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## Preprint

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*Presented at the 2019 International Solar Energy Society (ISES) Solar World Congress*
*Santiago, Chile*
*November 4–7, 2019*

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Contract No. DE-AC36-08GO28308

**Conference Paper**
NREL/CP-6A20-74386
July 2020

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**Suggested Citation**
Buster, Grant, Michael Rossol, Galen Maclaurin, and Manajit Sengupta. 2020. *A Physical Downscaling Algorithm for the Generation of High-Resolution Spatiotemporal Solar Irradiance Data: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-6A20-74386. https://www.nrel.gov/docs/fy20osti/74386.pdf.

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# A Physical Downscaling Algorithm for the Generation of High-Resolution Spatiotemporal Solar Irradiance Data

**Grant Buster, Michael Rossol, Galen Maclaurin, and Manajit Sengupta**

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**Abstract**

High-resolution solar resource data are required for solar generation models such as the System Advisor Model (SAM), power system models such as the Integrated Grid Modeling System (IGMS), and renewable integration studies. These models and tools require information at a temporal resolution of minutes and spatial resolution of 1–2 km. The National Solar Radiation Database (NSRDB) provides 20 years of solar resource information covering North and South America at a 30-minute, 4-km by 4-km resolution. This paper summarizes the development of a physics-based methodology to downscale the NSRDB to higher spatiotemporal resolution for use in various downstream models. The method uses the NSRDB radiative transfer models and is sufficiently generic to downscale any solar resource data from the NSRDB without any site-specific tuning required.

*Keywords: solar resource data, spatiotemporal data, downscaling methodology*

## 1. Introduction

High-resolution solar resource information is used in solar generation models such as the System Advisor Model (SAM) (Blair et al., 2017). The solar generation data are then used in production cost models for renewable integration studies and in capacity expansion models. Further, new electric power system modeling platforms, such as the Integrated Grid Modeling System (IGMS) (Palmintier et al., 2017), require high-resolution solar generation as input. Long-term high-resolution solar resource information can be reliably derived using satellite-based models such as the National Renewable Energy Laboratory's Physical Solar Model (PSM), which was used to develop the National Solar Radiation Database (NSRDB) (Sengupta et al., 2018). Although data from the NSRDB are available every 30 minutes at a 4-km by 4-km resolution, downstream models generally require significantly higher temporal and spatial resolution information. In this study, we develop a physics-based approach to generate 5-minute, 2-km data from the NSRDB. This methodology uses atmospheric input data including clouds and aerosols to generate the high-resolution solar resource data sets. The results of this approach are shown to be accurate when compared to high-temporal-resolution ground measurement data.

## 2. Methodology

### 2.1 Downscaling Methods

As illustrated in Fig. 1, the methodology presented here performs spatial and temporal interpolation on the PSM input variables, then leverages the PSM to calculate irradiance at the desired resolution.

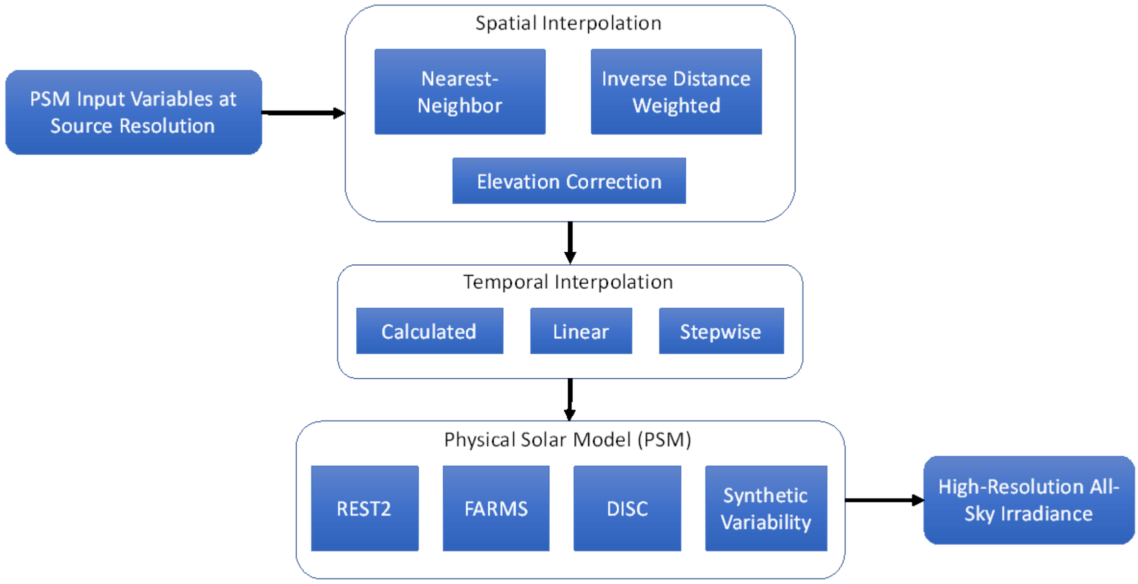


**Fig. 1: Physical downscaling methodology block diagram**

Spatial interpolation is performed first. This method uses a spatial downscaling method similar to that used in the NSRDB, as described by Sengupta et al. (2018), which downscales ancillary data from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), to the NSRDB grid. PSM input variables are calculated at a high-resolution grid cell by either taking the value of the nearest-neighbor native grid cell or performing inverse distance weighted (IDW) interpolation between several nearest-neighbor native grid cells. Variables with established elevation scale heights (temperature, pressure, aerosol optical depth, and total precipitable water) are corrected for changes in elevation that occur within native grid cells. Details on the spatial interpolation method of each PSM input variable are outlined in Tab. 1.

Temporal interpolation is performed on the high-spatial-resolution data. Variables such as the solar zenith angle can be readily calculated at higher spatiotemporal resolution and therefore add physical fidelity to the results. Continuous variables, such as aerosol optical depth and surface pressure, do not exhibit step changes throughout time, and a linear transition between time steps is assumed.

Cloud properties are discrete variables that exhibit step changes throughout time and space and are the most difficult to interpolate. Without additional cloud data in the high-resolution data set, several assumptions must be made. When moving from a coarse spatial grid to a finer spatial grid, the cloud data are copied to the fine-resolution nearest-neighbor grid cells. When performing the temporal interpolation, it is assumed that cloud type transitions are stepwise at the median time step between native time steps. Cloud properties (optical depth and effective particle radius) are linearly interpolated between their nominal values at native-resolution cloudy time steps and zero at native-resolution clear time steps. Cloud properties are only used in the PSM during cloudy time steps.

After the PSM input variables are downscaled to the desired spatiotemporal resolution using the methods summarized in Tab. 1, the PSM is executed to generate high-resolution all-sky irradiance data.

**Tab. 1: Summary of PSM input variables and their interpolation methods**

| PSM Input Variable Name | Spatial Interpolation Method | Elevation Correction | Temporal Interpolation Method |
|---|---|---|---|
| Aerosol Optical Depth (AOD) | IDW | Yes | Linear |
| Aerosol Single-Scatter Albedo (SSA) | IDW | No | Linear |
| Angstrom Wavelength Exponent (Alpha) | IDW | No | Linear |
| Angstrom Turbidity Coefficient (Beta) | Calculated from AOD and Alpha | | |
| Aerosol Asymmetry Parameter | IDW | No | Linear |

| PSM Input Variable Name | Spatial Interpolation Method | Elevation Correction | Temporal Interpolation Method |
|---|---|---|---|
| Cloud Optical Depth | NN | No | Linear |
| Cloud Particle Effective Radius | NN | No | Linear |
| Cloud Type | NN | No | Stepwise |
| Reduced Ozone Vertical Pathlength | IDW | No | Linear |
| Solar Zenith Angle | Calculated from the time index and spatial coordinate | | |
| Sun-Earth Radius | Calculated from the time index | | |
| Surface Albedo | IDW | No | Linear |
| Surface Pressure | IDW | Yes | Linear |
| Total Precipitable Water | IDW | Yes | Linear |

### 2.2 High-Temporal-Resolution Synthetic Variability

A method for adding synthetic variability to cloudy irradiance at high temporal resolution is added to the PSM. The synthetic variability is intended to represent some of the variability in optical transmittance that would be observed in thin clouds during sub-30-minute time steps. This feature is desired to mimic variable photovoltaic (PV) generation for high-resolution temporal modeling of renewable energy grid systems. The maximum variability at a given high-resolution time step is calculated as a triangular distribution based on the instantaneous clear-sky ratio (the all-sky irradiance divided by the clear-sky irradiance). A maximum variability of 5 percent is added to the global horizontal irradiance (GHI) when the clear-sky ratio is 0.9 (thin clouds). The maximum variability decreases to zero when the clear-sky ratio is zero or one (no synthetic variability is added to extremely thick clouds or clear-sky conditions). The variability added to the GHI is then propagated to the direct normal irradiance (DNI) via the DISC model. This method conserves cumulative solar energy and adds a simple representation of high-temporal-resolution cloud variability.

## 3. Validation

Validation is performed against high-temporal-resolution ground measurement data. The physical downscaling method is used to downscale 20 years of 30-minute native NSRDB data to 5-minute data for seven sites in the National Oceanic and Atmospheric Administration's Surface Radiation Budget Network (SURFRAD). The downscaled 5-minute data are benchmarked against available 5-minute ground measurement data. Similar to the NSRDB validation (Habte et al., 2018), the 5-minute ground measurement data are calculated based on a 1-hour moving average of the measurement data to account for the comparison of point ground measurements against the large spatial average represented by the physical downscaling method. Similar to previous NSRDB validation methods, the irradiance data are validated only for solar zenith angles less than 80 degrees. This comparison is intended to support the use of the physical downscaling algorithm as representative of realistic irradiance for a wide range of geographies and climates.

## 4. Results

### 4.1 Irradiance Validation Results

Fig. 2 shows the validation results when benchmarking the 5-minute downscaled data from the NSRDB against the 1-minute ground measurement SURFRAD data. Comparing Fig. 2 to the validation statistics from the NSRDB assessment (Habte et al., 2018) shows that there is a minor loss in accuracy in the downscaled 5-minute data. This minor loss in accuracy can be attributed to the synthetically created 5-minute data. Without the addition of accurate high-resolution input data (especially cloud data), the validation statistics are not expected to improve the NSRDB baseline validation (Habte et al., 2018); however, the limited difference from the baseline validation supports that the physical downscaling algorithm performs as expected.

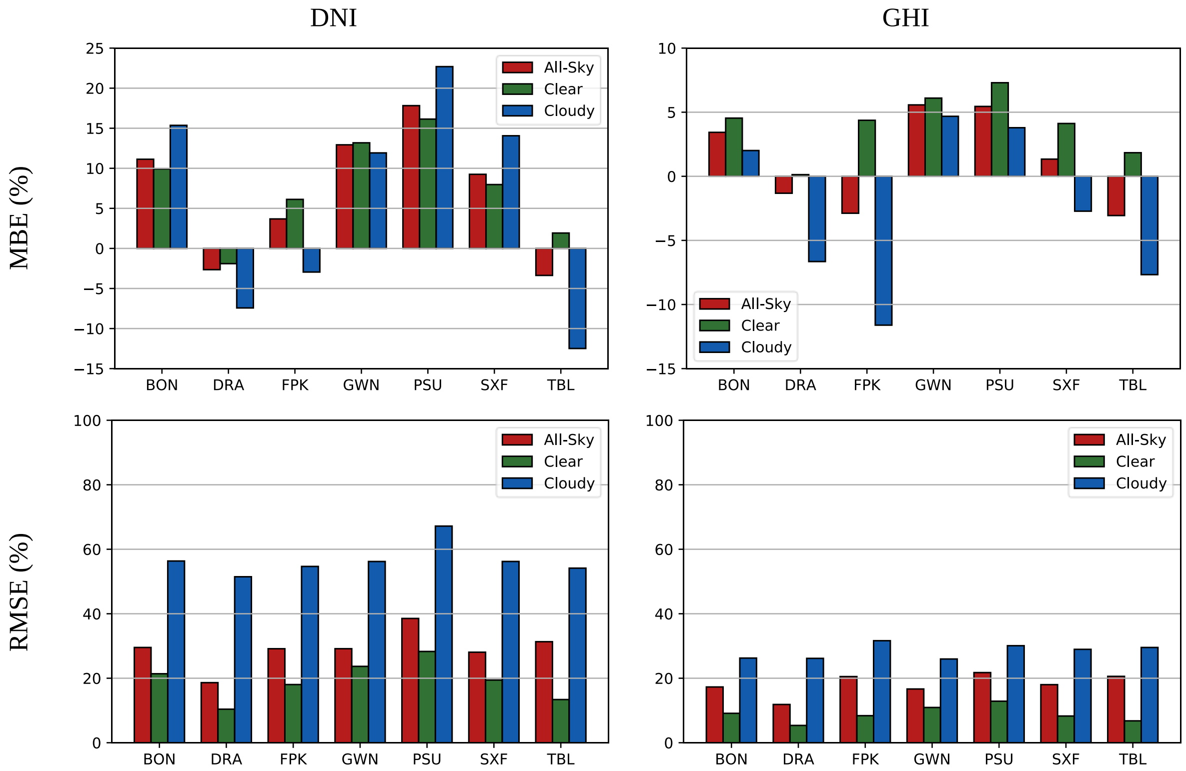


**Fig. 2: Validation statistics including mean bias error (MBE) and root mean square error (RMSE) of 5-minute DNI and GHI data generated from the physical downscaling algorithm. Downscaled data are validated against 20 years of ground measurements from seven SURFRAD sites.**

A time-series comparison of the downscaled data to the SURFRAD ground measurements in Fig. 3 shows some of the benefits and limitations of the downscaling methodology.

One useful feature of the downscaling methodology is an improved gap-filling methodology. Because the native NSRDB is a 30-minute time series, dramatic clear-to-cloudy or cloudy-to-clear transitions in 30-minute intervals can cause invalid irradiance results that get gap-filled from valid data from the nearest time steps. The gradual transitions in the 5-minute downscaled data makes these transitions less dramatic and can result in better irradiance calculations and less gap-filling. Additionally, the procedure for filling missing cloud property data is improved such that missing cloud properties are filled based on neighboring data before the irradiance is calculated. The improved procedure captures the cloudy time steps around hour 21:00 in Fig. 3.

The effect of the synthetic variability in the downscaling methodology is also shown in Fig. 3 around hour 21:00. Because the cloud is relatively thin (cloudy irradiance is approximately 90 percent of clear-sky irradiance), there is significant estimated variability in the GHI. The variability in the ground-measured irradiance is shown to be significant in the right of Fig. 3 (instantaneous 1-minute ground measurement data). The downscaled data are not intended to represent the variability at a point measurement and are successful in representing the variability somewhere between the averaged measurement and the instantaneous measurement.

The obvious limitation of the downscaling methodology is that it cannot capture the sub-30-minute cloud transitions that are apparent in the instantaneous point-measurement data. Without accurate high-temporal-resolution cloud input data, these high-frequency cloud transitions cannot be captured. Note, however, that the high-frequency 1-minute cloud transitions measured at a point source are not representative of the cloud transitions in the large grid cells that the NSRDB represents. The spatial disparity is a persistent issue when comparing downscaled NSRDB data to small solar power plants, as will be discussed in Section 4.3.

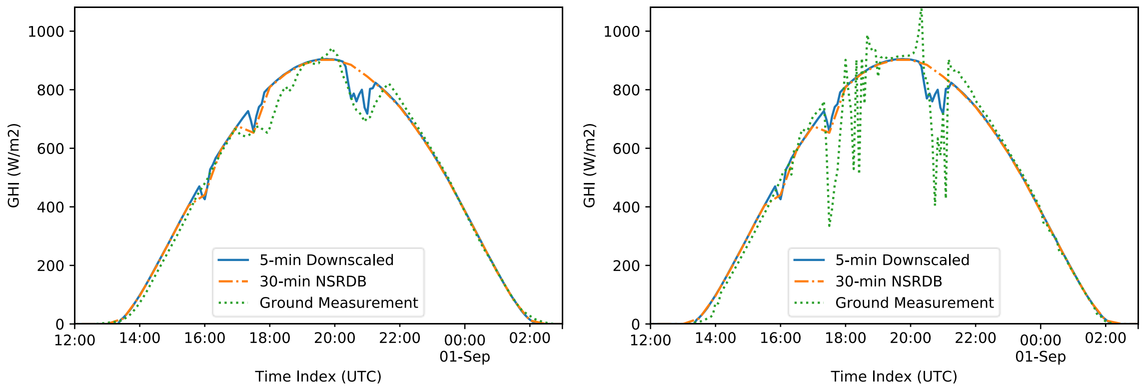


**Fig. 3: Comparison of GHI profiles for the 5-minute downscaled data, the NSRDB native 30-minute data, and SURFRAD ground measurement data. The left plot shows the ground measurement data as a 61-minute moving window average of 1-minute data, and the right plot shows the ground measurement data as instantaneous 1-minute data.**

## 4.2 High-Resolution Irradiance Data for Puerto Rico and the U.S. Virgin Islands

As part of a project funded by the U.S. Department of Energy, 20 years of 5-minute, 2-km downscaled NSRDB solar resource data was produced to assist in characterizing and evaluating available solar resource for Puerto Rico and the U.S. Virgin Islands, and to conduct a supply curve analysis for capacity expansion and production cost modeling. The figures below only focus on the main island of Puerto Rico, though data and analysis results were produced for the minor islands of Puerto Rico and the U.S. Virgin Islands. Fig. 4 and Fig. 5 show the downscaled irradiance data over the island. Fig. 4 shows how the algorithm downscales the native 4-km grid to a 2-km grid. The clear-sky irradiance in Fig. 4 shows how the spatial interpolation with elevation correction increases the resolution over the central mountain range. A time series of 5-minute downscaled solar resource data can be visualized for the whole island in Fig. 5. The transport of clouds in the downscaled data can be visualized as the cloudy regions move southwest throughout the image set.

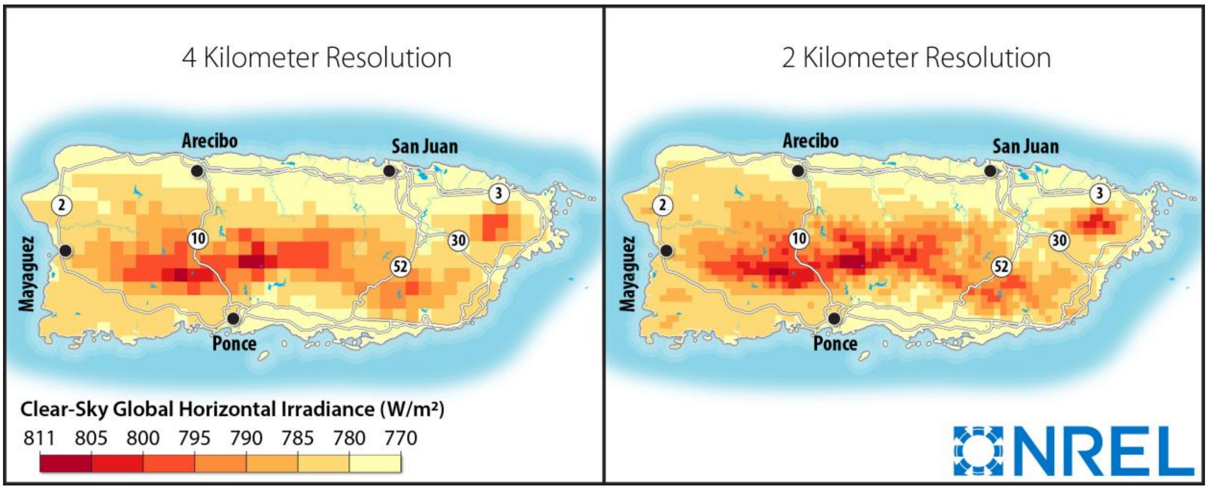


**Fig. 4: Instantaneous clear-sky GHI resulting from the spatial downscaling of 4-km data (left) to 2-km data (right) with elevation correction**

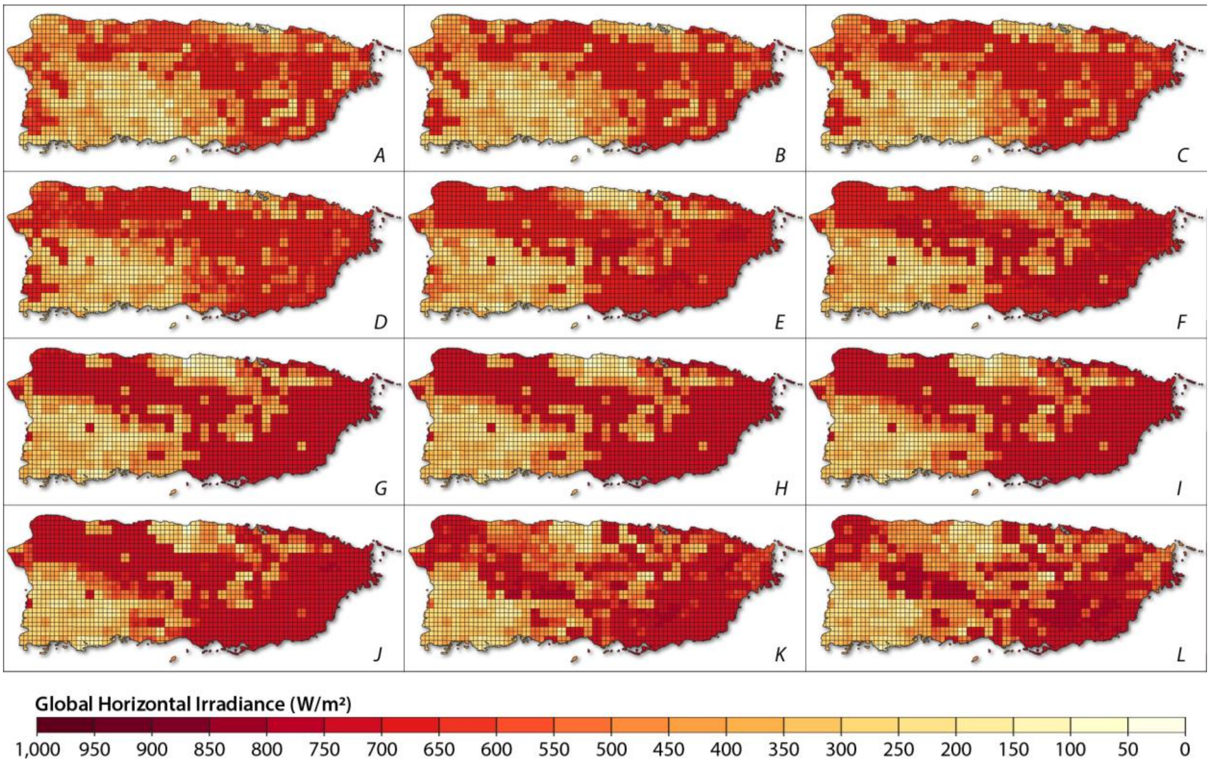


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**Fig. 5: DNI at 5-minute intervals for Puerto Rico during 1 hour on January 1, 2017**

### 4.3 Comparison to Real PV Plant Generation

Capacity factor profiles based on the 5-minute downscaled resource data are compared to 5-minute generation data from four utility-scale PV plants in Puerto Rico. The downscaled Puerto Rico resource data are run through the SAM PV performance model (Blair et al., 2017) to calculate 5-minute system capacity factor profiles. Fig. 6 shows examples of both good and bad comparisons for the generation data.

Qualitatively, the 5-minute calculated performance data benchmarks very well against the plant performance data, as shown in the left of Fig. 6. Nearly all the significant ramping events and even some momentary periods of clear or cloudy conditions are well captured. The actual generation data presented in Fig. 6 are understandably noisier than the calculated performance data because the actual generation data are from a solar plant approximately 0.4 $km^2$ in area (based on Google Maps satellite imagery), whereas the NSRDB cloud data are sourced from a 16 $km^2$ grid cell. Therefore, the actual generation represents a relatively small discrete location while the calculated performance represents a larger regional average.

As shown in the right of Fig. 6, however, some periods of generation show very poor comparisons. The plant data are shown to ramp dramatically between a seemingly unrealistically low generation value to the nominal generation during a period of approximately 20 minutes. The plant data frequently exhibit significant deviations from expected generation, resulting in a poor comparison to the calculated generation profiles. Data from all four plants contain numerous days that appear to be the result of curtailment, faulty measurement equipment, or other systemic errors. As a result, a long-term quantitative comparison of the calculated performance data to the plant measurement data was determined to not be meaningful and is not presented here.

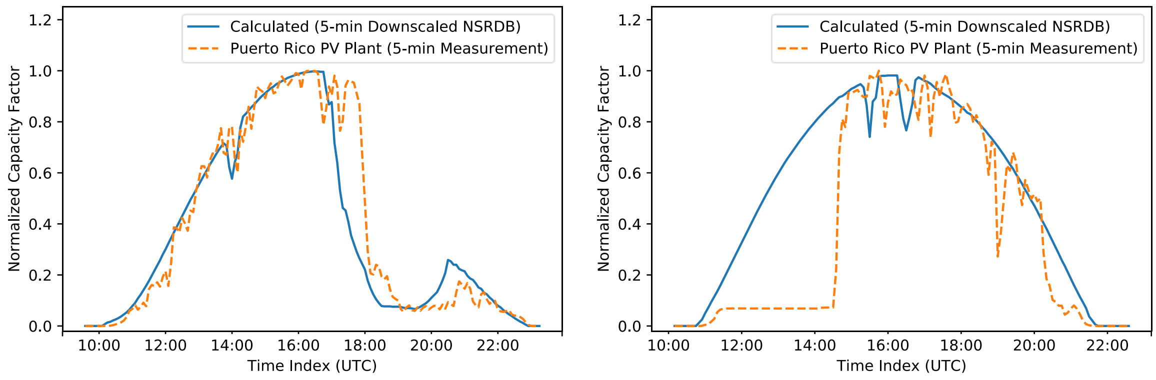


**Fig. 6: Comparison of calculated PV generation data from the 5-minute downscaled NSRDB resource data to 5-minute solar power plant data in Puerto Rico. Capacity factor profiles are normalized on a 7-day window.**

## 5. Conclusion

High-resolution solar resource information is a critical need for power generation, integration studies, and power system studies and can be provided by downscaling the data available from the NSRDB. This study summarizes the development of a physics-based downscaling methodology and presents the results of downscaled resource data. A validation study based on 20 years of ground measurement data is presented, supporting that the results from the downscaling method are sufficiently accurate. An example application of the downscaling methodology to provide high-resolution solar resource data to plan a renewable energy grid for Puerto Rico and the U.S. Virgin Islands is also presented. Finally, a comparison of a system performance analysis to actual PV plant data are presented, showing good agreement when measurement data.

Although the methodology presented in this study is useful given the relatively coarse NSRDB, it also provides a framework for developing more advanced methods to downscale PSM input data. Future work will focus on developing methods that can better predict downscaled data inputs to the PSM, thereby increasing the accuracy of the synthetically downscaled irradiance data.

## 6. Acknowledgments

The authors acknowledge Nick Grue, Aron Habte, Andrew Kumler, Billy Roberts, and Yu Xie for their support of the Puerto Rico project.

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

A portion of this research was performed using computational resources sponsored by the Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory.

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