location if portfolio expansion modeling is being conducted
- Knowledge of the weather variables driving demand at load centers
- Details of weather affecting other system assets, for example, weather that may cause thermal generator derates or outages or changes to the transmission or distribution system. In addition, the hydrological state needs to be known if there is significant hydro generation.

Long records are crucial to capture the range of atypical weather combinations that produce weather-related risk, and because the number of variables increases, the range of atypical combinations that produce risk also grows and requires longer records to capture.

Planners use historical time series of weather records to project likely future scenarios of supply and demand, adjusting for known or predicted changes in both. Power system studies, especially resource adequacy analysis, require many years (ideally several decades) of chronological weather data that capture the range of potential weather variables affecting load, resource availability, and forced outages. Long records are crucial to capture the range of atypical weather combinations that produce weather-related risk, and because the number of variables increases, the range of atypical combinations that produce risk also grows and requires longer records to capture. In addition, energy-limited resources (such as storage and flexible demand) create the requirement that the weather data not only be physically consistent in space, but also accurately represent the correct chronological evolution of the weather, as this will impact how they are managed (for instance, how storage is charged and discharged). Because many power system analysis tasks attempt to evaluate future portfolios of weather-driven generation, including determining where those generators should be built, the weather data need to be known not only at the location of current generators, but all other plausible generator locations.

Synthesizing Weather Datasets with Models: Why Do It and Why Is It Difficult?

When available, direct observations are the most accurate way to characterize atmospheric variables. However, such an archive is not available, and it would be impractical to build, as it would require a much denser network of atmospheric measurements than currently exists, with instruments every two or three kilometers in some locations. This would be prohibitively expensive to build and maintain. In any event, it would take at least a decade of gathering observations before anything close to a representative archive would be available.

As a result, models are used to fill in the temporal and spatial gaps. These range from simple models, often developed by power systems engineers with little or no meteorological training, to highly sophisticated physics-based weather models involving millions of lines of code and running on the world's most powerful supercomputers. 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.

Simple models are easy to understand but usually inaccurate. On the other hand, physics-based models tend to produce data that are much more accurate, but it is important to understand that synthetic data produced this way can still contain large errors even when they look realistic. In addition, expert knowledge is required to understand the inherent uncertainties in the modeling process, because the same weather model can produce vastly different output depending on how it is configured. The addition of artificial intelligence can further obfuscate how data are derived.

The atmosphere has many variables, including wind speed and direction; temperature; pressure; water vapor concentration (humidity); hydrometeor concentration, phase, and size (cloud droplets, rain drops, cloud ice, hail, snow); aerosol type, concentration, and size; incoming solar radiation; and outgoing infrared radiation. Each variable interacts with the others and responds to characteristics of the Earth's surface: altitude, slope, reflectivity, roughness, temperature, moistness, etc. The relationships among all of these factors are highly non-linear: multiple different variables influence one another, and changes may be muted or amplified in different circumstances. However, these relationships follow well-defined physical laws and are not random. This creates a dynamic, constantly changing environmental system with an almost infinite number of possible states with some variables changing rapidly over small distances.

Like the atmospheric system, the power system is also interconnected in time and space. Events occurring in one part of the system impact others and evolve in time. This is also true of the interactions between the two systems (e.g., a change in wind speed at the location of a wind generator affects the evolution of the weather elsewhere *and* changes the electricity system state). Therefore, each state has a specific impact on supply, demand, and other weather-influenced components of the electricity system.

Models that synthesize data for use in power systems analysis ideally should 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.

Therefore, models that synthesize data for use in power system analysis ideally should 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. A primary motivation of this document is to help users of synthetic data better understand how difficult this is and to communicate the limitations these challenges often confer onto synthetic data.

Importance of Understanding the Types and Sources of Data Uncertainties

The difference between an observation and reality ("truth") is mainly a function of the measurement uncertainty of the instrument used to take the observation. However, the difference between synthetic weather data

The uncertainty in synthetic data produced using physics-based models is not uniform in time and space, between different weather regimes and geographies, or for different configurations of the same model.

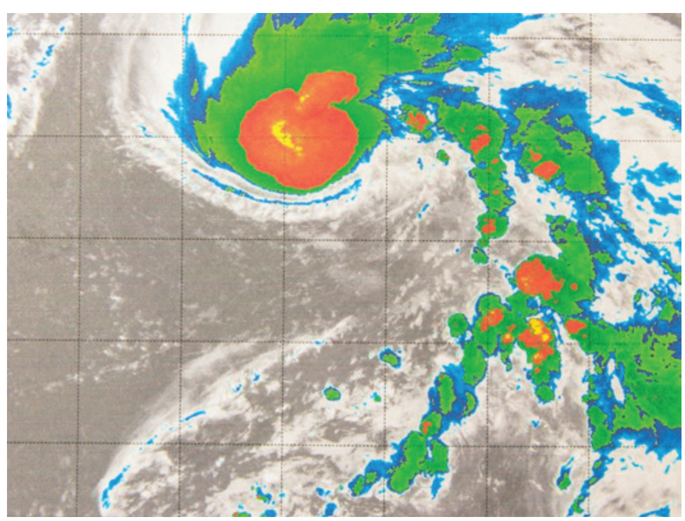
and truth, in addition to being subject to uncertainties in all the observations used in the modeling process, is mostly a function of the modeling method. Therefore, synthetic weather data have much more inherent uncertainty than weather observations. This is intuitive to most users when simple models are used, but it is also true of data that are synthesized by complex numerical weather prediction (NWP) methods, including reanalysis and reforecast datasets (discussed in detail shortly), which are widely used. While these methods use observations as inputs and produce detailed outputs with realistic weather patterns that reflect the input observations, the uncertainty of model output data is *not* similar to that of direct meteorological observations. In addition, the uncertainty in synthetic data produced using physics-based models is not uniform in time and space, between different weather regimes and geographies, or for different configurations of the same model. At the time of writing, this is not fully understood even by many savvy power system modelers, and it is almost never acknowledged in reports communicating the analysis of power system modeling that utilizes these inputs.

Furthermore, it must be remembered that few synthetic model data have been robustly validated against observations, in large part because in many cases such validation is not possible because the modeling was performed specifically to fill gaps where observations were unavailable. It is not correct to assume that if model output is similar to an available observation in one part of the model domain, that output in other parts of the domain will also be accurate.

This is not to say that synthetic weather data are not useful. When model configurations are thoughtfully designed to produce output for use in subsequent power system modeling, it is possible to produce valuable data. However, it must be understood that these data have much more inherent uncertainty than those coming from weather observations. As a result, regardless of the source of synthetic weather data, validation and uncertainty quantification are essential steps to ensure that invalid conclusions are not drawn from studies that utilize synthetic weather inputs.

The following discussion gives a basic description of the different sources of weather data for power system modeling. It is designed to help non-meteorologists make the best use of the guidance given in *Weather Dataset Needs for Planning and Analyzing Modern Power Systems* (summary report) and be able to intelligently use weather inputs in power system modeling. This discussion covers different types of weather observations, ways in which weather data can be synthesized using models, and the pros and cons of different approaches. It describes how model implementation and configuration can impact the output data, explains why this might matter for different applications, and discusses the importance of validating model data. More detailed information on these subjects can be found in the appendix.

Regardless of the source of synthetic weather data, validation and uncertainty quantification are essential steps to ensure that invalid conclusions are not drawn from studies that utilize synthetic weather inputs.



Weather Observations

Weather observations are usually the most precise way to quantify atmospheric conditions and should be used wherever practical; however, observations at the necessary locations or across the required time period often are not available for assessing weather impacts on the electricity system. Therefore, observations are usually used to validate and determine the uncertainty of model data and/or to bias-correct the data by identifying systematic relationships between model output and truth.

Weather observations are recorded by instruments that measure quantities such as temperature, pressure, humidity, wind, precipitation type; cloud type, level, and coverage; and visibility. For in situ observations, the measurement device is physically located where the observation is taken, and for remotely sensed observations, the instrument is physically removed from the locations being observed, such as on orbiting satellites.

In situ measurements are appealing, as their uncertainty and quality are usually easy to quantify and the instruments are cheap relative to remote-sensing devices; however, their spatial coverage is limited and tends to be clustered around population centers. Examples of in situ instruments include thermometers, anemometers, precipitation gauges, and barometers. In situ temperature measurements, typically taken at airports, have historically been the primary dataset used to assess the impact of temperature on electricity demand. Such records typically span several decades, and sometimes more than a century. In situ measurements are also taken at wind and solar facilities, but these records are much shorter, and the data typically are not available for input into power system modeling applications (see Box 1, p.6).

Remotely sensed data are a crucial input to models that are commonly used to produce datasets for power system analysis today and going forward. Remote-sensing instruments either observe atmospheric data from somewhere distant from the measurement location (known as passive sensing) or send out a signal and observe the interaction of the signal with the atmosphere (known as active sensing). Remote-sensing instruments

BOX 1

Observations Made at Existing Renewable Resource Facilities

Most existing renewable resource facilities in the U.S. are equipped with instruments to collect meteorological data, and observation archives for these facilities would be very valuable for validating and bias-correcting model data. These facilities' data collection is done in part because the Federal Energy Regulatory Commission (FERC) Order 764 requires that transmission operators be provided with temperature, wind speed and direction, and atmospheric pressure from each wind generation facility on their systems and be provided with temperature, atmospheric pressure, and irradiance from each solar generation facility, to aid in power generation predictions used in system operations. Many other countries have similar requirements. However, these data are usually not made public and so cannot be used for power system modeling studies. One result of this is the paradoxical situation where reconstruction of past generation estimates for planning is less exact than forecasting of future generation for operations.

Data are usually not made public and so cannot be used for power system modeling studies, resulting in a paradoxical situation in which reconstruction of past generation estimates for planning is less exact than forecasting of future generation for operations.

For analyses of electricity systems for planning studies, multi-decadal records are needed covering all possible current and future generation sites. Because most renewable generation facilities have been operational for under a decade, even if they were available, observational records are not long enough to fully capture the distribution of weather-driven generation outcomes. In addition, data at operational plants are not always a good proxy for generation at future plants more than a few miles away. Thus, the only current way to produce the required data is to use models. However, broad access to weather archives for existing weather-driven power plants is necessary to validate and bias-correct model data. Further, access to power and availability archives would allow much better generation estimates to be produced from model-synthesized weather data. For these reasons, the project team strongly recommends policy changes to improve overall access to observation archives for existing weather-driven power plants.

can gather data from large areas or volumes either by having a wide field of view or by scanning. Examples are cameras (passive sensors) and weather radars (active sensors). Modern remote sensing has revolutionized NWP, which requires the best possible estimate of the state of the atmosphere to forecast future states and/or synthesize a more detailed picture of the weather than is available from observations alone. More details about in situ and remote-sensing observations can be found in the appendix.

While observations are typically the most reliable measure of atmospheric conditions, they have major drawbacks.

- Observations are typically spatially sparse and often located in places that are not representative of the important meteorological properties driving supply and demand across a region. For example, many surface observing stations are located at airports, and those in populated areas tend to be the best maintained. This means the temperature data may be useful for developing relationships with load, but wind and solar data are unlikely to be representative of remote regional wind and solar plants.
- The instruments used by different observing networks are of vastly different quality and are maintained to different standards; quality control can be very tedious. One should not assume that one temperature, wind, or other measurement is as accurate as the next.
- Remotely sensed data are often voluminous and complex. They may require expert processing and interpretation, and measurements are often not uniformly organized in time and space. The sensing devices are typically expensive.
- Data discontinuities and biases can result from instrument updates, updated instrument calibrations, station relocation, and even environmental changes around the observation (e.g., new buildings or increased shading by trees).

Model Data

Given that the network of observations is insufficient to provide a representative view of generation potential for current and future renewables, the observations we have need to be augmented with model-synthesized data. This section explores the limitations of simple models and of the sophisticated NWP and machine learning methods used to produce more comprehensive datasets. More detailed information about NWP can be found in the appendix.

Modeling the Atmosphere's Complex Behavior

Because of the complex nature of the atmosphere, simple statistical models using variable(s) observed at one site (for example, temperature) are rarely able to estimate other variables at the same site, let alone at other locations. Any suggestion that such modeling is possible should be viewed with deep skepticism in all but the simplest cases. However, while the atmosphere is complex, its evolution in time and space does follow well-defined physical laws related to conservation of energy, momentum, and mass, and these laws can be described with mathematical equations. Solving these equations is the basis of physics-based modeling, which is widely used to produce synthesized weather data for a range of uses, including power system analysis.

In some cases, such as in the production of irradiance data for the National Solar Radiation Database (NSRDB), models are diagnostic and use observational data to infer (diagnose) an estimate for the value of a related quantity. An everyday example of a diagnostic model is seen in a mercury thermometer. The thermometer measures the expansion of mercury, and the diagnostic model converts this to temperature. But most physics-based models used to synthesize atmospheric data are prognostic: if the state of the atmosphere is known at many locations, such models can estimate the state of the atmosphere at other locations and other times. This is the realm of NWP models, commonly known as weather models or weather forecast models. While predicting the future state of the atmosphere is the most familiar use of NWP to the public, NWP models can also be used together with observations to estimate a denser array of historical meteorological data than is available from observations alone. NWP enables the production of datasets that are representative of the distribution of past weather conditions concurrently impacting wind, solar, and load and that capture the chronological evolution of these conditions in a realistic way.

Data produced by NWP models adhere to the physical laws governing atmospheric motions and processes and are produced on convenient regular geographic grids, with even temporal spacing. The distribution of each variable in time and space and its relationship to every other variable is consistent with these laws, which is important for producing chronological time series data of variables that represent the evolution of plausible weather scenarios. This means the data meet many of the requirements for use in modern power system

While NWP models can provide reasonable estimates, even they are far from perfect, and their output should not be viewed as a near-perfect representation of truth. Many factors associated with the input data and model configuration affect these models' output model, which can deviate significantly from reality.

modeling where wind and solar generation is broadly dispersed. However, as discussed below, while NWP models can provide reasonable estimates, even they are far from perfect, and their output should not be viewed as a near-perfect representation of truth. Many factors associated with the input data and model configuration affect these models' output model, which can deviate significantly from reality.

Simple Statistical Models

An estimate of the meteorological conditions at a particular location is often needed because there are gaps in an observing record or because the required variable is not measured. Simple statistical models are often employed to fill such gaps in the observed record by using correlations of the available observations at the site of interest and observations at a nearby location to predict the missing data. These models can be useful for minimal data filling or for extrapolating a record using data from a nearby site with a longer time series, but it is critical that their validity and uncertainty be evaluated carefully, because such models rarely capture the range of possible outcomes and can produce false and misleading data that will impact downstream analysis. One easy way to check the validity of simple statistical models is to withhold some of the data from the dataset used to establish the relationship and check how well the model predicts the withheld data.

It is critical to carefully evaluate the validity and uncertainty of simple statistical models, because these rarely capture the range of possible outcomes and can produce false and misleading data that will impact downstream analysis.

An example of a simple statistical model is "measure, correlate, and predict" (MCP), which is frequently used in wind resource assessment. Here, a (usually linear) correlation is developed between observations at an airport or other nearby observing location that has a long, good-quality meteorological record, and observations measured at a prospective renewable resource site. The relationship is used to put the data from the resource assessment measurement campaign into the context of the longer climate record to allow production estimates to be corrected up or down. If a good correlation can be established between the two observations, this method can work reasonably well to normalize average annual, monthly, and (with a strong correlation) daily output of a short measurement campaign (for example, two years) to the longer-term average. MCP is often applied with a long-term reference of about a decade. Because the climatological norm is considered as requiring 30 years to capture, most, but not all, of the average monthly variability can be captured in this way.

MCP-like methods are also sometimes used to synthesize load time series. Here, measurements from two sites are correlated, and a simple transfer function is developed that allows periods without observations to be estimated. Because load and temperature are generally strongly correlated, this application is typically useful if applied with careful validation.

Other models apply simple empirical rules, for example, the assumption that a constant wind shear in the lower atmosphere can be used to extrapolate the wind speed at one height using data at another height. Similar rules can estimate temperature using constant lapse rates (the change in temperature with height). Such empirical rules can be useful in some applications, but do not produce the required level of accuracy in others. Therefore, it is important for a data user to know when empirical rules have been applied and understand the nature and impact of the uncertainty introduced.

Another example of the use of statistical models is to predict the daily profile of wind and solar generation based on the temperature regime influencing load for days that occur around the same time of year; this use is problematic. For instance, the assertion may be that if a warm January day has a particular solar shape, solar generation on other warm January days for which no solar data exist will have the same daily profile. This seems intuitively compelling; however, the reality is much more complex. Cool summer days can be sunny, hot summer days can be cloudy, and, as anyone living in the U.S. Midwest knows very well, the coldest winter days are often blazingly sunny. When one includes additional coincident variables like wind speed, the situation quickly becomes complex, especially if correlations are being attempted between the conditions of two or more variables at different sites.

Statistical and empirical models like MCP typically relate one or two predictors (e.g., input variables like wind and temperature at location A) to the output variable (e.g., wind at location B) in a way that the output variable being predicted varies in a simple linear fashion with the input variable (first order, as opposed to quadratic, cubic, or higher order). These models are rough empirical approximations not representative of all the physical laws at play. They can produce apparently reasonable distributions with average errors but lead to very large errors in any given hour. This is problematic if the large error correlates with a weather condition that causes electricity system stress. Another problem with statistical and empirical models is overfitting, where a complex relationship between multiple variables is found within a sample, but validation outside of the sample shows that the apparent prediction capability is not present.

Models that attempt to reproduce the wind and solar profiles for a given day based on predictors like temperature may appear to produce a reasonable long time series where the range of output variables looks as though it reflects reality quite well. But careful validation will usually reveal a poor match with reality, especially when one looks at coincident combinations of variables impacting load and wind and solar generation across a region.

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Numerical Weather Prediction Models

While NWP models are best known as the basis of modern-day weather forecasts, NWP methods are also: (1) the core component in datasets utilized as weather inputs for power system modeling, and (2) used for global climate modeling designed to understand the potential consequences of anthropogenic climate change. NWP models mathematically represent the physical laws governing the weather and can be used together with observations to estimate a denser array of historical meteorological data than is available from observations alone. (See Box 2, p. 10, for three definitions of "forecast.")

BOX 2

Three Definitions of "Forecast"

The term "forecast" is used here in three distinct ways:

- To predict what is expected in **the operational time frame** (e.g., day-ahead or hour-ahead) to conduct reliable and efficient market and power system operations.
- To predict how a time series of a parameter such as load may change in **future years** based upon historical relationships of weather and past outcomes, and the expected overall change in the parameter's magnitude.
- To estimate a time series for a weather variable **for a period in the past** at locations for which no observational data are available, by using available weather data and a model. Typically, numerical weather prediction (NWP) models are used, and the main variants of this process are reforecasting and reanalysis, which are covered in detail in Section 3 of the full report, "Weather Inputs Needed for System Planning." While the data being predicted are for a period in the past, the models are the same as those used for weather forecasting, hence the term "forecast" is often used by meteorologists to refer to this modeling of periods in the past. However, because the term "forecast" has a strong connotation of "future" for most people, in this document and the full report we strive to use terms other than forecast when referring to the past—such as reforecast, reanalysis, modeled, and simulated—to minimize confusion.

However, there are many sources of uncertainty and approximation related to the data used as inputs to the NWP process and the specific model used.

NWP methods can be used to produce other types of datasets that are commonly used in power system planning, including reanalysis data[1] (defined in the footnote and described in more detail below), as well as in the high-resolution downscaling of both reanalysis data and global climate model (GCM) output. In what follows we introduce the basic principles of NWP modeling, some of the model configuration choices that have the most influence on the applicability of NWP data to power system modeling tasks, and gridded weather analysis data, reanalysis data, and downscaling. Warner (2011) provides an excellent summary of best practices for NWP modeling. Other recent works that provide useful summaries of NWP modeling for renewable resource applications include Haupt et al. (2017, 2019) and Jiménez et al. (2019).

Power system analyses where weather risk is high and important for decision-making should probably engage a meteorologist who is well versed in NWP to explore potential pitfalls to ensure that erroneous conclusions are not drawn from downstream power system modeling results because of imperfect weather inputs.

Power system modelers using NWP output must have a basic knowledge of things that impact the accuracy of the data they are using and the situations where larger errors might show up—the devil is in the details. Power system analyses where weather risk is high and important for decision-making should probably engage a meteorologist who is well versed in NWP to explore potential pitfalls and ensure that erroneous conclusions are not drawn from downstream power system modeling results because of imperfect weather inputs. Above all, one should always remember that garbage in will result in garbage out. Having enough knowledge to know when to question the quality of weather inputs is essential.

Basic NWP Principles

Atmospheric processes adhere to physical laws that can be described mathematically as a system of regular and partial differential equations. If we perfectly describe these laws

1 A weather analysis is a process that takes available weather data and uses it together with knowledge of the laws of physics to estimate the state of the atmosphere and is the first step in the forecasting process. It can be done manually, but today it is typically done using computer codes. Reanalysis is the term used for a similar process that occurs after the fact when all of the possible data are available, including what would have been the future state of the atmosphere. Through the use of sophisticated computer codes, reanalysis reconciles all the data from observations and past, current, and future model estimates in an effort to produce the most accurate weather analysis possible.

mathematically and we perfectly know the state of the entire atmospheric system at a given time, then we can, in theory, determine the entire atmospheric state at all future times. This situation is known as an initial value problem. NWP is the branch of atmospheric science dedicated to determining the initial value as accurately as possible and solving the initial value problem for subsequent times by representing as closely as possible the physical laws governing the motions and processes that are occurring, using mathematical equations that can be solved using numerical methods. NWP models are physics-based models (sometimes referred to as physical models) that perform this modeling on computers. They require extensive and accurate data inputs (the initial value) and apply these inputs to the physics-based equations to model the atmosphere, including the development and decay of weather systems and their movement across a geographical area. NWP models can either be run over the entire globe or over a particular region of interest.

By discretizing the three-dimensional model domain into grid cells (i.e., grid volumes),[2] NWP models represent and predict values for numerous variables (including temperature, wind speed, and solar irradiance) at every grid cell in the domain, regardless of whether or not an observation exists for that grid cell. Because the modeling is physically based, where interpolation/extrapolation of observations leads to initial conditions that are not consistent with the physics of the system in some locations (typically due to a lack of data), the model will tend to evolve the fields to remove the physical imbalance; this adjustment process will usually produce a more accurate representation of the atmosphere than was available by simple interpolation of available observations. This is a powerful feature of NWP that is particularly useful in regions of complex topography where fields may vary rapidly with distance and observations are sparse.

NWP models can be run at different grid spacing in both the horizontal and the vertical, which determines the granularity (or resolution) of the geography and attendant physical processes that the model can simulate. A high-resolution grid is critical for power system studies so that the weather impacting existing and potential future wind, solar, and other plants can be accurately determined, along with concurrent weather impacting load. These weather data can then be used in power system models to evaluate how weather will affect the concurrent performance of these resources and loads on the power grid so that studies can identify potential points of weather-driven reliability risk.

It is reasonably intuitive that we cannot measure the state of the atmosphere perfectly even at one location (due to measurement uncertainty), let alone everywhere. In addition, we do not have the computer power necessary to represent every turbulent eddy or cloud droplet explicitly even if these details could be measured. Moreover, numerical methods are inherently approximations because they deal with finite differences versus the infinitesimal differences of pure calculus. Therefore, perfectly predicting weather variables at any given time or place is not possible. In addition to these limitations in our ability to model the atmosphere, the laws governing the atmosphere's behavior involve non-linear interactions among many variables. Systems like this are highly sensitive to small changes in the initial conditions, and their behavior is inherently chaotic. Small perturbations in the initial state ultimately result in large differences in the future state. The metaphor that a butterfly flapping its wings in

2 NWP models track the state of the atmosphere at a finite number of grid points. The closer together these grid points are in the horizontal and vertical, the higher the resolution of the model. It takes at least three grid points to represent a simple feature on the Earth's surface or in the atmosphere. An intuitive example of the representation of terrain is that a V-shaped valley requires three grid points to resolve, and a U-shaped valley requires four, so if the grid points are 1 km apart, the smallest valley that can be represented is 2 km wide. All features below this scale are not explicitly resolved.

In addition to the limitations in our ability to model the atmosphere, the laws governing the atmosphere's behavior involve non-linear interactions among many variables. Such systems are highly sensitive to small changes in the initial conditions, and their behavior is inherently chaotic. Small perturbations in the initial state result in large differences in the future state.

Africa can affect the development and path of a hurricane in North America is apt.[3]

The amount of time a modeled system remains predictable depends on how accurately the initial state is measured, the dynamics in the system, and the length scales of interest. Therefore, since measurements can never be performed everywhere or with perfect accuracy, and since those observations cannot be perfectly represented by analytical functions, even with infinite computer resources, there are fundamental limits to the accuracy of the predictions that NWP models can make. That is, while the data are useful, they are imperfect, and these imperfections must be quantified and considered when the data are used as an input to power system modeling. Predictability depends on the scale of the weather features of interest, on the order of minutes for small-scale phenomena a few meters across (such as dust devils), to a few weeks for the planetary waves[4] encircling the Earth that are thousands of kilometers across and drive large-scale weather systems (Judt, 2018, 2020).

Figure 1 (p. 13) provides a simplified representation of how atmospheric data are represented in an NWP model and the process of iteratively running such a model. All NWP modeling starts with an initial condition that is a three-dimensional representation of the atmosphere. The initial condition is produced by taking a first guess of the atmospheric state (also known as the background field) from a prior model run (usually a short-range prediction of one, three, six, or twelve 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 is a complex process that incorporates the observations into the model in a way that considers both model and observational uncertainty and produces an initial condition that is physically consistent with the model topography. For regional NWP models, lateral boundary conditions must also be specified at regular intervals (typically every one to six hours) for the entire duration of the simulation, from either a global model or a larger regional NWP model. These lateral boundary conditions are another source of model error; eventually this "boundary creep" can contaminate results throughout the domain. See Warner, Peterson, and Treadon (1997)

3 The atmospheric system was where chaotic systems were first explored. Edward Lorenz showed in his famous 1972 talk, "Predictability: Does the Flap of a Butterfly's Wings in Brazil Set off a Tornado in Texas?," that for such a system, while the exact present determines the future, the approximate present does not approximately determine the future (Lorenz, 1972).

4 Planetary waves (also known as Rossby waves) can be thought of as broad undulations in the jet stream, and they drive the large-scale weather patterns (periods of storminess and quiescence). There are typically four to eight waves (ridges and troughs) spanning the globe. They result from the rotation of the Earth and are modified by temperature gradients as well as interactions with surface features and other processes that move energy around.

FIGURE 1

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

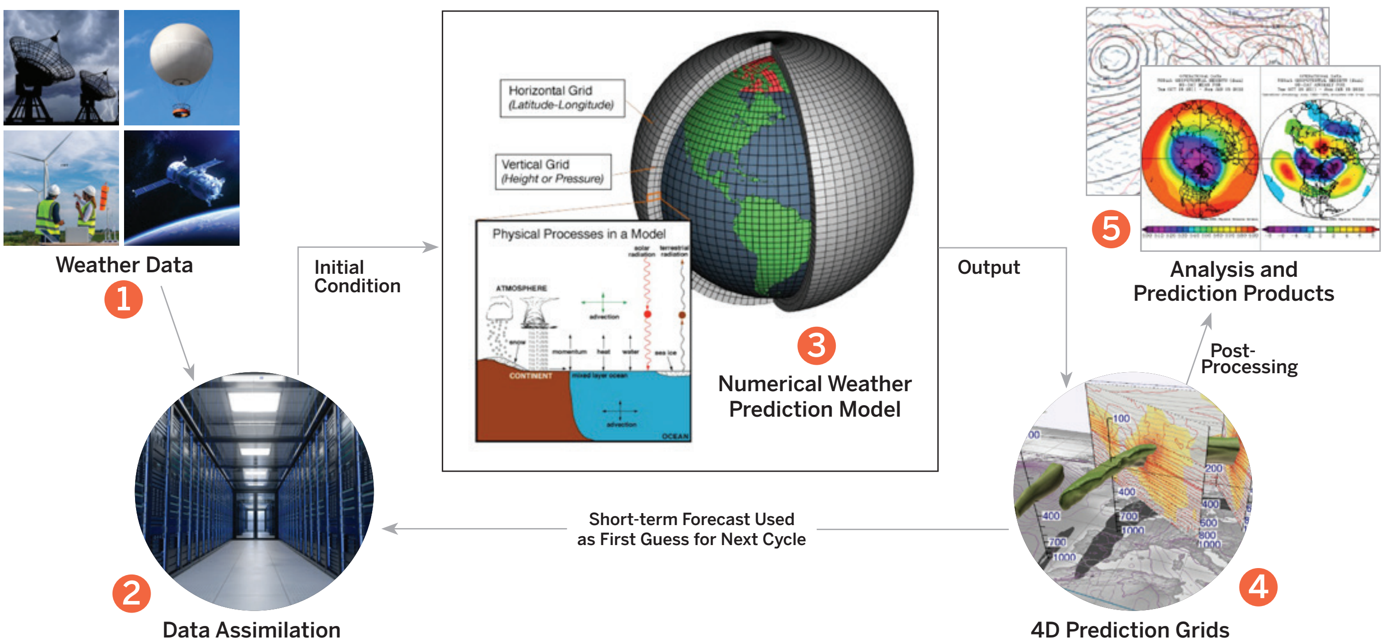


Illustration of the cyclical NWP process. Gridded weather data output from a prior NWP iteration becomes the background field (or first guess) to the next iteration. This first guess is then nudged toward observations, while keeping it consistent with differences between how the model configuration represents 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.

for a more in-depth treatment of lateral boundary conditions for NWP modeling.

After weather observations are assimilated (data assimilation to be explained further below), the atmospheric state at the next time step is determined by numerically solving the governing equations at each grid point. This process is repeated until the user-configured model end time is reached. Gridded model output is written to a file at regular intervals.[5] The prediction accuracy depends on the accuracy of the initial condition, how many time step iterations are performed, and how accurately the atmospheric conditions can be represented in the model. The latter is a function of the model resolution (for example, a fair weather cumulus cloud that is 500 m across cannot be represented in a model with 10 km grid spacing) and of how well the physical processes can be represented and solved in computer codes, which itself is a function of the accuracy of the numerical methods used to solve the governing equations and whether those equations can even be represented at the scales being modeled.

The Impact of Model Resolution

Understanding the importance of model resolution is crucial, as small-scale features can have a strong impact on the weather that drives wind generation, solar generation, and load. Static features in the real world—such as steep valleys or sharp transitions from forest to grassland or ocean—that occur at scales smaller than the grid spacing will not be accurately represented in the model. Consequently, the effects of these features will be represented inaccurately or not at all. Similarly,

5 A common misconception is that the integration time step is the same as the output time interval. This is rarely true, although the integration time step represents the minimum output interval. The integration time step is a function of the model spatial resolution (with higher resolution requiring a short time step) and is usually a few seconds to a few minutes. The output interval just defines how frequently the atmospheric state is archived.

fine-scale weather phenomena like sharp warm or cold fronts or small thunderstorm cells will be different in model space than in reality. Differences between model data and reality are particularly important to consider in regions with complex (i.e., hilly or mountainous) topography. This is because the smaller-scale weather phenomena are a projection of the larger-scale weather pattern onto the topography and associated surface characteristics (like gaps, passes, slopes, and roughness). Therefore, where model topography is considerably different from actual topography, even if the large-scale weather pattern is correctly modeled, the projection of it onto the smaller scale will be consistently incorrect, and modeled values may be very different from those of reality.

Horizontal resolution. Figure 2 (p. 15) provides a vivid example of the impact of model resolution on model topography. This poorly represented terrain in turn profoundly affects how local-scale weather features such as the flow through mountain gaps (known as gap flows), sea breezes, and mountain-valley circulation evolve in the NWP model in response to larger-scale weather systems. In the western U.S., these phenomena drive the power output of many gigawatts of wind energy facilities, and areas of clouds and clearing associated with mountain ridges could impact vast swaths of solar generation, especially in the future.

Figure 2 shows the model representation of topography in the Pacific Northwest at horizontal grid spacing of 36 km, 12 km, 4 km, and 1.33 km. This includes the Columbia Gorge, where the actual elevation is less than 100 m at river level, with steep sidewalls rising rapidly to the crest of the Cascade Mountains at a height of over 1000 m. Mount Hood (3429 m) and Mount Adams (3743 m) lie to the south and north of the gap. Several other large volcanoes are located in this region, as are several mountain ranges and a large inland basin. The key message here is that at low resolutions, many of the topographic features like tall mountains, steep canyons, and river drainages are not properly represented; thus, the weather they drive in reality will diverge from the weather that develops in the model. For comparison, a configuration with a grid spacing of 1.33 km has 784 grid points and 729 grid cells within the same geographical area as a single 36 km grid cell represented by four corner points.

Where model topography is considerably different from actual topography, even if the large-scale weather pattern is correctly modeled, the projection of it onto the smaller scale will be consistently incorrect, and modeled values may be very different from those of reality.

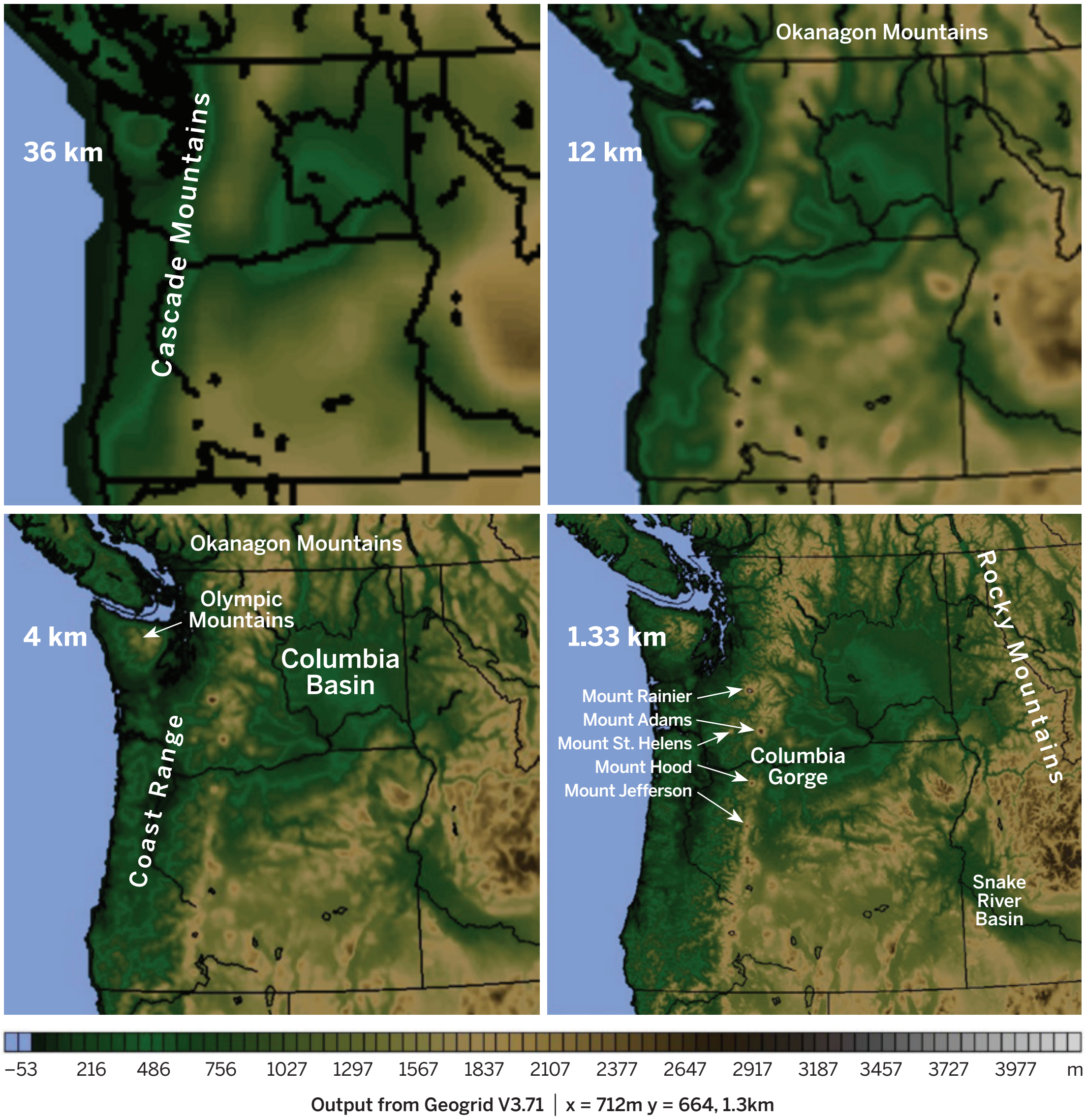
At a grid spacing of 36 km (which is close to the resolution of the frequently used ERA5 reanalysis dataset (Fifth-Generation European Center for Medium-Range Weather Forecasting (ECMWF) Atmospheric Re-Analysis of the Global Climate), the gross features of the terrain are present, including smoothed versions of the mountains and rivers; however, tall volcanoes and mountain ranges are barely captured. At 12 km grid spacing, the largest peaks can be seen as only smooth areas of high terrain, and, similarly, low passes appear as smooth valleys. Details of the Columbia Gorge and the coastal range can be seen. At 4 km grid spacing, most of the major mountain gaps, tall mountains, and valleys in the main mountain ranges can be seen, and the important lowlands are represented as being near sea level as in reality. It is not until a 1.33 km grid spacing is used that the Columbia Gorge is resolved accurately. Resolving the Gorge is crucial to correctly predicting the wind generation from the large number of wind farms at its eastern terminus.

Figure 3 (p. 16) shows hypothetical cross-sections through terrain similar to that in Figure 2. Using 3 km, 9 km, and 27 km grid spacing, it illustrates the profound differences in surface elevation and terrain features at different resolutions. The divergence between each model resolution and reality affects elevation-dependent values such as surface temperature and precipitation phase, but more importantly, model resolution affects how meteorological phenomena like cold pools, downslope winds, and upslope precipitation evolve in the model.

Model resolution has similar impacts on land surface characteristics with the placement of urban, forest, farm, and desert areas all becoming progressively more accurate as resolution increases. Each type of

FIGURE 2

Model Representation of U.S. Pacific Northwest Topography at Different Grid Space Resolutions



Topography represented in the four progressively finer-scale domains used for the University of Washington's Department of Atmospheric Sciences's operational NWP model. The four domains have a grid spacing of 36 km (top left), 12 km (top right), 4 km (bottom left), and 1.33 km (bottom right).

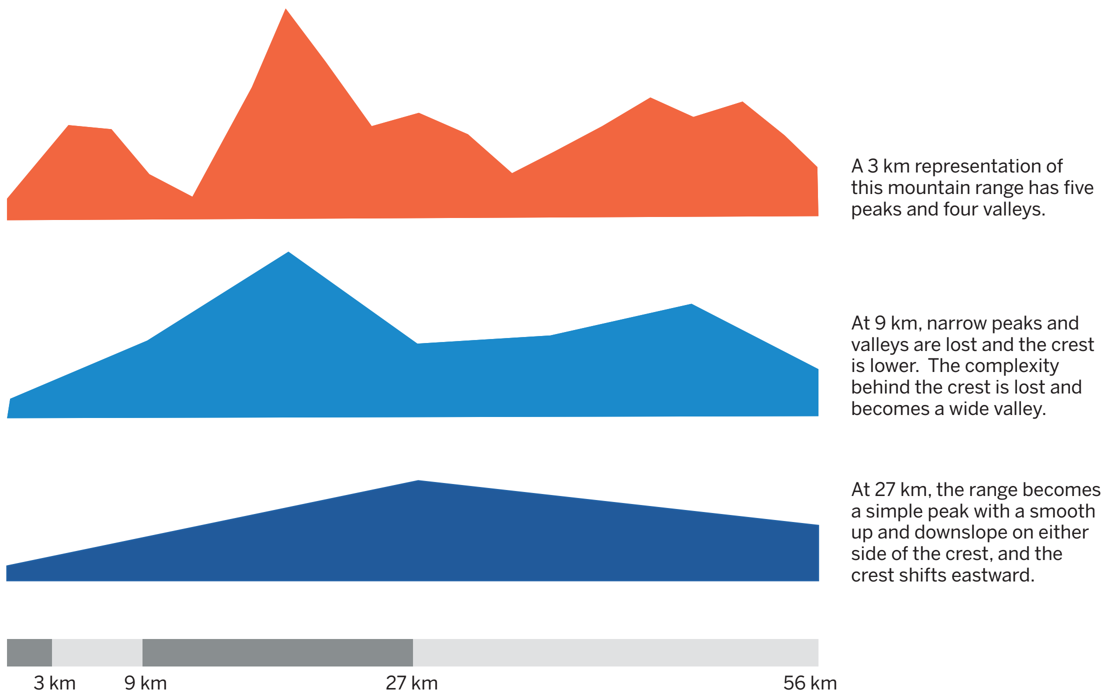
Source: University of Washington. Available at the web page Pacific Northwest Mesoscale Model Weather Forecasts: Information (https://a.atmos.washington.edu/wrfrt/info.html).

land surface has different values defining properties like surface roughness, albedo, emissivity, and heat capacity, properties that have a profound influence on how the real and modeled atmosphere respond to the surface.[6] For example, surface roughness dramatically impacts the low-level wind speed, wind shear, and turbulence. Albedo, emissivity, and heat capacity change the rates of surface heating and cooling, affecting low-level

6 Albedo is the diffuse reflectivity of a surface. Surfaces with an albedo of 1 reflect all the sunlight that hits them, while those with an albedo of 0 absorb it all. Emissivity is the effectiveness of a material for emitting thermal (visible light and infrared) radiation. Heat capacity is the amount of heat supplied to a unit mass of material to achieve a unit temperature rise.

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.

temperature and therefore mixing of the low-level air, which in turn impacts the vertical distribution of near-surface wind speed, temperature, and humidity.

While it is typically 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. For example, in Figure 3 there are no valleys whatsoever in the 27 km resolution cross-section; therefore, it is impossible for the model to create the valley inversion (and the calm conditions that come with it) that will sometimes be present in reality.[7] In other cases, for example, where a deep valley exists in reality but the model resolution is only sufficient to represent a shallow mountain pass, the model may produce the gap winds that occur in reality but their magnitude is very muted compared to reality. Both examples directly impact the accuracy of wind generation estimates. The errors in the way the weather evolves will also propagate downstream and grow as the simulation progresses, potentially impacting other regions.

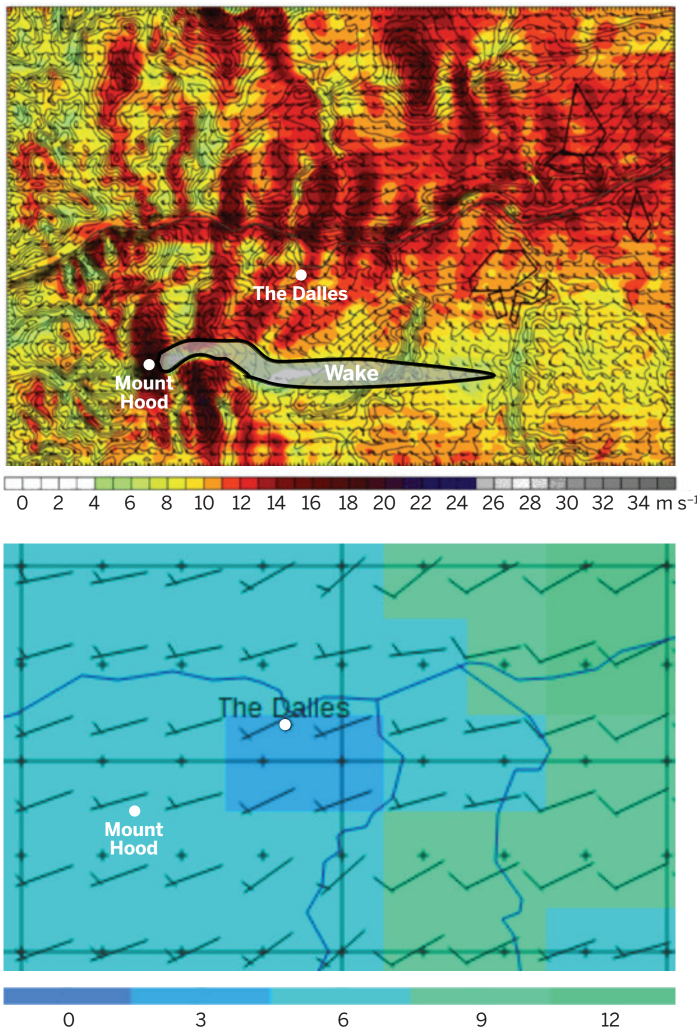
Figure 4 (p. 17) provides an illustrative example, again from the Pacific Northwest, of the impact of resolution on the wind field. Just as a large boulder in a river creates

7 An inversion is an atmospheric layer where temperature increases with height. Inversions often occur in winter in basins and valleys because surface cooling on the valley sides causes cold air to drain down the valley floor. Without significant daytime heating it is difficult to remove the cold layer, as the air above it is warmer and does not mix down into it.

a wake behind it where the flow is slower or may even reverse, Mount Hood creates a significant wake in the atmosphere, and in the right conditions this wake can persist for tens of kilometers and impact many wind plants downstream. The top of Figure 4 shows the wind field simulated with an NWP model running at 1 km grid spacing so that it has sufficient resolution to resolve both the wake and the atmospheric waves (manifested in the figure as periodic lines of stronger wind) created by narrow ridges. Areas of stronger winds are also seen behind some slopes and associated with width changes in the Columbia Gorge. These structures were first indicated in high-resolution NWP simulations like this one and confirmed to exist through analysis of turbine winds.[8] Their presence was subsequently evaluated in detail in the Wind Forecast Improvement Project Part 2 (WFIP2) field campaign (Draxl et al., 2021).

FIGURE 4

Wakes and Waves Observable in a 1 km, But Not 30 km, Simulation of the Columbia Gorge in the U.S. Pacific Northwest



The output from a 1 km Weather Research and Forecasting (WRF) simulation (top) clearly shows mountain wake and wave activity to the east of Mount Hood, whereas the output from the 30 km ERA5 dataset (bottom) for the same hour in April 2010 does not show this activity.

Sources: Iberdrola Renewables (top), and Sharply Focused with data from the European Center for Medium-Range Weather Forecasting (bottom).

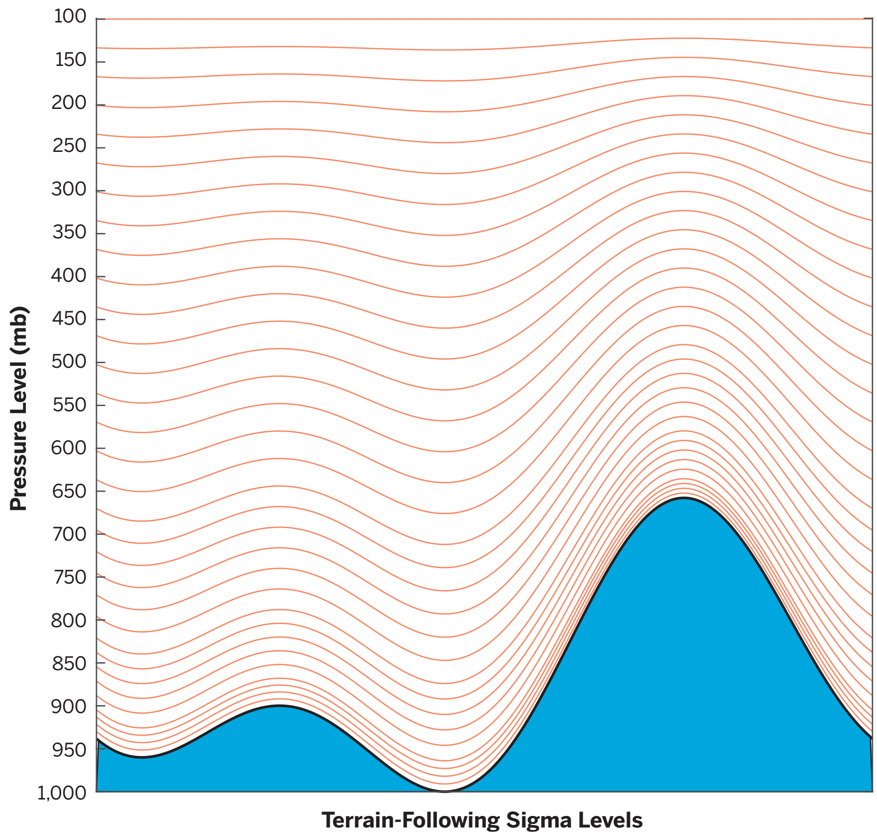
However, the bottom of Figure 4 shows the output resulting from a much lower grid spacing of about 30 km. The difference is dramatic, because simulations at this resolution cannot capture the detailed structures seen in the 1 km simulation. The topography that causes the phenomena does not exist at this resolution, and the grid spacing is insufficient to represent the rapidly varying wind field. The waves observed in reality and in 1 km simulations create significant mixing of the lower atmosphere and impact the evolution of the airflow. Therefore, a lower-resolution model, in addition to being unable to resolve the features of the terrain, will not capture the impact these features have as the model proceeds, causing the model output to diverge significantly from reality.

Vertical resolution. Vertical resolution is also important. Vertical gradients of atmospheric properties like wind speed, temperature, and humidity tend to be largest near the surface, as this is where most of the sun's energy is transferred to the atmosphere during the day and where most cooling occurs at night. The surface is also where most evaporation of water occurs and where topography and land surface characteristics have the largest impacts on weather. Therefore, higher vertical resolution is needed near the Earth's surface, but, in the interest of model efficiency, lower vertical resolution can be used higher in the atmosphere. A hybrid coordinate system is therefore used in NWP models that follows the terrain near the surface and gradually migrates toward a non-terrain-following coordinate away from the surface, as illustrated in Figure 5 (p. 18). This allows the strong surface gradients to be resolved regardless of the elevation of the terrain while reducing the resolution needed farther above the surface.

8 Observed by Justin Sharp and meteorologists at Iberdrola Renewables.

FIGURE 5

Illustration of a Hybrid Coordinate System Used in NWP Models



Vertical gradients of atmospheric properties are largest near the surface, necessitating higher resolution there. However, the surface does not have constant elevation, and there is also no need to perform calculations below ground. Therefore, a hybrid coordinate system is used which follows the surface elevation at ground level and gradually relaxes with height above ground to a constant-pressure level coordinate away from terrain. The blue area is a cross-section profile of the terrain, and the bold black line references sigma = 1, which represents the model surface level. Each orange line above represents a sigma level at which properties of the atmosphere are calculated. The levels follow the terrain most closely near the ground regardless of pressure (a proxy for elevation above sea level) and in this example are closest together near the ground, which is how they are configured in actual NWP models.

Source: Justin Sharp.

Figures 6 and 7 (p. 19) provide a schematics of a three-dimensional grid illustrating terrain-following coordinates in 3D and the high-level aspects of performing NWP (solving the forecast equations with the available computer resources). Many details in the topography, surface properties (water, grass, woodland), and weather features (like clouds) cannot be resolved at the grid spacing used (where data only exist at the intersections of the grid lines), illustrating the importance of resolution. Figure 7 also shows how the weather stations (white and red icons) do not coincide with the grid points. Subgrid-scale parameterization schemes are used for processes that cannot be explicitly modeled, discussed next.

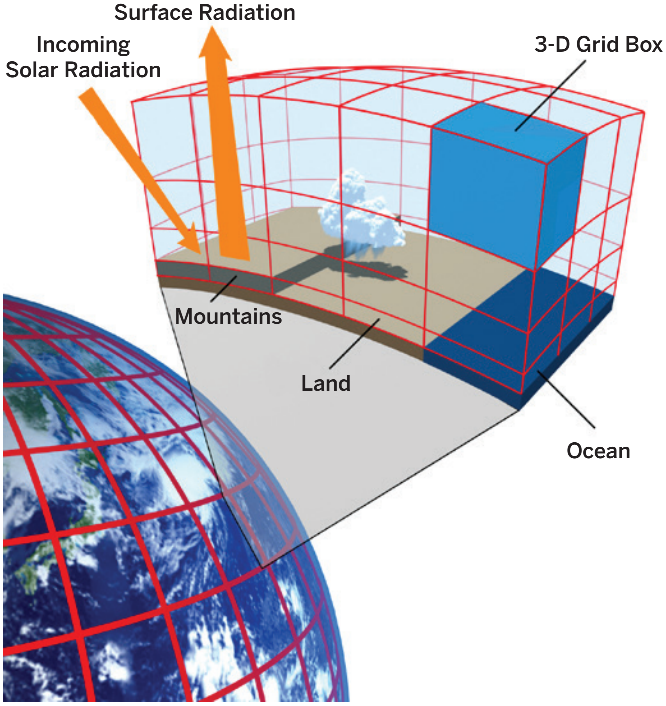
The Impact of Parameterizations

Even as computer resources have allowed for a dramatic increase in the resolution at which NWP models can be run, there are still physical processes relevant to power system planning that cannot be modeled, as they occur at scales smaller than the grid scale of even the highest-resolution model configurations, are too poorly understood or too complex to model explicitly, or occur too rapidly. These processes that cannot be explicitly modeled must be parameterized.

Figure 8 (p. 20) shows physical processes and features that need to be parameterized by NWP. The average

FIGURES 6 AND 7

Illustrations of How Features are Discretized in an NWP Model Domain



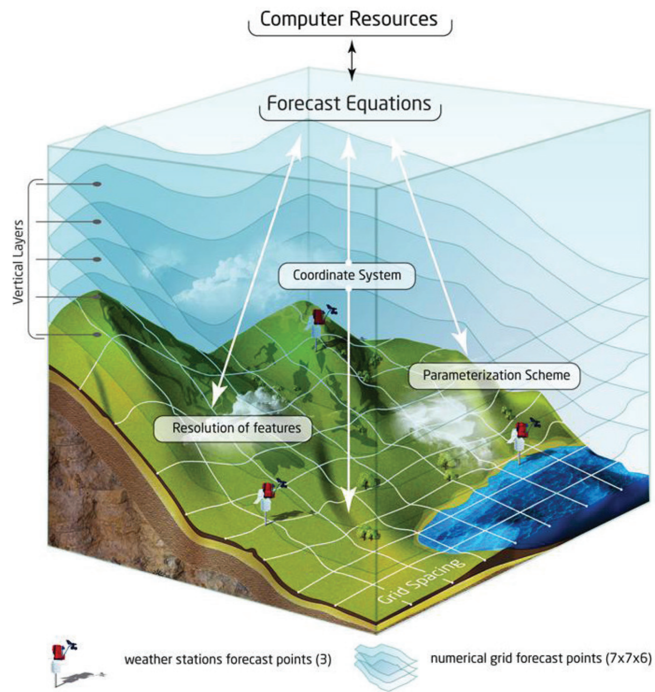


Figure 6 shows how some or all of the planetary domain is broken down into grid cells in an NWP model, while Figure 7 zooms into a small sub-domain. This shows how model grid cells follow the terrain near the surface, how a single grid cell does not perfectly represent everything within it, and how weather observations do not typically coincide with model grid points.

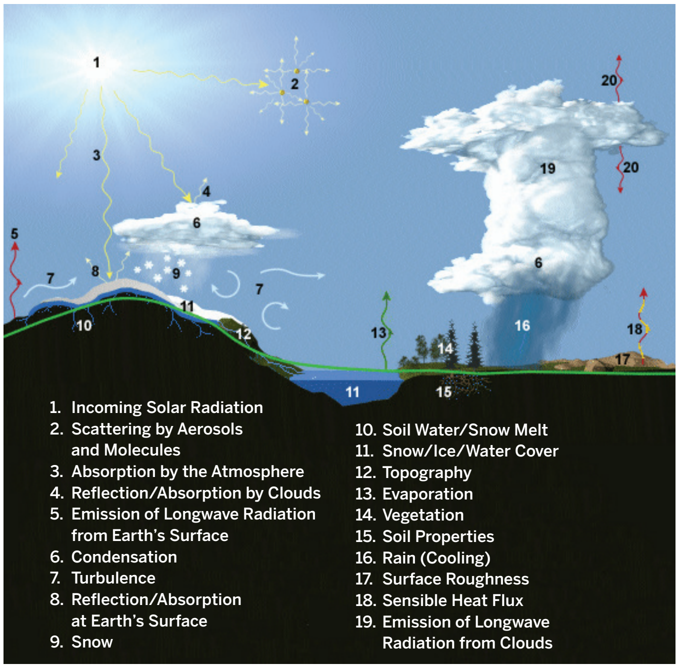
Sources: Figure 6: COMET® website at http://meted.ucar.edu/ of the University Corporation for Atmospheric Research, sponsored in part through cooperative agreement(s) with the National Oceanic and Atmospheric Administration. © 1997–2023 University Corporation for Atmospheric Research. All Rights Reserved; Figure 7: meteoblue (https://content.meteoblue.com/en/research-education/educational-resources/weather-model-theory/model-domain)

(or bulk) effects of these processes can be determined using reasonable statistical relationships that are based on well-validated empirical observations or using sub-model processes that, while physics-based, determine the bulk average properties within the grid cell. For instance, the physics defining how raindrops form and fall to earth is well understood and can be modeled explicitly, but modeling the condensation, growth, and coalescence of every cloud droplet and raindrop is impractical for NWP purposes. Instead, a parameterization—also known as a scheme—is used which is essentially a sub-model that simulates a particular meteorological process. In the case of the formation of cloud droplets, it is known as the cloud microphysics parameterization. The scheme provides a physically sound approximation of the bulk effect of the physical processes occurring in the formation of clouds and precipitation.

Because parameterizations are approximations, there are often several different versions that perform the same task, and each version may contain adjustable coefficients, settings, or parameters that can be tuned to make the approximation more accurate in different circumstances. For example, different schemes, and different parameter settings within a scheme, might work better in different seasons of the year, in different regions, or at different model resolutions. Sometimes schemes performing some of the different tasks in Figure 8 (p. 20) may be designed to work well together, while others should not be used concurrently. Others sacrifice accuracy in favor of lower computational overhead; this is common for operational forecasting applications where timeliness is vital. The choice of parameterizations and corresponding parameter settings within a scheme is usually based on informed

FIGURE 8

Commonly Parameterized Components of NWP



A summary of the various parts of NWP modeling that are parameterized.

Source: COMET® website at http://meted.ucar.edu/ of the University Corporation for Atmospheric Research, sponsored in part through cooperative agreement(s) with the National Oceanic and Atmospheric Administration.

experimentation and validation, and the consequences of the choices can be profound. It is important for data users to at least be aware that the choice of parameterizations can impact output biases.

Figure 9 (p. 21) shows the sensitivity of hub-height wind speeds to changes in parameter settings related to turbulence and surface roughness.[9] The model configuration is identical in both cases, including the choice of parameterization schemes. The only modification is in the choice of settings for parameters related to turbulence and surface roughness. The upper plot shows line plots of wind speed for many different combinations, while the lower plot translates these wind speeds to estimates of wind generation. Note that the spread in wind speed solutions is significant, but is greatly amplified by the cubic relationship between wind speed and power output. If completely different schemes were used, versus just fine-tuning the parameters, the impacts could be even larger.

Data Assimilation

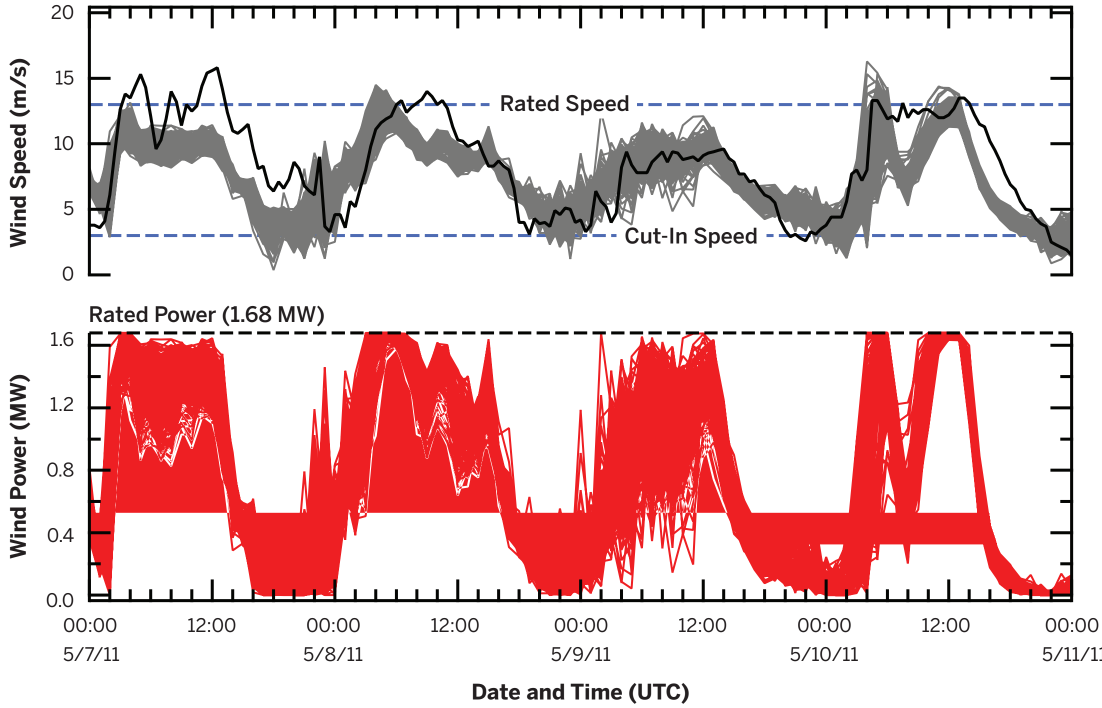
In the data assimilation component of the NWP modeling cycle (see Figure 1, p. 13), the model first-guess field—the best initial guess at the state of the atmosphere usually obtained from a prior short-range NWP forecast—is adjusted to produce an initial condition that is as close to reality as possible. This process uses observations that are collected throughout the atmosphere, including at the surface. As illustrated by the three weather stations shown in Figure 7 (p. 19), these observations typically are not collocated with the model grid points. The data assimilation process melds the observations with the first-guess field in a way that nudges the first guess toward observational truth and takes care of spreading the influence of the observation to nearby grid points, while at the same time maintaining the mathematical balance of the model's representation of the Earth's surface and atmosphere, which has less detail than reality. This is one of the most difficult-to-grasp aspects of NWP.

In short, we want the model initial condition to represent real-world conditions seen in observations as closely as possible, but at the same time it is important for the new initial condition to be as close to mathematical balance as possible in model space, and not lose important details about the state of the atmosphere that prior model runs have inferred. Models contain a less detailed representation than reality of things like terrain slope, elevation, and surface attributes like roughness, albedo, and heat capacity. These differences between model space and real space are largest close to the surface, especially where the real surface details are complex. Observations are generally more accurate than the model first guess, but the first guess contains details that have developed in the prior NWP cycle as the dynamic fields (temperature, pressure, wind speed and direction, etc.) have adjusted to the static model fields (topography, slope, land surface characteristics, etc.) in order to balance the physical equations. These details are also most important near the surface and where surface details are complex. It may

9 The parameter settings tune the Mellor-Yamada-Nakanishi-Niino (MYNN) planetary boundary-layer parameterization (Nakanishi and Niino, 2006) and MM5 surface-layer parameterization (Jiménez et al., 2012). The surface layer and planetary boundary-layer (PBL) parameterizations are codes that handle the complex atmospheric physics associated with exchanges between the surface and the atmosphere, including things like exchange of heat and moisture with the surface and interactions between the free atmosphere and the layer impacted by the surface.

FIGURE 9

The Different Outcomes When Using Different Parameter Settings with the Same Model Configuration



Traces of wind speed and wind power for many different iterations of a model run with everything held constant except parameters related to turbulence and surface roughness. The upper plot shows the range of wind speeds generated by numerous model runs. The lower plot translates these wind speed differences to estimates of wind generation. The wider spread seen in the lower plot shows the profound impact of parameter choice when the cubic relationship between wind speed and power output amplifies these differences.

Source: Yang et al. (2016).

be the case that, for instance, a temperature observation in a valley might be more accurate than the model first guess; however, that observation should not carry much weight because it represents a phenomenon that is at a scale the model cannot represent.

Thus, data assimilation is about much more than creating a new initial condition by interpolating available observations onto a grid: the assimilation process seeks to strike a balance between pushing initial condition features that drive weather at scales the model can represent toward observed truth, while maintaining the details that have been inferred by the model in regions where observations are sparse. In addition, assimilation accounts for differences that are due to the different level of detail the model resolution can represent relative to reality. For example, if the model surface elevation is higher than the real elevation where an observation was taken, the temperature expected in the model will be different from that observed in reality. If these differences between the model first guess and observations are naïvely pushed toward the observations, then the model initial condition may be moved far from physical balance (in model space), and, just like the real Earth system, a physics-based model will respond to remove imbalance when model integration starts. If the imbalances are large, then phenomena that are physically unrealistic (like strong winds that would not occur in reality) will develop and the model may even become unstable and cause the simulation to fail (i.e., crash).

NWP Principles Takeaways

Power system planners often need data of a higher spatial resolution than are available from observations and need these data to be representative of the real conditions that are occurring in time and space, including how different weather variables coincide. NWP provides a way to synthesize such data. Because many of the meteorological features driving weather variables that impact supply and demand, especially those determining renewable resource generation, are driven by topography or small-scale weather features, the NWP modeling must either be conducted at sufficiently high resolution or use a post-processing method (described later in this section).

While the structures in high-resolution models can look very compelling, they are difficult to validate due to the small number of observations that are available relative to the number of grid points.

Running at higher resolution is usually the more accurate approach. However, it is not a panacea. First, even if vertical resolution is held constant, the computational resources needed to increase horizontal resolution scale by at least the third power because the number of required time steps increases by the same factor as the resolution change to keep the model computationally stable. Hence, a 1 km simulation takes at least 27 times the resources of a 3 km simulation, and takes 27,000 times the resources of a 30 km simulation. The volume of output data also expands by the power of two, as does time to output them. And while the structures in high-resolution models can look very compelling, they are difficult to validate due to the small number of observations that are available relative to the number of grid points. This is especially true in complex terrain, where the meteorological fields are most in need of validation but observations tend to be sparse. Ultimately, a compromise must be made between the benefits of higher resolution and the computational and data storage resources that are available.

In addition, regardless of resolution used, NWP models depend on an accurate initial condition. How good this starting point is depends on past model runs and on the amount and quality of available observations. Data assimilation takes a representation of the atmosphere produced by a prior model run and applies observations to it to produce the initial condition. This process is very complicated and is a source of significant uncertainty that varies in time and space.

Even when using high-resolution configurations, some processes that need to be modeled still occur at scales finer than the model grid scale. These are represented by subgrid-scale parameterizations. Many different choices of parameterizations and associated settings exist, and their choice in the model configuration can greatly impact the model accuracy. Furthermore, some work better in some locations, seasons, and/or weather regimes than others.

Some grasp of these factors is necessary when utilizing data produced by NWP processes to ensure that the data are applied appropriately versus being considered as a simple proxy for observations.

NWP Applications Relevant to Synthesizing Power System Weather Inputs

It is widely recognized that the basis for modern day weather forecasting is the regular collection and assimilation of data into NWP models and then running those models to produce a forecast of the weather expected in the coming days, and this use case is deployed to produce source data for operational load and generation forecasting. NWP models can also be used to produce estimates of weather conditions for many power system analysis tasks. This section describes the key applications of NWP modeling that are relevant to power system applications.

Producing Operational Forecast Data

NWP models are the foundation of all operational weather forecasting products including forecasts produced for the power sector. While the operational application is not the main focus of the report from which this document is extracted, a short description is given so that the process can be compared to how NWP is used to produce other datasets that are the report's central concern. Additionally, there are some instances in which archived operational NWP has been utilized for power system analysis, and a few words need to be said about this.

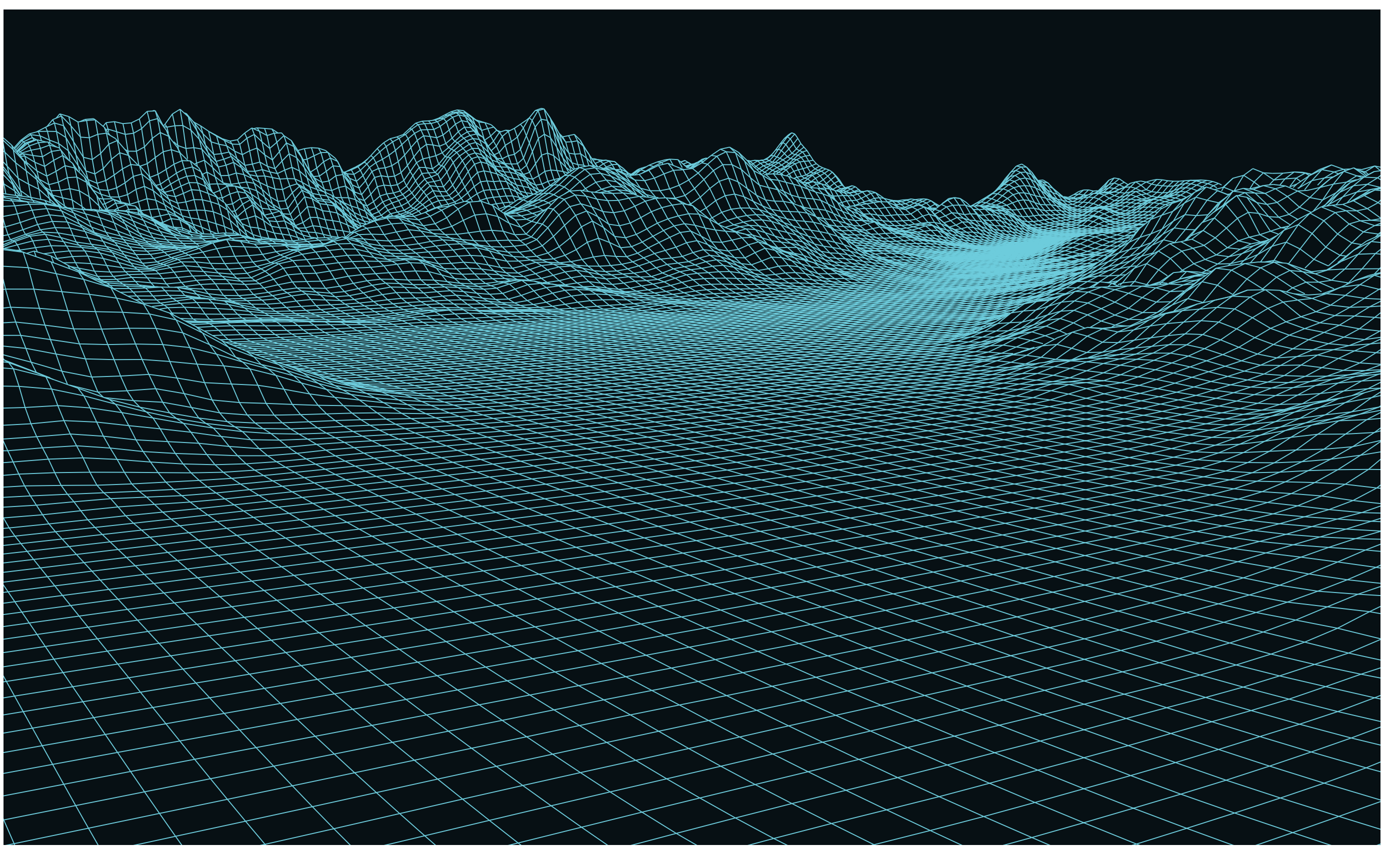
When producing NWP output for operational forecasts of future weather, the first few forecast hours need to be produced as fast as possible, as they are only valuable if they represent a forecast of the future; if they are not produced quickly, they become an estimate of conditions in the past. This means making compromises regarding when to cut off ingestion for the data assimilation cycle so that a good enough initial condition can be produced, and the process of integrating the NWP model to produce estimates of future atmospheric conditions can begin. Choices also need to be made about model resolution and parameterizations that prioritize model speed as well as accuracy. Lastly, choices of output variables and output frequency need to be made that provide the best overall value for all end users, not just those in the power sector.

Operational forecast models are regularly updated to incorporate the latest enhancements in NWP techniques and increasing computer power. Thus, the model configuration is not static in time, meaning that output resolution, skill, and biases are not constant.

Factors like early data cut-off, configurations set up for speed, and dissemination designed to be for all generic users mean that NWP data produced for operational weather forecasting by national forecast centers (e.g., the National Oceanic and Atmospheric Administration's National Centers for Environmental Prediction (NOAA/NCEP) in the U.S.) are not ideal for use in power system modeling. For power system uses we would like weather inputs to be the best possible representation of the state of the atmosphere, with variables and output level selected to match sector needs and model configuration being held constant to prevent unexpected changes in model biases.

Producing Reanalysis Data

One of the most widely used types of atmospheric data, including for power system analysis, is reanalysis data. Reanalysis datasets have many strengths. However, they are often misunderstood as being able to serve as a proxy for observations, and thus are often misused.



Reanalysis datasets have many strengths. However, they are often misunderstood as being able to serve as a proxy for observations, and thus are often misused.

Reanalysis datasets are produced by NWP modeling systems configured specifically to produce as accurate a representation of the atmosphere as possible for a given model resolution and the available input data across long periods. Unlike using NWP to produce a prediction of the future, reanalysis seeks to produce a spatially and temporally complete representation of *conditions in the past* by incorporating all useful observations and using the model physics to approximate atmospheric states where and when no observations are available. Reanalysis data provide an easy-to-use, four-dimensional representation of the state of the atmosphere, often across the entire globe, using a single consistent method. The data are provided on regularly spaced grids, across long time periods (years, and often decades) at moderately high horizontal grid spacing (typically tens of kilometers, sometimes better) and moderately high temporal resolution (usually one- to three-hour intervals). Moreover, all the variables output at all locations are time-coincident and physically consistent: the same physical phenomena simultaneously impact every variable, and the cross-correlations between the variables are captured in the model. Another feature of reanalysis datasets is that, unlike for operational forecasts, the same configuration of the model is used to produce the entire archive, which means modeling system skill is static. All of these features are important for power systems work.

However, reanalysis datasets are often misused by end users. Many believe that reanalysis data can be used as a proxy for actual observations and that they have a similar accuracy level. But it is crucial to understand that reanalysis data are an *estimate* of the state of the atmosphere across an area, not a finite point. Reanalysis data are not observations. The quality of the estimate depends on several factors including the quality of the model used to produce the reanalysis, the configuration of parameters within the models, the horizontal and vertical resolution used in the modeling, and the quality, quantity, and distribution of observations assimilated into the model. In addition, the representativeness of the reanalysis output can differ under different atmospheric conditions and in different regions. As was described in the previous section, when weather conditions are heavily influenced by phenomena at scales smaller than an NWP model configuration can resolve (phenomena too small for the model to "see"), the results can deviate substantially from the reality of the finite point where observations are measured. While the variables are all physically consistent according to the mathematical relationships governing the atmospheric system, this consistency exists at the resolution of the model and is only as good as the background field and observations going into the reanalysis *and* the ability of the model to resolve the phenomena present at the resolution used.

To begin the reanalysis, the first background field used (the first guess of the atmospheric state) comes from archived output from a high-quality operational forecast model's initial condition. For example, a reanalysis dataset beginning in 1990 would utilize an initial condition from 00 UTC January 1, 1990. All available observational data are assimilated into this analysis. Reanalysis employs the most sophisticated assimilation methods available to produce the reanalysis field. This is usually a method called 4D-Var, which considers not just how observations vary in space, but how they vary in time and space relative to the model background field and relative to short-range model predictions forward and backward in time.[10] Observations from about six hours either side of analysis time are analyzed for this purpose. The output from this process is the first interval of the reanalysis. NWP integration then moves the reanalysis state forward to the next output time, for example, 01 UTC January 1, 1990. The short-range forecast from this step then becomes the first guess for the next assimilation cycle.[11] The data assimilation cycle is then repeated with appropriate observation archives, followed by integration to the next reanalysis time. The process repeats until the

10 An accessible introduction to 4D-Var, which is used in producing ERA-5 reanalysis data—probably the most utilized reanalysis datasets for renewable energy applications—can be found at: https://www.ecmwf.int/en/about/media-centre/news/2017/20-years-4d-var-better-forecasts-through-better-use-observations.

11 The short NWP integration creates fields like accumulated precipitation that are also archived.

entire dataset has been created. This usually takes months or years and millions of CPU (central processing unit) hours utilizing a supercomputer.

Raw model output from the reanalysis process is archived, but the data provided to users are usually processed into datasets that provide a standard set of atmospheric variables on a regular grid that is typically mapped to a sphere on constant-pressure levels. The transformation process can lead to the loss of useful resolution in the vertical and interpolation artifacts in the horizontal grid, and expert users may want to use raw grids where available. See the appendix for details.

Deriving Downscaled Regional Datasets

NWP and GCM models only resolve atmospheric phenomena at a scale equal to about six to eight times the grid resolution (Skamarock, 2004). For instance, a 30 km model will resolve weather features that have a length scale of 180 km or more, which is much broader than many regional-scale weather impacts. However, downscaling can be used to produce higher-resolution datasets from lower-resolution ones, although it must be used with care. Output produced by the low-resolution models can be used as input to higher-resolution NWP models in order to reproduce the atmospheric conditions present in phenomena occurring at smaller scales that are driven by larger-scale weather patterns. For example, a low-resolution GCM can produce the strong winds associated with a deep low-pressure system (a large-scale phenomenon), but it cannot translate these winds to the heavy precipitation that will result from these winds along a steep mountain range (a small-scale phenomenon), because the mountains cannot be properly represented in the GCM. Examples of other small-scale phenomena driven by the large scale include circulations like sea breezes, gap winds, mountain-valley circulations, thunderstorm cells, cloudiness on the windward side of hills and mountains, and clouds clearing on the leeward side. Some of these smaller-scale phenomena are known to affect wind energy generation, especially in regions of more complex terrain, and other small-scale phenomena impact solar generation. These phenomena typically occur at scales below those of most national operational NWP forecast models (although this is changing as computer power increases) and well below the scales resolved by best-in-class reanalyses like the ECMWF's ERA5 and the U.S. National Aeronautics and Space Administration's (NASA's) MERRA-2 or any current GCMs. Downscaled NWP output is also produced for certain operational forecasting needs, for instance, fire weather and air quality, which require very high-resolution modeling.

Importantly, the process of downscaling can be applied to historical output, like reanalysis output for use in power system modeling, or to the output of GCMs. The best-in-class Wind Integration National Dataset (WIND) Toolkit dataset from the National Renewable Energy Laboratory (NREL) is produced this way.

When performing downscaling, the lower-resolution initial condition is first interpolated onto the higher-resolution model grid in a process that also adjusts the meteorological fields to account for the different elevations present in the higher-resolution domain. Once the NWP modeling begins, the effects on the initial field from the higher-resolution terrain will cause the meteorological fields to realign and include the impact of the finer-scale topography that causes such phenomena as channeling of the wind, forced lifting over terrain, damming of cold stable air behind narrow gaps, and differences in heating across slopes. This adjustment process is known as spin-up, and once the model is spun up, the output will represent the phenomena present at the finer scales.

Because the area being downscaled is regional versus global, the weather entering and exiting the edges of the domain needs to be provided to the model as it runs forward in time. These boundary conditions from the larger-scale analysis or forecast feed the edges of the finer-scale domain with accurate data about the larger-scale weather pattern. This keeps the fine-scale domain anchored to the larger scales that are well represented in the lower-resolution data, while at the same time allowing the model to fill in the smaller-scale effects in a physically consistent way. In some cases (where the larger-scale features are trusted), scale-selective nudging can also be used to ensure that the larger-scale features within the domain do not drift during the finer-scale forecast run. This means the model can run for longer without needing to be reinitialized. This creates fewer seams in the model output and minimizes computationally expensive spin-up time, the output from which is not useful (generally the first few hours).

An example of the power of downscaling to yield more accurate representations of the weather fields is modeling in complex topography, such as the western U.S., the Appalachian Mountains, or the European Alps. Better-resolved mountain barriers will better block cold, stable air in the models, and better-resolved steeper mountain slopes can accelerate winds more in line with reality, which can be to speeds several times larger than seen in lower-resolution models. As with all NWP output, once the model is spun up, the resultant downscaled data are physically consistent between weather variables. For instance, a sharp mountain barrier will be much taller at high resolution and thus reduce the air flow at lower levels (an impact on wind speed) across a barrier, compared to air flow modeled by a lower-resolution model. This in turn can change the temperature on the downstream side of the mountain because the air is coming from a different elevation with different atmospheric stability. At the same time, a gap or pass in the mountain barrier shown in downscaled data will be better defined and lower in elevation, also reflecting reality more closely. This will create stronger winds in its lee, and the air immediately downstream of the gap will be colder than in the original low-resolution output; it may also be drier and remove fog present in nearby locations not impacted by the gap. These more accurate representations of the weather fields will result in more accurate estimates of the wind and solar resources in the region, as well as temperature at load centers and weather-related outages at traditional generators. The more accurate representations also greatly improve estimates of precipitation that occurs in steep terrain that may feed a hydro system.

NWP downscaling is a powerful tool for providing consistent information about local effects and developing long time series at a level of detail not possible with available observations. However, it must be used with care for precisely this reason. The lack of observations means that only a small fraction of the NWP data points can be validated against ground truth.

NWP downscaling is a powerful tool for providing consistent information about local effects and developing long time series at a level of detail not possible with available observations. However, it must be used with care for precisely this reason. The lack of observations means that only a small fraction of the NWP data points can be validated against ground truth,[12] so it is especially important to make sure that the model output is validated where it can be to understand how well the model is performing. It is also important to remember that since model performance will vary with weather regime, validation should be more than just calculating average errors.

Producing Global Climate Models

GCMs can produce datasets that represent weather conditions for decades into the future. Therefore, GCM output is potentially useful if one wants to simulate conditions affecting the electricity system in a future affected by climate change, although it must be understood that there are considerable uncertainties in climate predictions, and expert climatologists should be engaged to understand how large the signal is relative to the

12 Ground truth is actual wind and solar realization measured with instrumentation, as opposed to data from a model that is estimating the quantity.

model uncertainty. GCMs are, at their core, a type of NWP model, and like other forms of NWP output, the data from these models are dynamically consistent across output fields. While the core atmospheric modeling functions of GCMs are basically the same as those of other NWP models, GCMs have tighter coupling to modeling of other aspects of the Earth system such as the cryosphere, oceans, and atmospheric chemistry (including greenhouse gas concentrations), because over long time frames, feedbacks between these systems become increasingly important. GCMs also typically use much lower resolution to make long simulations computationally tractable, although, like regular NWP models, GCM resolution is constantly improving. Using a GCM, it is possible to create accurate representations of the distribution of weather over longer periods. We know this because GCMs can accurately recreate historical distributions of, for example, temperature and rainfall across broad regions. The premise of climate modeling is that if statistical descriptors of the past climate can be simulated accurately, then simulations of the future will provide insight into how those distributions change as greenhouse gas concentrations change, and the climate warms.[13]

It was noted above that the atmosphere is inherently chaotic and thus completely unpredictable at time scales beyond two to three weeks. Therefore, just like a standard NWP model, when a GCM is given a reasonable initial condition, it can accurately predict the evolution of the weather systems in this initial condition with some skill for a week or two, and, just like a standard NWP model, its prediction skill will fade beyond this horizon. How then is it possible to make predictions about Earth's future climate with GCMs? This paradox is explained by the fact that chaos theory states that within the apparent randomness of a chaotic system there are underlying patterns, feedback loops, repetition, and self-organization. The objective when running a GCM is not to predict the weather at any given time in the future, but rather to predict the distribution of future weather events that can evolve at the scales the model simulates, for different Earth system conditions (like the amount of CO_2 in the atmosphere).

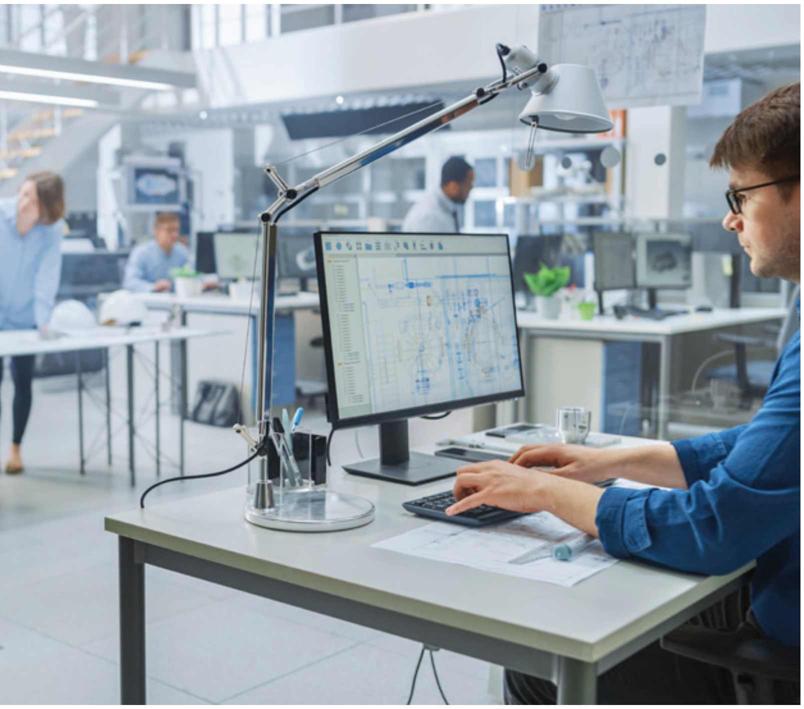
While GCMs can potentially simulate conditions affecting the electricity system in a future affected by climate change, this matter is considerably more complicated than it first appears, and there are several important caveats to understand before considering using GCM output for this purpose. These caveats, briefly laid out below, form the basis for why the full report, *Weather Dataset Needs for Planning and Analyzing Modern Power Systems*, does not focus on power system weather inputs under climate change.

Because there is no observational method to validate the predictions of a GCM in the future, the standard validation process is to use GCMs to simulate conditions over the last century or so, using the changes that are known to have occurred in the atmosphere (like increasing CO_2 and the oscillation of solar output through the 11-year solar sunspot cycle)[14] as a boundary condition. These simulations have been found to produce consistent and reasonably accurate results using many different GCMs (Hausfather, 2017). Once a GCM configuration is validated by showing it can produce a reasonable estimate of past climate, it is assumed that it can be used to model many future decades for different scenarios (such as changing CO_2 concentrations or changes in atmospheric aerosols). The results from these simulations are compared between different GCM models, and where they are similar for the same changing boundary conditions (e.g., CO_2 concentration), a higher degree of confidence is ascribed to the predicted distribution changes.

Almost all GCMs indicate significant future warming, and many produce patterns of temperature and precipitation changes that are similar to one another. However, there is much more uncertainty around how wind and irradiance patterns might change. Further, GCMs do not run at sufficient resolution to be able to diagnose how large-scale changes even in fields like temperature

13 GCMs are not only used for studies of anthropogenic climate change and can provide insight into changes due to any manner of slow changes in the Earth system.

14 The energy output of the sun oscillates over time in a quasi-regular and predictable way, with an average cycle from the solar minimum through solar maximum and back to the minimum of approximately 11 years.



and precipitation may translate to changes at smaller scales in regions of more complex topography, which are necessary to model for power system planning. One approach to examining these smaller-scale changes is to use the GCM output as input to higher-resolution NWP models in order to downscale it as described in the previous sub-section. When this is done, there is again some consistency in results for temperature and precipitation. However, the results of downscaling exercises are mostly inconclusive when examining phenomena like local wind circulations and cloud cover.

Post-Processing of NWP Data

NWP output and climate projections are not free of errors. Sources of error include the initial conditions used in NWP models and how they are constructed (observations, assimilation), accompanied by boundary condition errors and model physics errors. For power system uses, even high-resolution model output can display significant deficiencies, resulting in systematic biases and less weather variability than expected. For example, even comparatively fine resolutions of NWP simulations provide an average temperature for each grid box of, say, 2 km x 2 km for local scale and 20 km x 20 km for a global scale, which can fail to reflect variability that has important impacts for both supply and demand in future power systems.

Post-processing can address some of the above deficiencies, by enhancing NWP or GCM output using simple methods such as determining and removing bias errors or performing more complex tasks for applications such as wind plant production estimates. The conversion from grid box to point estimates (point-based post-processing) or from coarse grid box to very fine grid box (grid-based post-processing) is called calibrated post-processing. Promising new machine learning methods offer an advanced form of grid-based post-processing, with the possibility of downscaling NWP output without the large computational expense of running very high-resolution NWP simulations.

Statistical Post-Processing

A wide range of techniques are used for post-processing. Regardless of the method used, post-processing should produce an estimate as close as possible to the truth, while respecting the climatological probabilities and producing results that are physically consistent between the different meteorological parameters. Given enough training data (i.e., observations that can be compared with NWP output), these methods can improve both spatial and temporal representation of NWP estimates, but care should be exercised because the techniques tend to smooth the data and produce outputs that underrepresent the upper and lower tails of variables like temperature, wind speed, and irradiance. In addition, the large amount of observational data needed to train them is often not available. Thus, while statistical post-processing can improve NWP output accuracy by some measures, it can also adversely impact important aspects of the original data distribution that could affect results when the data are used for tasks like resource adequacy analysis.

A simple post-processing example is bias correction in combination with a distribution correction, where one corrects the current estimate with the model's bias and distribution of errors from past estimates. For ensembles,[15] other methods based on the idea of a weather generator can be used to search for past simulations that are very close to the current forecast

15 An ensemble in the context of NWP is a set of NWP simulations utilizing different NWP models or configurations and/or slightly different initial conditions. The resulting sets of output can be statistically analyzed and the dispersion between them utilized to assess simulation uncertainty.

and use the past corresponding observation as new forecast, such as the analog ensemble (AnEn) approach (e.g., Delle Monache et al. 2013; Alessandrini et al., 2015a, 2015b; Alessandrini and McCandless, 2020). Statistical methods are relatively easy to implement and apply, once the data are available and prepared.

Machine learning and other artificial intelligence methods can also be used to improve NWP output. The link between model and observations contains non-linear relationships, which are difficult to capture with traditional statistical methods; however, using non-linear machine learning methods such as support vector machines, decision trees, and artificial neural networks, these relationships can be detected between observational data and NWP output. Once trained, machine learning methods can correct other NWP output. However, these methods can be challenging to design, need a lot of tuning and computing power, and require a significant amount of data to train on (ideally at least a year to capture all four seasons, and preferably multiple years to account for inter-annual variability).

Recent advances in machine learning are indicating that in the near future there is the possibility that some of these methods may not only be able to correct and/or downscale NWP output, but may, given enough existing NWP training data and observations, actually be able to produce better estimates by operating on low-resolution NWP output and observations than can be produced using high-resolution models. While detailing these developments is beyond the scope of this discussion, they are likely to become very important within the lifecycle of the full report, and interested readers are referred to McGovern et al. (2019) and Lam et al. (2022) for more details.

Generative Machine Learning for Weather and Climate Data

Recent advances in machine learning techniques for computer vision and generative models have inspired a new class of methods for the post-hoc downscaling of NWP outputs. Generative models can learn and sample virtually any conditional joint probability distribution such that they can produce realistic multivariate spatio-temporal fields given some conditional input. For example, a generative model can be trained to produce continuous gridded multivariate (e.g., wind, temperature, etc.) data-sets that are physically realistic across both space and time given a lower dimensional input such as a set of point observations or a low-resolution climate model dataset. These methods promise to reduce the burdensome computational requirements of high-resolution NWP simulations while maintaining high-quality data outputs. If these methodologies can be proven to work well, they will enable the production of higher-resolution and longer time series of weather input data suitable for power system modeling applications, as well as ensembles of these datasets that capture the uncertainty of the weather inputs and therefore allow electricity system studies to model sensitivity to this uncertainty.

Deep convolutional neural networks (CNNs) have been recently shown to excel at a wide range of computer vision tasks, including meteorological applications (Alzubaidi et al., 2021; McGovern et al., 2019). These networks are designed to the dimensionality and structure of image, video, and NWP simulation data. This results in powerful non-linear parametric models that can learn to emulate physical phenomena such as the momentum

balance for wind flows on a spatio-temporal grid, much in the same way that finite-difference or finite-volume methods execute physical equations from cell to cell in NWP models. Note that this comparison between trained convolutional operators and physics-based finite-difference/finite-volume methods cannot be directly proven for large dimensional relationships such as multi-dimensional weather fields but can be demonstrated in simple 1D examples (Rackauckas et al., 2021), which supports the utility of these trained models in physical domains. The result is a learned model that can emulate a physical simulation similar to an NWP but at a fraction of the computational cost.

In practice, a major problem is that a basic convolutional network can exhibit regression to the mean in the form of blurring or smoothing when producing forecasts or enhancing the resolution of data. This can result in an underestimation of extremes such as heavy rainfall intensities at small spatial scales (Ayzel, Scheffer, and Heistermann, 2020). One solution to this problem is adversarial training with generative adversarial networks (GANs) (Stengel et al., 2020; Hess et al., 2022; Wang et al., 2021; Rosencrans et al., 2023; Gagne et al., 2018), where a generative model must produce data that are not only accurate but also sufficiently realistic to fool a discriminative network. That is, the generative model produces outputs that are mathematically and statistically indistinguishable from NWP outputs from the perspective of a sophisticated classification model. For downscaling data with GANs (often called "super-resolving"), the generative network is trained to produce an enhancement of the low-resolution input data that the discriminator believes is similar to real data, while simultaneously minimizing the numerical deviation from a corresponding true high-resolution dataset. This method has been shown to be effective in creating highly realistic enhancements for many types of data.

GANs with deep convolutional networks have only recently been applied to the task of downscaling NWP data, but have already shown considerable promise with high-quality physics-based validation of the outputs (Stengel et al., 2020). To the knowledge of the authors, only a small handful of public datasets have been published at the time of this writing that leverage GANs to downscale historical reanalysis data or future climate data (Buster et al., 2023; Rosencrans et al., 2023; Hess et al., 2022). However, several additional wind datasets are known to be in development that leverage GANs to do a final spatio-temporal enhancement on coarse NWP data instead of running the NWP down to the final desired resolution. The benefit of this hybrid NWP+GAN approach is a significant reduction in computational costs compared to what would be required by a full high-resolution NWP simulation (estimated at one to two orders of magnitude in compute time savings).

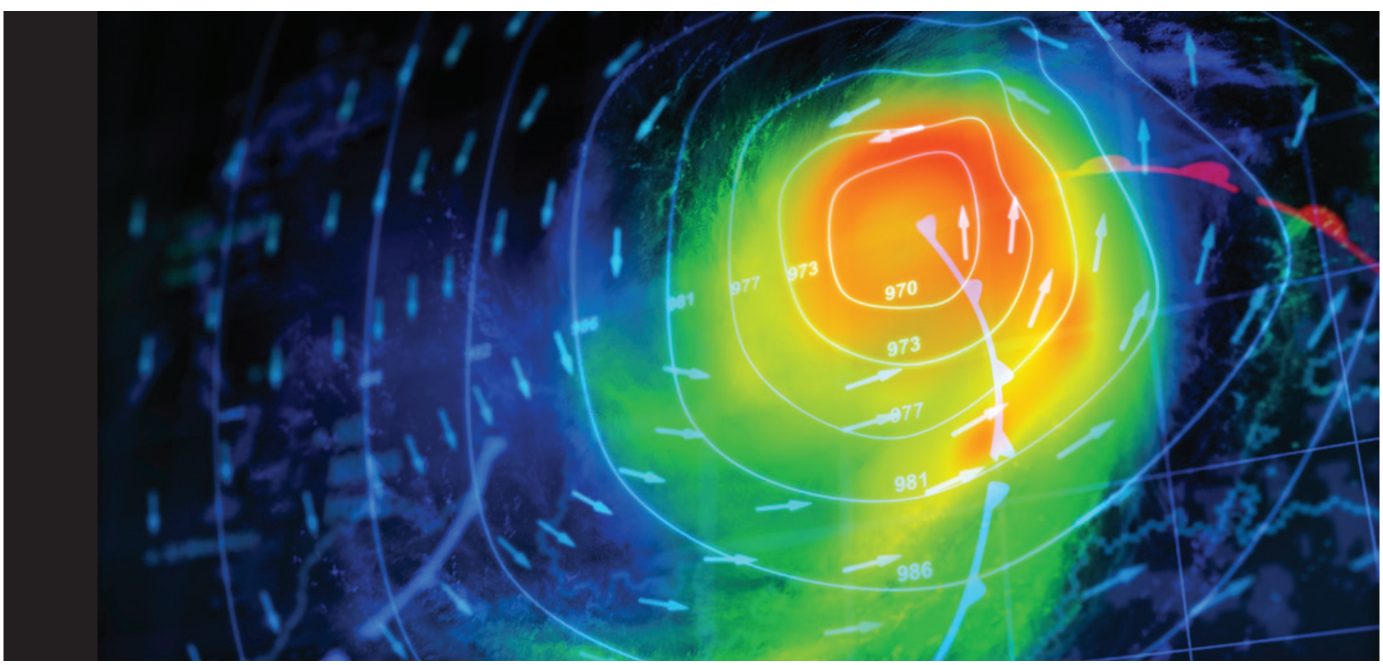
The main drawbacks of using GANs for downscaling are that this requires significant investment in machine learning expertise, machine learning–specific computing infrastructure, and high-quality training data, and can result in a loss of methodological interpretability including the possibility for data outputs that do not respect physical constraints. This last problem is clearly the most concerning, as low-quality data with poor physical constraints could compromise power system planners' ability to accurately predict and plan for future system needs. The methods described above have the potential to greatly benefit the renewable energy and meteorological communities, but rigorous validation needs to be of the utmost priority. Statistical benchmarking, validation against ground-truth observations, and careful examination of physical data characteristics like turbulence should all be regular practice when implementing these methods.

Crucial Takeaways for Power System Modelers Using NWP and GCM Data

In summary, NWP is a complex subject with many nuances. It requires expert knowledge to determine what model resolution, parameterizations, and parameter settings are best for the problem being solved and/or 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. Understanding the limitations and possible pitfalls of the models' output requires deep knowledge of NWP systems. 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 unaware of how the data are being used 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.

Even meteorologists with NWP backgrounds are sometimes unaware of how the data are being used 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.

Using data derived from NWP seems compelling because their regular format and general geographical and temporal completeness make them easy to use. But



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

it is essential to understand that NWP data are not the same as observations—even data coming from reanalysis datasets that are often touted as suitable substitutions for observations. In addition, the performance of one NWP model or configuration is not a predictor of the performance of another model or even the same model used in a different region, with a different configuration, or with different input data. Even with well-chosen selections of resolution, parameterizations, and other configurable options, NWP models sometimes perform poorly. This poor performance does not occur randomly and is often related to specific atmospheric conditions and/or regions. When these factors align with weather situations that result in stress on the electricity system, the weather inputs going into power system models may be poor and compromise the results. Garbage in, garbage out.

Therefore, it is crucial that for any study using NWP data as a proxy for observations, NWP data not be utilized as a black box dataset that is equivalent to quality-controlled observations. Users need to have at least a basic understanding of how 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 systems 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. NREL recommends such validation be performed before using the WIND Toolkit data.[16] Unfortunately, such validation is uncommon, and those validations that have been performed, such as for the overall NREL NSRDB and WIND Toolkit datasets, have looked mostly at bulk average statistics for a handful of sites and have not evaluated the dataset accuracy in the context of electricity system risk periods.[17] It is important to note that these limited validations indicate significant differences between the NWP data and the ground truth; however, the results are not widely publicized. For example, a narrowly targeted simple evaluation of the WIND Toolkit data during a period of system stress in the western U.S. indicated substantial over-predictions of wind energy potential in the U.S. Pacific Northwest.[18] But such validations are not standard industry practice. This lack of validations is due in part to the limited data availability to perform thorough evaluations and in part to a lack of understanding of the need. The project team recommends the development of a best practices guide for validating weather inputs prior to use, and suggests that this be an integral part of any project that is developed to address the need for better weather input datasets.

16 https://www.osti.gov/biblio/1166659/.

17 For validations for the overall NSRDB, see https://doi.org/10.1016/j.rser.2018.03.003 and https://www.nrel.gov/docs/fy22osti/83015.pdf. For the WIND Toolkit, see https://www.nrel.gov/docs/fy15osti/61740.pdf and https://www.nrel.gov/docs/fy14osti/61714.pdf.

18 https://gridlab.org/wp-content/uploads/2022/05/GridLab_California-2030-Meteorological-Deep-Dive.pdf.

Appendix: Weather 201

In-Situ Observations

In-situ observations provide measurements specific to their location. In-situ measurements are appealing, as their uncertainty and quality are usually easy to quantify, the instrumentation is relatively cheap, and they often have long records. However, their spatial coverage is typically limited.

In-situ measurements have been taken around the world for centuries, and long records are available at some sites. Examples include thermometers, precipitation gauges, and barometers. Uncertainty and accuracy depend on the instrument specifications, placement, and maintenance. Most in-situ observations are fixed in space and are typically surface-based, with towers used to gather measurements from multiple near-surface levels. Another form of in-situ measurement uses radiosondes, an instrument package carried aloft by a weather balloon. These instruments report the instrument location as part of the data collected.

Remotely Sensed Observations

Remote-sensing instruments either observe atmospheric data from somewhere remote from the measurement location (passive sensing) or send out a signal and observe the interaction of the signal with the atmosphere (active sensing). This means that remote-sensing devices can gather data from large areas or volumes by scanning across them. Examples include cameras (a passive sensor) flying on orbiting satellites and weather radars (an active sensor that sends out a pulse of radio waves and measures the reflected signal).

Remotely sensed data from a vast array of instruments located both on satellites and on the ground are now recorded in large quantities, often at high spatial and temporal resolution. Examples are weather radars, atmospheric sounders, and atmospheric imagers. These instruments usually measure at multiple locations along a line or within a volume. Often, the instruments are space-based, in which case they may either be in geostationary orbits, which always have the same field of view of the Earth and thus provide frequent observations within their view, or be in an orbit that transits different parts of the planet, thus covering a broader field of view but with less frequent observations at any given location. Remotely sensed data have revolutionized our ability to diagnose the four-dimensional state of the atmosphere and are a critical input to models that produce widely used gridded datasets derived from numerical weather prediction (NWP) and other types of modeling.

Some major complexities are associated with remotely sensed data that need to be understood if one is using the data directly without expert guidance. The quantities measured sometimes have complex relationships to the atmospheric variables that are derived from them and require significant processing to arrive at the atmospheric data. Further, atmospheric conditions can affect sensitivity, accuracy, and range. For example, weather radar measures atmospheric reflectivity, and this is a function of precipitation type among other factors, and heavy precipitation will limit range.[19] The instrument response may be quite nuanced; therefore, care is needed in interpretation of data. For example, lidar and radar, both of which can be used to remotely sense wind, can "see" farther in clear conditions; however, if the air is exceptionally clean, these instruments will not be able to sense the wind conditions. For scanning instruments, the volume being sensed increases with distance from the radar and the average resolution decreases, because the scan produces ever larger concentric circles. Similarly, visible satellite imagers can detect the tops of clouds, but the same

19 Rain has a much higher radar reflectivity than snow, except melting snow produces more reflection. Large hail produces even larger returns than rain or snow.

clouds prevent the imager from seeing clouds at other levels.

The Impact of the Era of Satellite Remote Sensing on Weather Observations and Modeling

The year 1978 is generally considered the beginning of the satellite era for weather prediction purposes. Continuous monitoring by weather satellites began in 1974, and the first polar-orbiting environmental satellite (POES) was launched in 1978. The POES program greatly improved the data available for assimilation, as polar-orbiting satellites orbit at a much lower altitude (about 850 km above the surface, versus 35,780 km for the Geostationary Operational Environmental Satellite (GOES)), allowing much higher-resolution sampling. These satellites also use active sounding sensors that in many cases can penetrate clouds and provide more information about the environment, including ocean temperature and surface winds on the ocean, and can estimate temperature and humidity profiles. Subsequent satellites have been equipped with increasingly sophisticated and high-resolution instrumentation, leading to a dramatic increase in the quality of atmospheric analyses as observations from large volumes of the atmosphere became available.

Numerical Weather Prediction

All weather inputs for operational load, wind, and solar forecasts in the electricity sector are based on foundational data coming from government-operated NWP programs. This is because the process of collecting and assimilating data is costly and requires cooperation across nations, and the models themselves require vast quantities of computer resources. In some cases, additional NWP tasks are performed by users or providers in the energy sectors in the process of producing sector-specific products, but for the most part, at this time, the NWP output of the major national centers—the European Center for Medium-Range Weather Forecasting, the UK Meteorological Office, the U.S. National Oceanographic and Atmospheric Administration's National Centers for Environmental Prediction, and the Canadian Meteorological Center—is difficult to improve upon in a timely and cost-effective manner. Most providers in the energy sector focus on statistical post-processing of the raw NWP data, usually using machine learning techniques.

Reanalysis Output Refactoring

Raw model output from the reanalysis process is archived, but the data provided to users are usually refactored into datasets that provide a standard set of atmospheric variables on a regular grid that is typically mapped to a sphere with multiple vertical levels. For spectral models, the raw model archive consists of spectral coefficients or gridded data on a reduced Gaussian grid,[20] so it is usually interpolated to a fixed latitude and longitude spacing when provided to end users. This means that grid spacing in the north-south direction is constant but west-east spacing varies with latitude. For example, a 0.25° latitude x 0.25° longitude grid has north-south spacing of 27.8 km everywhere,[21] while the west-east spacing is 27.8*cos(latitude), which is 27.8 km at the equator, 24.1 km at 30 degrees, 19.7 km at 45 degrees, and 13.9 km at 60 degrees. It is important to note that in this case the apparent increased horizontal west-east resolution at higher latitudes is an artifact of this interpolation and is not an indication of increased resolution at high latitudes.

Reanalysis data are usually provided to end users on familiar vertical coordinates like height or pressure levels. For example, ERA5 (Fifth-Generation ECMWF Atmospheric Re-Analysis of the Global Climate) data are provided at 25 hPa intervals starting from 1000 hPa. However, the native model output represented on a terrain-following vertical coordinate has far better vertical resolution near the surface. This can be useful for wind energy purposes as it provides wind speed estimates at several levels across the rotor diameter, for those willing to deal with transforming from the native format.

20 A discussion of spatial referencing, reduced Gaussian grids, and spectral coefficients can be found at https://confluence.ecmwf.int/display/CKB/ERA5%3A+What+is+the+spatial+reference.

21 The polar circumference of Earth is 40,008.8 km, or 111.13 km per degree.

Deep Convolutional Neural Networks for Downscaling NWP Output

Recent advances in machine learning techniques for computer vision have inspired a new class of methods for the post hoc downscaling of NWP outputs. These methods promise to reduce the burdensome computational requirements of high-resolution NWP simulations while maintaining high-quality data outputs. If these methodologies can be proven to work well, they will enable the production of higher resolution and longer time series of weather input data suitable for power system modeling applications, as well as ensembles of these datasets that capture the uncertainty of the weather inputs and therefore allow electricity system studies to model sensitivity to this uncertainty.

Deep convolutional neural networks (CNNs) have been recently shown to excel at a wide range of computer vision tasks, including generative models. Convolutional kernels are designed to match the dimensionality and structure of image, video, and NWP simulation data, and the convolutions are repeatedly layered to extract and process data features at both large and small scales. The result is a powerful nonlinear parametric model that can learn physical phenomena such as the momentum balance for wind flows on a gridded hypercube in much the same way that finite-difference or finite-volume methods operate in NWP models.

In practice, a major problem is that a naïve convolutional network can exhibit regression to the mean in the form of blurring when producing forecasts or enhancing the resolution of data. Statistically, this may be a reliable output for the convolutional network that will minimize its objective function, but it greatly reduces the practical value of the data. One solution to this problem is adversarial training with generative adversarial networks (GANs), where a generative model must produce data that are not only conditionally accurate but also sufficiently realistic to fool a discriminative network. For downscaling data with GANs (often called super-resolving), the generative network is trained to produce an enhancement of the low-resolution input data that the discriminator believes is similar to real data, while simultaneously minimizing the numerical deviation from a corresponding true high-resolution dataset. This method has been shown to be effective in creating highly realistic enhancements for many types of data.

GANs with deep convolutional networks have only recently been applied to the task of downscaling NWP data but have already shown considerable promise with high-quality physics-based validation of the outputs (Stengel et al., 2020). To the knowledge of this project team, only a single public dataset has been published at the time of this writing that leverages GANs to downscale climate data, in this case a precipitation dataset from CMIP6 (Hess et al., 2022).[22] However, several wind datasets are known to be in development that leverage GANs to do a final spatio-temporal enhancement on coarse NWP data instead of running the NWP down to the final desired resolution. The benefit of this hybrid NWP+GAN approach is a significant reduction in computational costs compared to what would be required by a full high-resolution NWP simulation (estimated at more than two orders of magnitude in compute time savings).

The main drawbacks of using GANs for downscaling are that this requires significant investment in machine learning expertise, machine learning–specific computing infrastructure, and high-quality training data, and can result in a loss of methodological interpretability including the possibility for data outputs that do not respect physical constraints. This last problem is clearly the most concerning, as low-quality data with poor physical constraints could compromise power system planners' ability to accurately predict and plan for future system needs. The methods described above have the potential to greatly benefit the renewable energy and meteorological communities, but rigorous validation needs to be of the upmost priority. Statistical benchmarking, validation against ground-truth observations, and careful examination of physical data characteristics like turbulence should all be regular practice when implementing these methods.

22 See the World Climate Research Programme's Coupled Model Intercomparison Project at https://www.wcrp-climate.org/wgcm-cmip.

Data Produced for Solar Generation Calculations

Satellites contain instruments that measure the reflection of solar radiation within the atmosphere and the emission of infrared radiation by it. Several factors including the presence of water vapor, clouds, and the temperature profile all impact these measurements, and through complex model algorithms these measurements can be used to make inferences about the properties of the atmosphere that result in the measurements and/or about irradiance at the surface. The methods can be used specifically to produce irradiance measures, as is the case for the National Solar Radiation Database (NSRDB), or in conjunction with NWP models where the assimilation process uses the measurements to improve the initial condition and then the model determines the evolution of the surface irradiance properties.

Irradiance data produced by NWP models are subject to many of the same caveats regarding model resolution that have been highlighted for wind data. In addition, radiation calculations are computationally expensive because they model all the reflection, absorption, emission, and scatter of both longwave and shortwave radiation throughout the atmosphere and by the ground. Because of this computational intensity, they are usually performed at longer time step intervals than other model calculations. For example, the calculation may be performed as infrequently as every 30 to 60 minutes, although every 5 to 15 minutes is more common. This is important, because short-interval irradiance data in some NWP datasets may be static or interpolated between radiation calculation periods even if other fields are updated more frequently. Also, most NWP models only need to calculate global horizontal irradiance (GHI) as part of the modeling radiative processes and may not calculate direct normal irradiance (DNI) and/or diffuse horizontal irradiance (DHI). However, many modern models (for example, WRF-Solar) have options that allow GHI at the ground to be calculated as frequently as the regular model time step. They also have options that allow direct irradiance at the surface to be calculated. From this, DNI can be calculated, and together with GHI, DHI can be deduced.

The NSRDB has 4 km grid spacing, which is reasonably good, but a finer grid is better, especially when dealing with smaller clouds. The National Center for Atmospheric Research has developed the MAD-WRF model (Multi-sensor Advection Diffusion Weather Research and Forecasting) for intra-day forecasting applications, which uses satellite observations (and surface-based ceilometer observations, where available) to correct the cloud and other model fields at initialization (Jiménez et al., 2022).[23] It inserts clouds where the model has none (and estimates the level(s) at which to add cloud and modify other model fields accordingly) and eliminates clouds where the satellite shows that none exist. Application of newer techniques like this will further improve irradiance data in future datasets.

23 See https://ral.ucar.edu/solutions/products/mad-wrf.

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Meteorology 101: Meteorological Data Fundamentals for Power System Planning

This overview is available at https://www.esig.energy/weather-data-for-power-system-planning.

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

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