Evaluation of the National Solar Radiation Database (NSRDB Version 2): 1998–2015

Aron Habte, Manajit Sengupta,
and Anthony Lopez
National Renewable Energy Laboratory

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NREL/TP-5D00-67722
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Prepared under Task No. ST6S.0810

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Acknowledgments

This work was supported by the U.S. Department of Energy under Contract No. DE-AC36-08-GO28308 with the National Renewable Energy Laboratory (NREL). The authors acknowledge Dr. Tassos Golnas, technology manager for the Systems Integration team of the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Solar Energy Technologies Office, for his support of this project. The authors would like to acknowledge Dr. Andrew Clifton, manager of NREL's Sensing, Measurement, and Forecasting Group for his leadership and thorough review of this report. We express our appreciation for Billy Roberts from NREL's Data Analysis and Visualization Group for producing the maps for this report. The authors would also like to thank Dr. Yu Xie of NREL's Sensing, Measurement, and Forecasting group; and Thomas Stoffel and Stephen Wilcox, retired NREL employees, for reviewing and providing input to this work. We also gratefully acknowledge Katie Wensuc, technical editor with NREL Communications for her continuous support in the publication process.

List of Acronyms

AMMMDT	Annual mean monthly mean daily totals
ARM	Atmospheric Radiation Measurement
COV	Coefficient of variation
DNI	Direct normal irradiance
GHI	Global horizontal irradiance
GOES-R	Geostationary Operational Environmental Satellite-R Series
MAE	Mean absolute error
MBE	Mean bias error
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications, Version 2
MMDT	Monthly mean daily totals
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
PSM	Physical Solar Model
RMSE	Root mean square error
SAM	System Advisor Model
SGP	Southern Great Plains
SRRL	Solar Radiation Research Laboratory
SURFRAD	Surface Radiation Budget Network
BON	Bondville, Illinois
TBL	Table Mountain, Boulder, Colorado
DRA	Desert Rock, Nevada
FPK	Fort Peck, Montana
GWN	Goodwin Creek, Mississippi
PSU	Penn. State Univ., Pennsylvania
SXF	Sioux Falls, South Dakota

Executive Summary

Achieving higher penetrations of solar energy conversion on the national electricity grid and reducing system integration costs requires accurate knowledge of the available solar radiation resource. Specifically, understanding the impacts of clouds and other meteorological constituents on the solar resource and quantifying intra-/inter-hour, seasonal, and interannual variability are essential for accurately designing utility-scale solar energy projects. Recognizing the importance of this need by industry and other stakeholders, the U.S. Department of Energy has funded the multiyear development of the National Solar Radiation Database (NSRDB) by the National Renewable Energy Laboratory (NREL). First released in 1992, the original NSRDB (1961–1990) contained data for 239 locations for the period from 1961–1990. To meet the increased need for more current data from as many locations as possible, the NSRDB has been updated three times, resulting in the most recent NSRDB (1998–2015).

Solar resource information can be obtained from ground-based measurement stations and/or from modeled data sets. The availability of solar irradiance measurements is scarce, both temporally and spatially, because it is expensive to maintain a high-density solar radiation measurement network that collects good quality data for long periods of time. On the other hand, high temporal and spatial resolution gridded satellite-based observations of the atmosphere and reflected radiation data can be used to estimate surface radiation for long periods of time and is extremely useful for solar energy development. Because of the advantages of satellite-based solar resource assessment, NREL developed the physics-based Physical Solar Model (PSM). The PSM produced gridded solar irradiance—global horizontal irradiance (GHI), direct normal irradiance (DNI), and diffuse horizontal irradiance—for the NSRDB at a 4-km by 4-km spatial resolution and half-hourly temporal resolution covering the 18 years from 1998–2015. The NSRDB also contains additional ancillary meteorological data sets, such as temperature, relative humidity, surface pressure, dew point, and wind speed. Details of the model and resulting data are available at https://nsrdb.nrel.gov. Additional details about the PSM are also described in Xie, Sengupta, and Dudhia (2016) and Sengupta et al. (2015c).

A validation of the performance of the PSM-based data set in the NSRDB was conducted to quantify the accuracy of the magnitude and the spatial and temporal variability of the solar radiation data. Comparisons of the PSM estimates with selected ground-measured data were conducted under both clear- and cloudy-sky conditions and covered the period from 1998–2015 for seven Surface Radiation Budget Network stations as well as NREL's Solar Radiation Research Laboratory and the Atmospheric Radiation Measurement program's Southern Great Plains ground station. These locations provide a variety of geographical locations and climates.

The evaluation was conducted for hourly values, daily totals, monthly mean daily totals, and annual mean monthly mean daily totals. The modeled data were challenged because the satellite pixels cover a large area for which a snapshot is used to represent a time span, whereas the ground-based measurements represent a relatively small area above the measurement station at a higher temporal frequency (usually every minute).

The temporal and spatial evaluation was performed by comparing the NSRDB data to concurrent ground-based measurements. The results described in this paper show that the hourly-averaged satellite-derived data have a mean bias error of approximately ±5% for GHI and less than ±10%

for DNI; however, the scatter (root mean square error [RMSE]) difference is higher for the hourly averages: the GHI of the satellite demonstrates up to 20% RMSE when compared to the ground-based GHI measurements and up to 40% RMSE when compared to the ground-based DNI measurements. The interannual variability was investigated using a coefficient of variation, and the results demonstrate that the NSRDB and ground-measured data are comparable. This provides confidence that the NSRDB data set represents the variability in surface measurements ("ground truth") throughout time. Both data sets demonstrated 5% variability on average. The annual solar radiation anomalies to the long-term mean were also investigated; 2015 was found to be the cloudiest year for the central and southern locations, with an approximate 10% reduction in GHI compared to the previous 18 years.

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1 Introduction

High temporal and spatial resolution solar resource information is critical for each phase of solar energy conversion project, ranging from the conceptual definition to routine solar power plant operations. Solar resource and meteorological data are also used as inputs to various performance and economic models, such as the System Advisor Model (SAM). The resource data and the performance and economic models are designed to assist policymakers in making informed decisions, enable feasibility studies of a solar energy project, and conduct engineering design during due-diligence studies as well as to provide intelligence for day-to-day operations and improve resource forecasting for solar energy conversion systems. Solar resource data sets can be measured at a solar meteorological station or modeled through empirical-based or physics-based methods using geostationary satellite data; the latter provide continuous spatial and temporal coverage that is favorable for solar energy conversion applications. Ground-based solar meteorological stations are sparse, expensive to deploy and operate, and generally deployed for limited periods of time; however, data from these measurement stations are important for validating modeled solar resource data, and well-maintained stations can provide relatively accurate solar resource information. The National Renewable Energy Laboratory (NREL) has been developing, updating, and disseminating the modeled National Solar Radiation Database (NSRDB) during the last two decades. The data set is publicly available and has been the flagship source of solar resource and surface meteorological information for many renewable energy applications. Further, the various releases of the NSRDB have been used in governmental decision-making for developing high-level projects such as the U.S. Department of Energy's SunShot Initiative.

Historically, versions of the NSRDB have comprised the best available data from ground measurement stations and modeled solar irradiance data based on surface meteorological observations (e.g., cloud cover) or, more recently, satellite remote sensing methods for retrieving properties of the atmosphere. The current version of the NSRDB (1998–2015) was developed using the Physical Solar Model (PSM), which follows a physics-based approach wherein cloud and other atmospheric properties are retrieved from the Geostationary Operational Environmental Satellite data and used as inputs to a radiative transfer model to compute the surface radiation. In the resulting current version of the NSRDB, data are available from 1998–2015 at a half-hourly temporal resolution and a 4-km by 4-km spatial resolution. The spatial coverage extends from southern Canada to parts of Brazil (longitude: -25°E to -175°W, latitude: -20°S to 60°N). Details on the model as well as the data are available from the NSRDB website at https://nsrdb.nrel.gov.

The goal of this report is to investigate the accuracy of the PSM-based global horizontal irradiance (GHI) and direct normal irradiance (DNI) NSRDB data set (1998–2015) relative to selected high-quality ground-based measurements. Further, the report assesses the ability of NSRDB (1998–2015) to accurately capture interannual variability, which is essential information for solar energy conversion projects and grid integration studies.

2 Method

Seven stations from the National Oceanic and Atmospheric Administration's Surface Radiation Budget Network (SURFRAD), NREL's Solar Radiation Research Laboratory (SRRL), and the Atmospheric Radiation Measurement (ARM) program's Southern Great Plains (SGP) Central Facility, in Billings, Oklahoma, were selected for this validation study (Figure 1). The station locations are superimposed on the climatic regions of the United States; this shows the fair distribution of the locations representing the climatic areas. The evaluation was conducted for instantaneous hourly values, daily totals, monthly mean daily totals (MMDT) and annual mean monthly mean daily totals (AMMMDT) periods. The varying time intervals help capture the temporal resolution of resource data required for each phase of a solar energy project, as shown in Figure 2. For instance, beginning with the conceptual phase, policymakers and technologists require long-term averages of the solar resources over regional areas (e.g., long-term annual means for provincial areas); therefore, they need to know the uncertainty for the timescale of interest. On the other hand, during due-diligence studies, engineering design requirements for solar resource information are based on hourly or higher temporal resolutions.

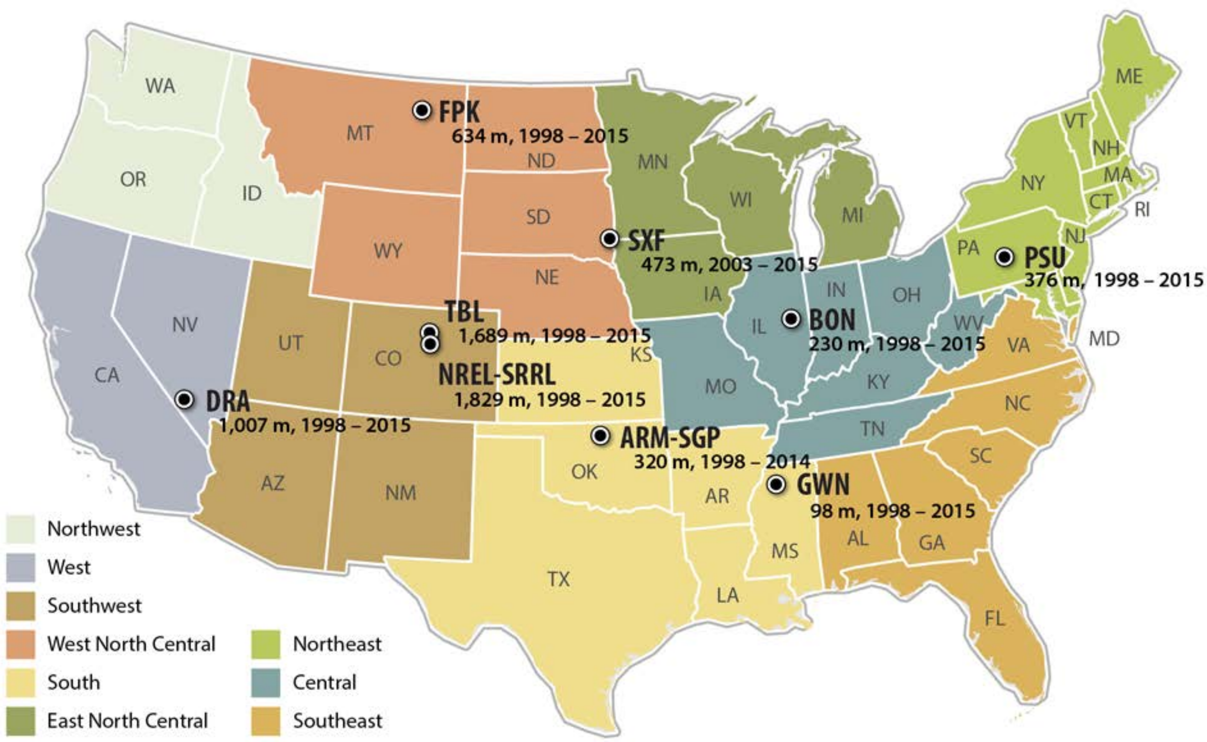


Figure 1. SURFRAD Network, NREL's SRRL, and the ARM's SGP locations overlaid on the United States climatic regions. ***Image modified with permission from the National Centers for Environmental Information***[1]

The reference solar irradiance ground-measured data are available either every minute or every three minutes, depending on the station and the year of data collection. The ground-measured data were averaged to an hourly interval, centered on the 30-minute NSRDB time interval to

[1] See https://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php#references.

approximate the spatial coverage of the satellite data. In this report, we illustrate the comparison results and information about systematic (bias) or random (scatter) tendencies in the satellite-derived NSRDB data.

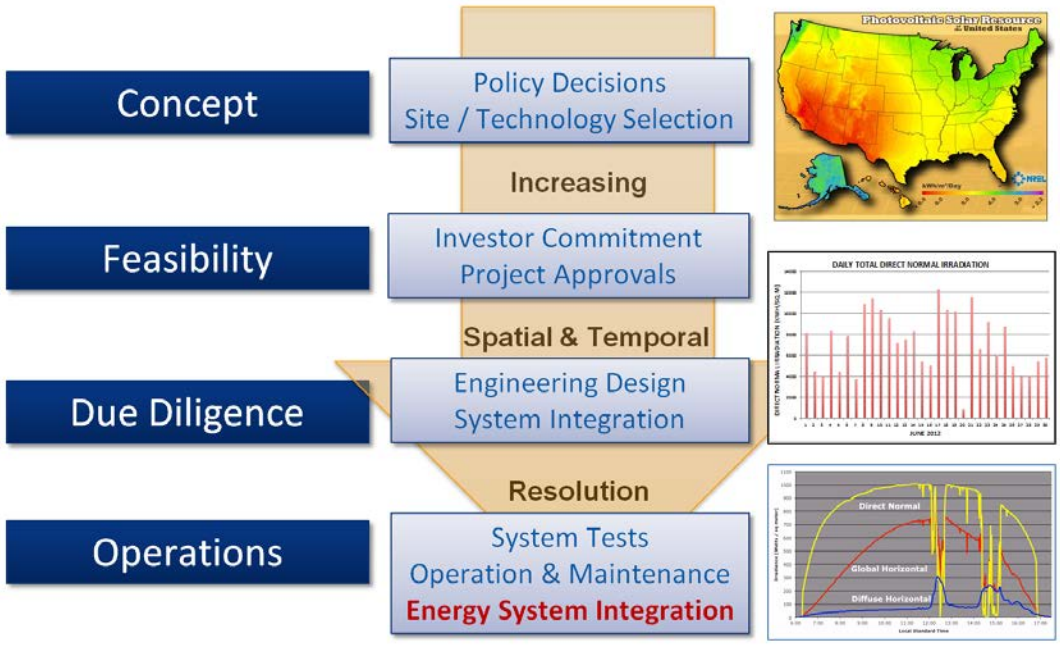


Figure 2. Phases of a solar energy project in relation to the temporal and spatial resolutions of the solar resource. ***Illustration from Sengupta et al. (2015a; 2015b)***

2.1 NSRDB Data Description

The NSRDB DNI and GHI data from 1998–2015 were analyzed in this study. The data set has 4-km by 4-km and half-hourly spatial and temporal resolutions; however, for this evaluation, we compared the hourly NSRDB (1998–2015) data set to the hourly averaged surface measurement data set. This minimized the effect of subpixel variability in clouds and the subsequent surface irradiance differences that cannot be captured using the NSRDB data sets. As reported in Sengupta et al. (2015c) and Habte, Sengupta and Wilcox (2012), this method helps explain why a point surface measurement represents a finite area covered by a satellite pixel, and it provides a temporal average estimate that the satellite data are meant to represent.

2.2 Surface Station Description

Data from the high-quality measurement network stations were used to evaluate the NSRDB data set. The ground-measured data were available in time resolutions from 1 minute to 3 minutes, and they were averaged to hourly resolutions, centered at the satellite time stamp to be compared to the hourly resolutions of the NSRDB data set. The data from these stations were collected using well-maintained thermopile pyranometers and pyrheliometers consistent with Baseline Surface Radiation Network protocols (McArthur 2005), including calibrations traceable to the World Radiometric Reference (Fröhlich 1991), and they were selected as the basis for this evaluation. It should also be noted that well-maintained radiometers can achieve an estimated typical uncertainty of 3%–5% (Reda 2011; Myers et al. 2002; Habte et al. 2016; Wilcox and Myers 2008). This means that a poorly maintained station could have more than 5% uncertainty.

The availability of ground measurements determined the data period of record used for the analyses (seven locations had data for 1998–2015). The station at Sioux Falls, South Dakota, was commissioned in 2003; therefore, only data from 2003–2015 were used for the validation analyses). Due to data processing lag, the available data for the ARM-SGP site were from 1998–2014.

2.3 Data Selection Criteria for Use in the Validation Analysis

To conduct a valid and reasonable data comparison, data-filtering techniques were implemented for both the reference ground measurements and NSRDB (1998–2015) from the PSM. The following criteria were used to produce a quality-controlled data set for the NSRDB (1998–2015) validation study:

1. Solar zenith angles (SZA) must be less than 80°.
2. Irradiance must be greater than zero.
3. Data records with missing values from the surface measurements were excluded from both the surface measurements and NSRDB data sets.
4. Cloud types from the satellite data were used to determine sky conditions.

2.4 Statistical Reporting Metrics

Statistical measures were used to investigate the performance of the NSRDB relative to ground-based measurements. These included:

Mean bias error (MBE) in units of irradiance (W/m^2) and percent of reading (%) were calculated using the following equations:

$$MBE(W/m^2) = \frac{1}{n}\sum_{i=1}^{n}(x_i - x_{true})$$

$$MBE(\%) = \frac{\left(\frac{1}{n}\sum_{i=1}^{n}\ (x_i - x_{true})\right)}{\left(\frac{1}{n}\sum_{i=1}^{n}\ (x_{true})\right)} * 100$$

where x_i represents values from the NSRDB (1998–2015) satellite-derived data, and x_{true} represents the concurrent ground-measured data for both GHI and DNI, which were evaluated separately. Mean absolute error (MAE) was calculated using a method similar to that used for the MBE calculations but by using absolute values of the difference.

Similarly, the root mean square error (RMSE) values were computed using on the ground measurements (x_{true}):

$$RMSE(W/m^2) = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}\ (x_i - x_{true})^2\right)}$$

$$RMSE(\%) = \sqrt{\frac{\left(\frac{1}{n}\sum_{i=1}^{n} \ (x_i - x_{true})^2\right)}{\left(\frac{1}{n}\sum_{i=1}^{n} \ (x_{true})^2\right)}} * 100$$

These statistics provided insight into the performance of the modeled data set relative to the ground-based measurements (Šúri and Cebecauer 2014; Sengupta et al. 2015c). For instance, RMSE and MAE are useful in determining the error distribution (Chai and Draxler 2014). A large difference between the RMSE and MAE indicates a greater variance in the individual errors or differences. MBE describes the direction (+/-) of the error or difference bias.

To understand and quantify the overall uncertainty of the modeled data set, the approach outlined in the *Guide to the Expression of Uncertainty in Measurement* was used.[2] The method applies RMSE, MBE, and the ground-based measurement uncertainties as sources of estimated combined measurement uncertainty. This approach provides uncertainty estimation on a 95% confidence interval representing two standard deviations (coverage factor of 2.0) and assuming a Gaussian or normal distribution of the data:

$$U_{95} = 2 * \pm \sqrt{\left(\frac{U_{meas}}{2}\right)^2 + \left(\frac{MBE}{2}\right)^2 + \left(\frac{RMSE}{2}\right)^2}$$

where U_{meas} is the estimated uncertainty of the surface measurement (ground truth), and MBE and RMSE are derived from the model validation analyses. As reported in Habte et al. (2014) and Reda (2011), the expanded uncertainties—such as U_{meas}, *MBE*, and *RMSE*—have a normal distribution, therefore these values are divided by 2 (coverage factor) to get the standard uncertainty.

Further, interannual variability was assessed for both the ground-measured and NSRDB (1998–2015) data sets using the percentage of the coefficient of variation (COV):

$$std_n = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n} \ (a_n - \hat{a})^2\right)}$$

$$COV(\%) = \frac{std_n}{\hat{a}} * 100$$

where *n* in *std* is the number of years in each computation in the standard deviation (e.g., n = 5,10, 18 or all years; see Table 2), and a_n is the irradiance of the individual *n* years. The mean irradiance over 18 years (1998–2015) is shown as â.

The solar irradiance anomaly was estimated by subtracting the mean irradiance of the individual years (a_i) from the long-term average—in this case, 18 years:

$$Solar\ irradiance\ anomaly = (a_i - \hat{a})$$

[2] See http://www.bipm.org/en/publications/guides/gum.html.

3 Results

Figures 3, figures 5–9, Table 1, and the figures and table in the appendices demonstrate the random and bias differences between the ground-measured and the NSRDB (1998–2015) satellite-derived data. Appendix A demonstrates the statistical results of the comparison between the NSRDB and surface measurements. Appendices B and C demonstrate the scatter and bias distribution of the daily totals for both the GHI and DNI. Further, the study computed overall uncertainty, interannual variability, and interannual deviation from the long-term mean of the NSRDB (1998–2015) data. The methodology used is consistent with common methodologies that exist in the literature (Wilcox and Gueymard 2010; Cebecauer, Suri, and Gueymard 2011).

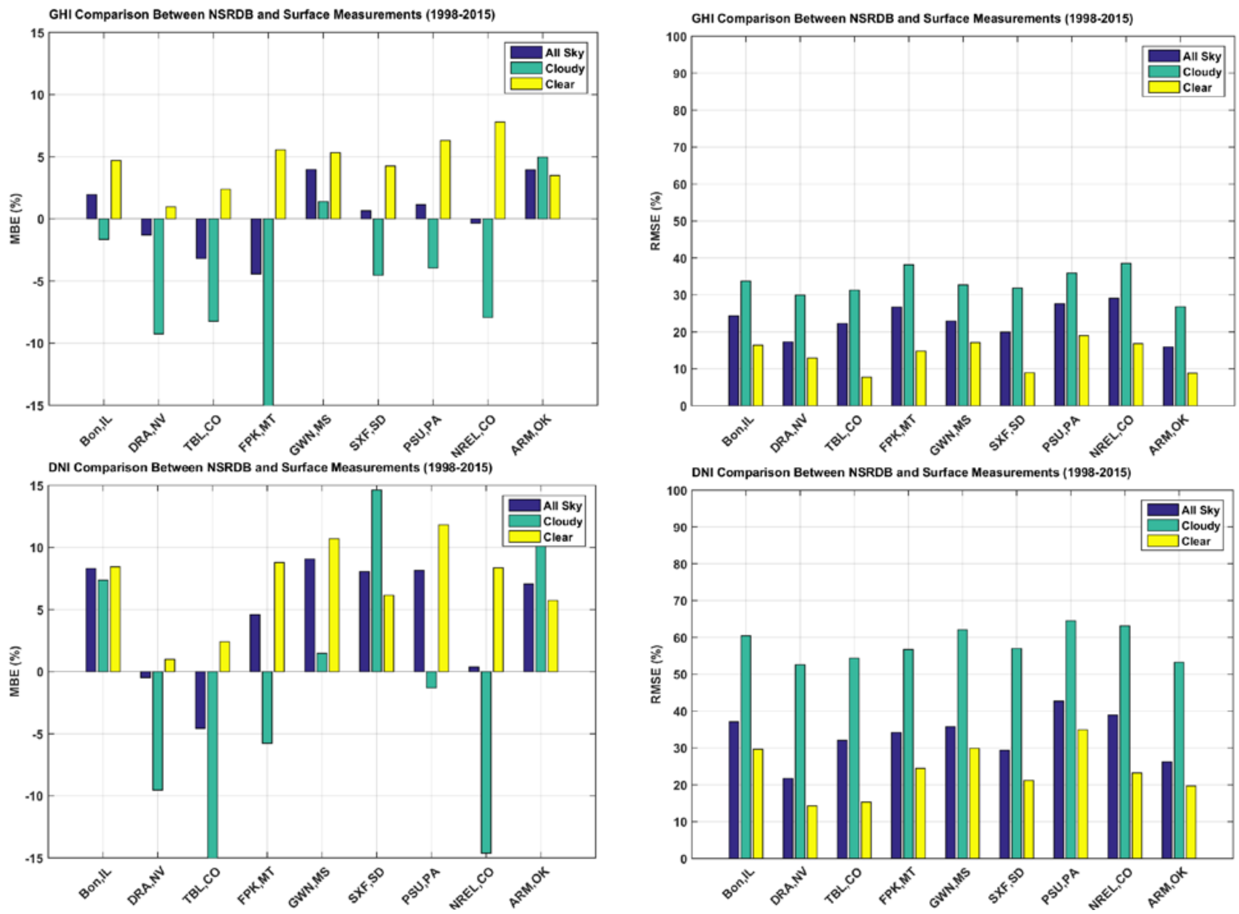


Figure 3. MBE percentage (left) and RMSE percentage (right) comparison results for both GHI (top) and DNI (bottom) between the NSRDB and ground-measured data for nine locations

Under clear-sky conditions, both MBE and RMSE are relatively small, indicating good performance of the PSM. The MBE is less than 5% on average for the GHI; however, it is biased in a positive direction, suggesting the NSRDB (1998–2015) overestimates GHI under clear skies by about 5% (Figure 3). This could be related to the underestimation of aerosol optical depth when scaling down monthly averaged data to daily aerosol values. Under cloudy-sky conditions, the difference between the NSRDB (1998–2015) and the ground-based measurement stations is positive or negative depending on the location; however, on average, the difference is within ±7%. The NSRDB (1998–2015) data appear to have some challenges in quantifying the GHI accurately for areas susceptible to high occurrences of clouds, snow, and bright surfaces, such as Fort Peck, Montana; Boulder, Colorado; and Desert Rock, Nevada. The issue will be investigated and addressed in future releases of the NSRDB.

For the DNI, the MBE is within ±10% for clear and cloudy skies; however, again the clear-sky data contain a positive bias.

The GHI comparison demonstrated relatively higher RMSE, as described in Sengupta et al. (2015c). This is partly because the NSRDB pixel represents a 4-km by 4-km area, whereas a ground-based station represents only a small area above the measuring station. As reported in Sengupta et al. (2015c), the RMSE in the DNI contains higher spatial differences under cloudy conditions because the ground-based measurement uses a pyrheliometer, with its approximate 5° field of view, represents a column through the atmosphere with a diameter of perhaps a couple centimeters; however, the satellite DNI represents the 4-km by 4-km area. Further, the subpixel variability and the parallax effect in clouds appear to contribute to higher RMSE differences in both GHI and DNI, as suggested by previous studies—such as Cebecauer, Suri, and Gueymard (2011) and Zelenka et al. (1999).

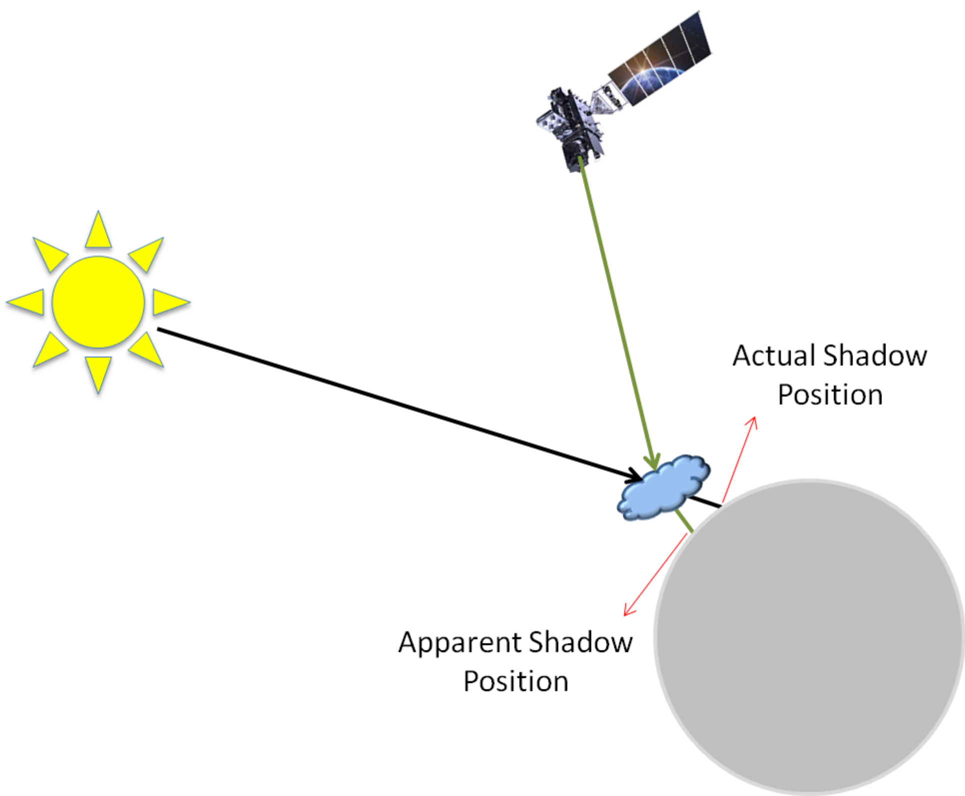


Figure 4. Parallax effect wherein the actual cloud position is affected by the satellite viewing angle

Figure 4 illustrates the effect of parallax wherein the cloud position is misplaced in the surface due to the satellite viewing angle. Under clear conditions there is no parallax effect; however, during cloudy conditions, there will be misplacement of clouds. This issue will be investigated in future releases of the NSRDB.

Figure 5 and Appendix A contain the results from the hourly GHI comparison. Then the hourly data were reduced to various averaged timescales, which helps understand the risks associated with each phase of solar energy deployment projects. Routine project operations require high temporal and spatial resolution solar resource data, whereas monthly or annual solar resource data sets may be sufficient during the conceptual phases of a solar energy project.

Overall, as shown in Figure 5 and Appendix A, the MBE does not change with timescale average; however, the RMSE or scatter decreases as the averaged time increases (Appendix A). This is due to the cancellation of the random differences over longer averaged timescales. For all stations, the percentage difference between the RMSE and MAE is small, which indicates that there is less variance in the individual errors.

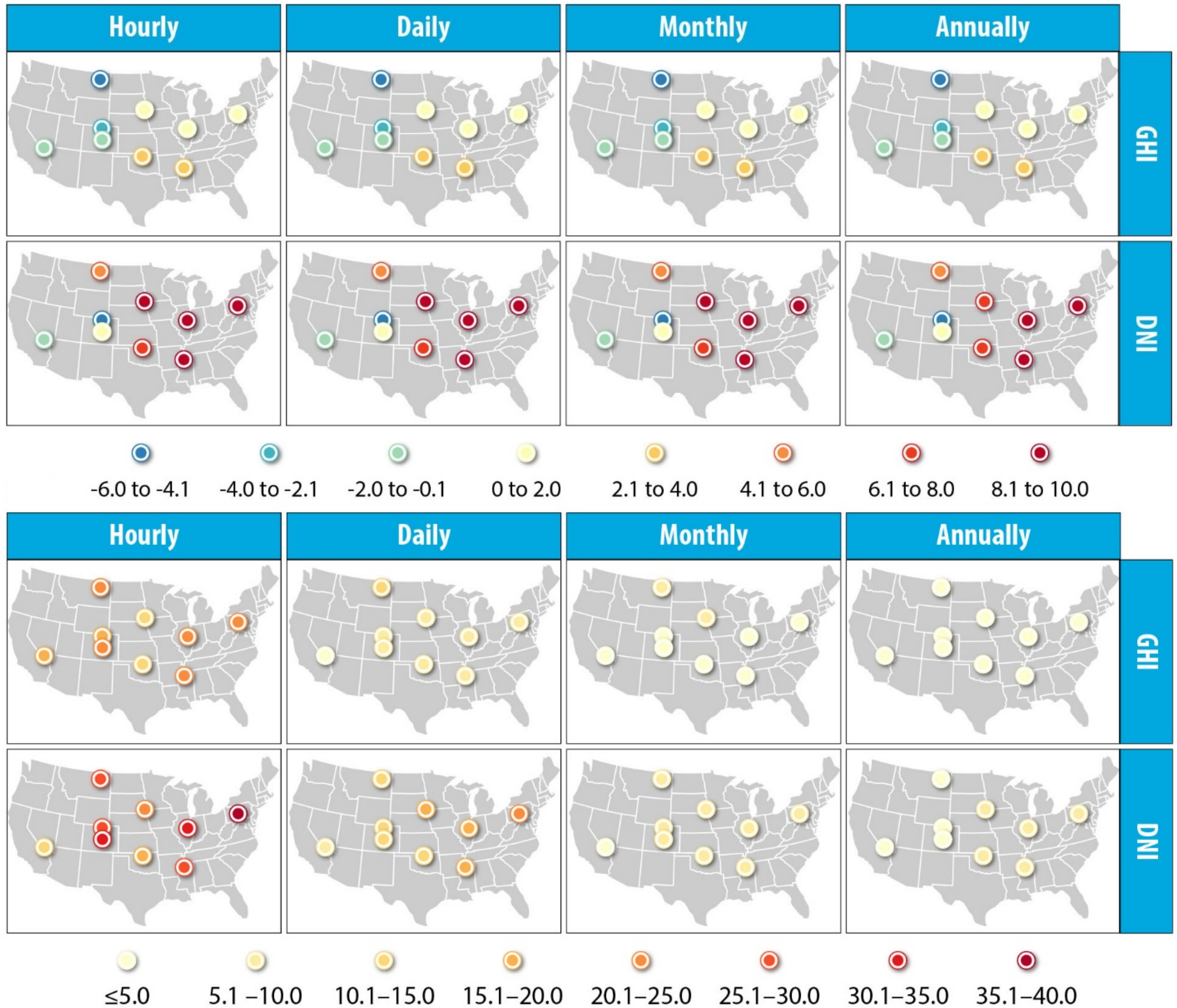
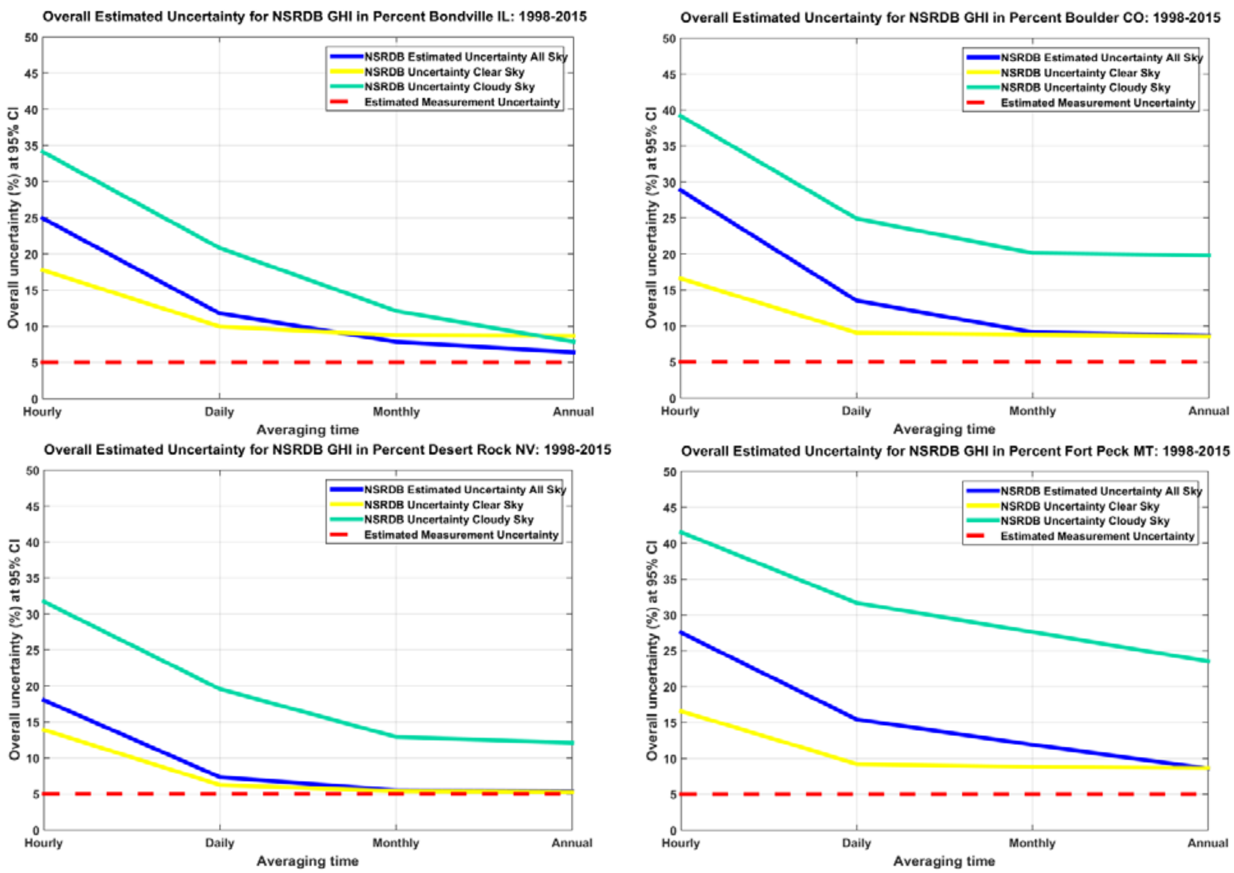


Figure 5. MBE (top) and MAE (bottom) show the statistical results in percentage of the comparison between the NSRDB and surface measurements for both GHI and DNI

3.1 Overall Measurement Uncertainty

Accuracy and uncertainty determination of the satellite-derived data set are based on a wide range of approaches and data analysis techniques. Some of these techniques use MBE and RMSE as statistical measures; however, to perform comprehensive uncertainty estimation, all known sources of uncertainties must be included (Wilcox 2012; Šúri and Cebecauer 2014), and one of these sources of uncertainty is the ground-based measurement uncertainty. Many studies have reported that the uncertainty of the ground-measured data from pyranometers could range from 3%–5% (Reda 2011; Myers et al. 2002; Habte et al. 2016; Wilcox and Myers 2008). In this report, we considered the conservative value of 5% uncertainty for the ground-based measurement data. Figure 6 shows the uncertainty estimation of the NSRDB when the hourly data demonstrated higher uncertainty. As the time average increased, the uncertainty decreased and approached the measurement uncertainty.



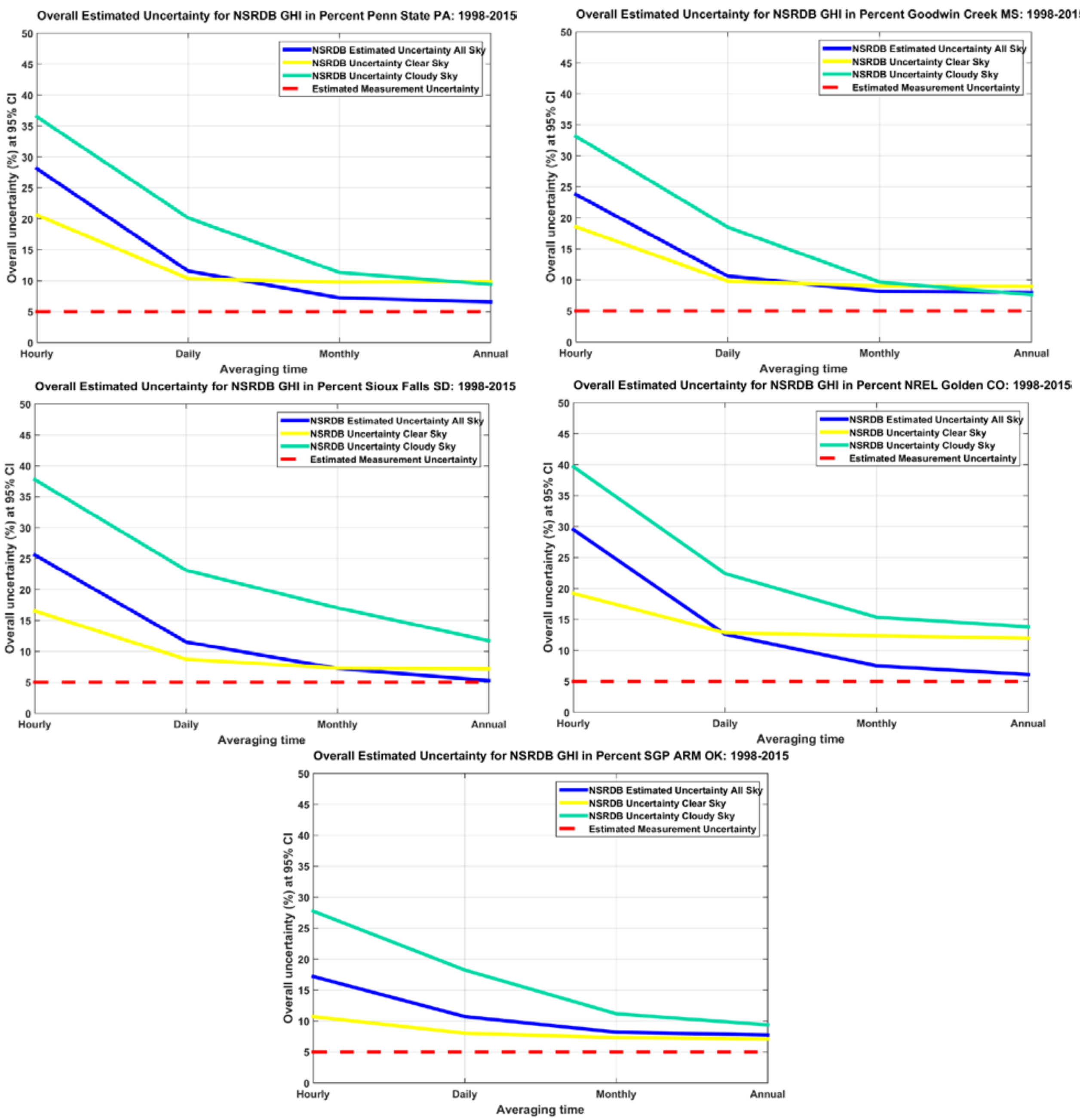


Figure 6. NSRDB uncertainty under various time averages

The 5% uncertainty of the ground measurement was derived using the method outlined in the Guide to the Expression of Uncertainty in Measurement, which applies both the statistical and nonstatistical sources of uncertainty (Reda 2011; Habte et al. 2014). The ground measurement uncertainty was left unchanged at 5% throughout the averaging period because the inherent uncertainties of the radiometers should remain the same throughout the averaging. The 5% uncertainty does not include the random component, which requires a statistic, such as standard deviation; however, the inherent nature of changing weather during the ground-based measurements, cannot be considered as a source of uncertainty to determine the standard deviation because that it is not about the instrument that measures the changes. In future studies, the random component statistical sources of uncertainties of measurements could be included by analyzing the time response and stability of the radiometer that measures the solar resources and the data acquisition system. We believe that these sources will not have a significant effect in reducing or increasing the estimated uncertainty of the ground-based data as the averaging time increases, but this needs further investigation. On the other hand, the RMSE in the NSRDB (1998–2015) decreases significantly with the increase in the time average due to cancellation of error. This is also reported in Vignola, Stoffel, and Michalsky (2013).

3.2 Interannual Variability

Both the surface reference ground measurements and NSRDB (1998–2015) PSM estimates differ by less than 1% COV in most locations for all sky conditions for both GHI and DNI (Figure 7 and Table 1); therefore, they show similar trends. The COV for the GHI results obtained in this report are similar to those from the Wilcox and Gueymard (2010) study under all sky conditions. The COV for the DNI was reported to be twice that of the GHI in Wilcox and Gueymard (2010); however, in this current version of the NSRDB, the COV of the DNI is closer to GHI. This could be explained by the inherent differences in the models used to generate the two NSRDB versions, wherein the current NSRDB (1998–2015) is a physics-based model and the data used in Wilcox and Gueymard (2010) is based on empirical model.

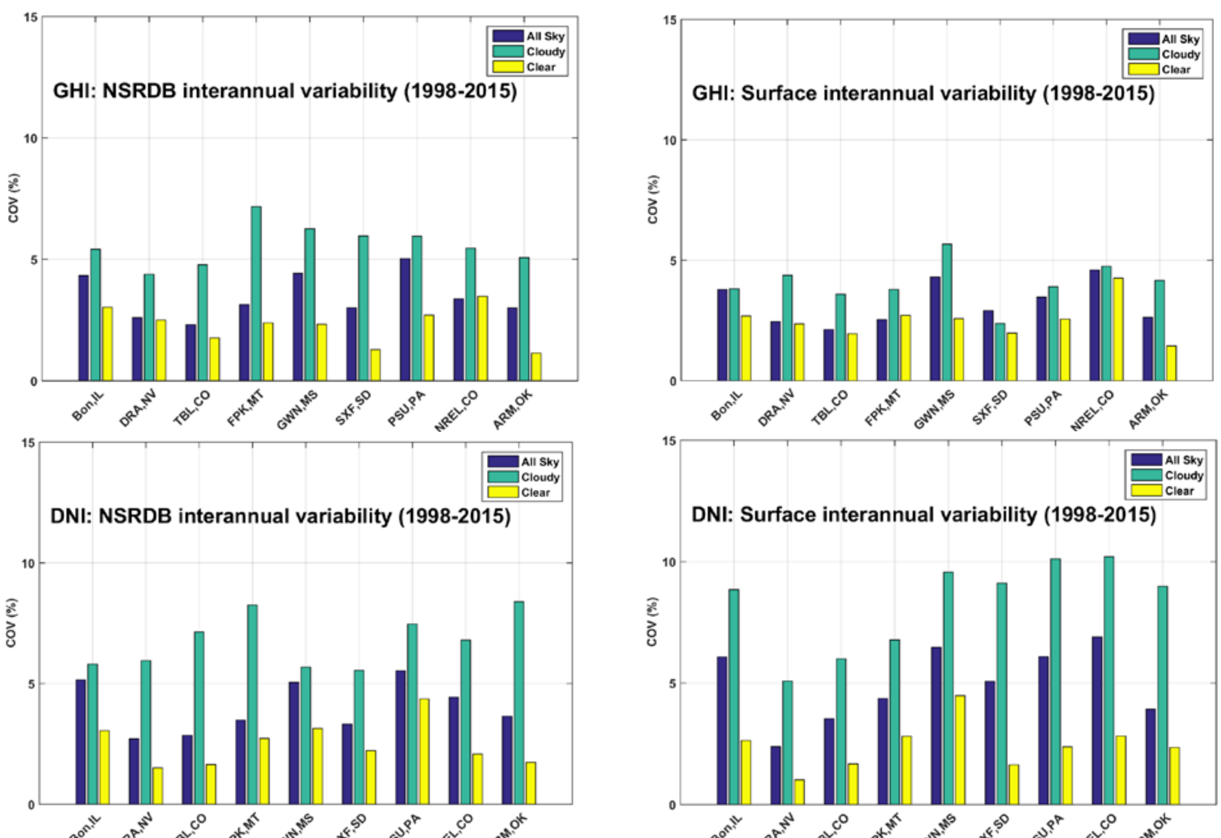


Figure 7. NSRDB and surface measurement interannual variability

Note: The variability for the SXF location is assessed using only the 2003–2015 data sets (see Figure 1).

Figure 7 shows the GHI interannual variability for the 18 years, implying an average of less than 5% variability from one year to another under all sky conditions. As shown in Table 3, we also investigated variability by considering fewer years at a time (5 and 10 years). For instance, the 5-year range we considered 1998–2002, 1999–2003, and so on to derive the ranges described in Table 3, and the same method was applied to the 10-year range. The 5-year range demonstrated a wider percentage range of interannual variability compared to the 10-year range (Figure 8). This shows that using fewer years is not a good metric for determining interannual variability; more years are preferable to accurately define interannual variability. Previous reports, such as World Meteorological Organization (2011), described that 30 years of data were sufficient to determine interannual variability; however, in this study we demonstrated the available 18 years of NSRDB data could depict a fairly accurate relative interannual variability.

Moreover, clear locations such as Desert Rock, Nevada, demonstrated less interannual variability compared more cloudy areas such as Sioux Falls, South Dakota; however, as mentioned above this station has a shorter analysis period than the others (2003–2015).

Table 1. GHI and DNI Interannual Variability for the Averages of Different Years under All Sky Conditions

Station Name	Irradiance	NSRDB (1998–2015) COV%			Surface Measurement COV%		
		5 Yrs. (Ranges)	10 Yrs. (Ranges)	All Yrs. (18)	5 Yrs. (Ranges)	10 Yrs. (Ranges)	All Yrs. (18)
BON	GHI	1.4–6.6	2.6–5.2	4.3	1.1–4.8	2.3–4.0	3.8
	DNI	1.6–7.5	3.3–5.5	5.2	2.7–7.9	4–6.0	6.1
DRA	GHI	0.5–4.3	1.3–3.3	2.6	0.8–3.7	1.5–2.9	2.4
	DNI	1.4–4.2	1.8–3.3	2.7	1.0–3.1	1.8–2.7	2.4
TBL	GHI	1.5–3.0	1.7–2.4	2.3	1.4–2.5	1.9–2.2	2.1
	DNI	1.1–4.0	1.8–3.4	2.9	1.9–4.5	2.6–3.7	3.5
FPK	GHI	1.7–4.1	2.5–3.6	3.1	0.7–3.4	1.5–2.5	2.5
	DNI	1.7–4.8	2.7–3.8	3.5	1.6–5.6	2.8–4.4	4.4
GWN	GHI	3.1–5.5	3.2–4.7	4.4	3.1–4.8	3.5–4.6	4.3
	DNI	3.1–6.7	4.3–5.6	5.1	4.0–8.1	5.3–6.9	6.5
SXF	GHI	3.3–8.8	3.9–6.8	5.7	2.6–7.4	3.1–6.0	4.9
	DNI	2.0–4.7	3.4–3.8	3.7	3.7–6.0	4.7–5.3	5.2
PSU	GHI	2.5–6.2	3.7–5.1	5.0	2.5–4.7	3.0–3.9	3.5
	DNI	2.9–7.6	4.6–6.1	5.5	3.7–8.5	5.1–7.2	6.1
NREL-SRRL	GHI	2.1–4.6	2.5–3.8	3.4	2.7–6.7	3.0–5.2	4.6
	DNI	2.6–6.5	3.4–5.2	4.4	4.3–9.3	5.4–7.6	6.9
ARM-SGP	GHI	2.1–5.2	2.8–4.4	3.7	1.7–3.9	2.3–3.4	2.7
	DNI	2.1–6.4	2.7–4.8	4.0	2.6–5.5	3.1–4.3	3.9

The interannual variability information has benefits in understanding the application of a typical meteorological year data set. As stated in Habte et al. (2014), the temporal variability of a long-term data set is essential when developing the typical meteorological year data set because a typical month created from years with higher variation would lack a full depiction of the monthly variations.

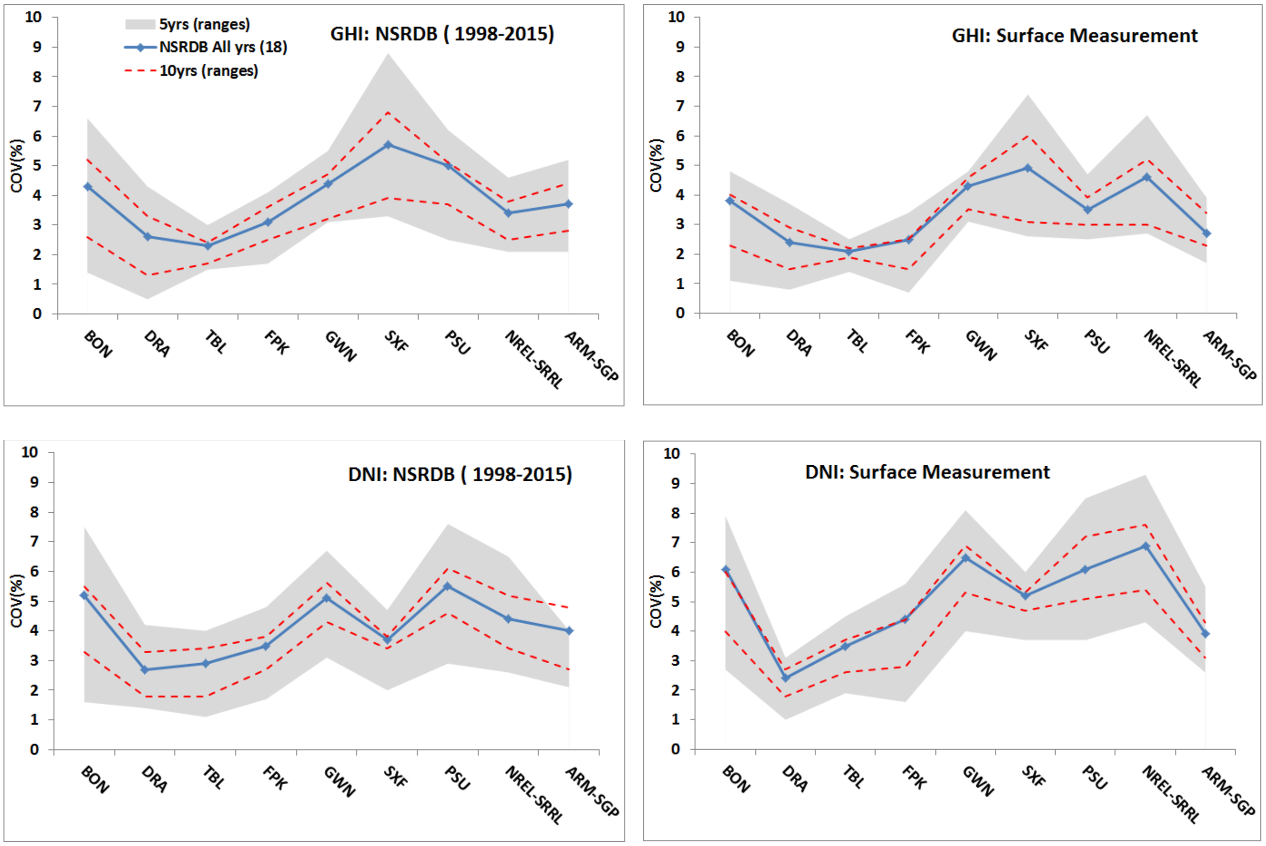
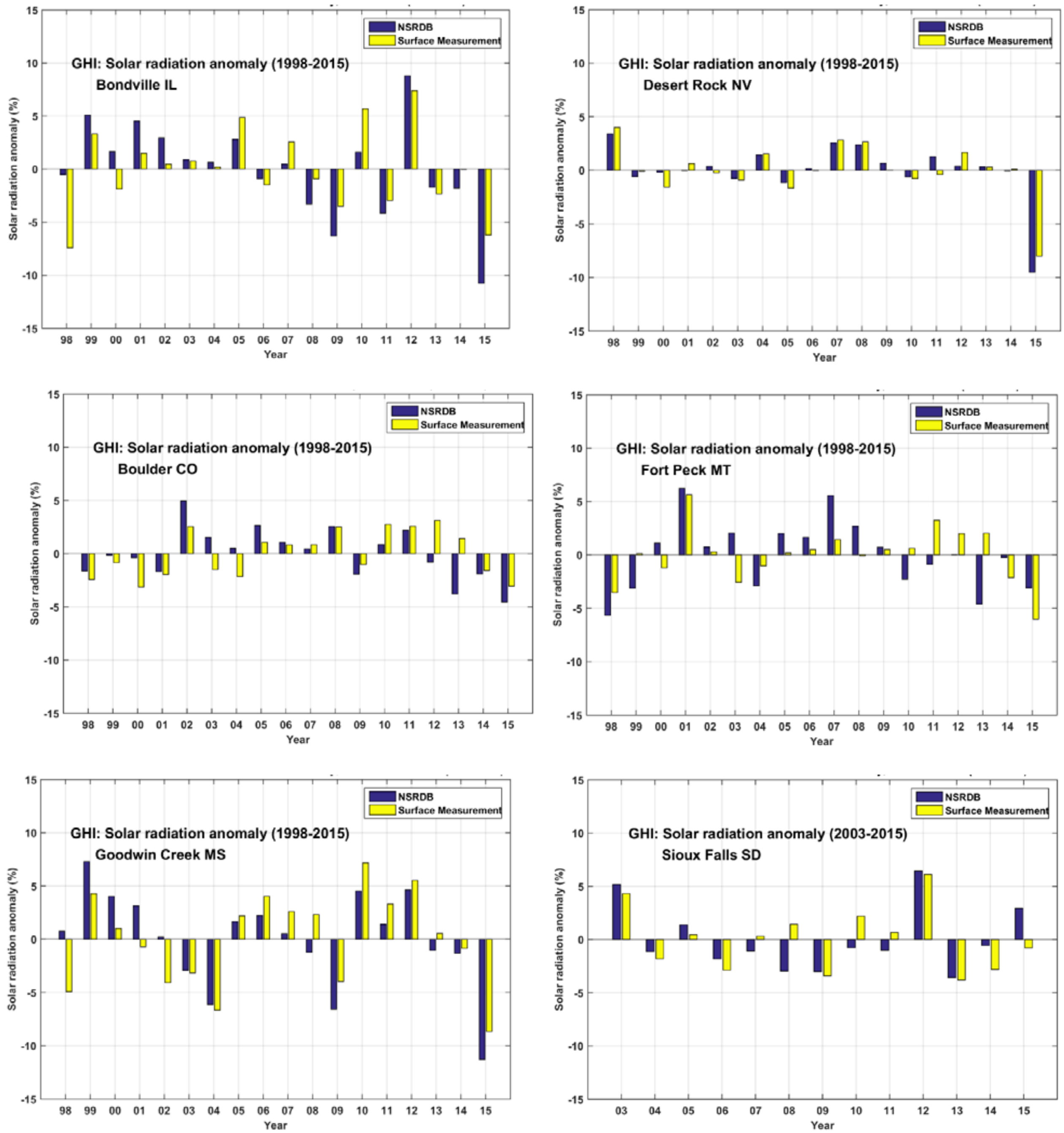


Figure 8. Effects of averaging years on interannual variability for both the NSRDB and surface measurement GHI (top) and DNI (bottom)

3.3 Solar Radiation Anomaly

Climate anomalies due to El Niño, La Niña, volcanic eruptions, or unique climatic events can have significant impacts on the incoming solar radiation (Chiacchio et al. 2010; Stoffel and Nelson 1993). Understanding and quantifying these anomalies is essential for policymakers, financiers, project developers, and grid integration studies. Analyses of data from year 2015 demonstrated reduced incoming solar radiation by approximately 5%–10% relative to the long-term mean. This is more apparent in most of the central and southern locations, such as Bondville, Illinois; Desert Rock, Nevada; Boulder, Colorado; and Goodwin Creek, Mississippi (Figure 9). Bender (2016) also reported similar results, wherein the central and southern plains demonstrated a strong negative anomaly for the year of 2015. As stated in Bender (2016), solar resource anomalies cause a proportional reduction or increase in power generation. This type of information can have significant impacts on utility-scale projects.


GHI: Solar radiation anomaly (1998-2015)
Bondville IL
GHI: Solar radiation anomaly (1998-2015)
Desert Rock NV
GHI: Solar radiation anomaly (1998-2015)
Boulder CO
GHI: Solar radiation anomaly (1998-2015)
Fort Peck MT
GHI: Solar radiation anomaly (1998-2015)
Goodwin Creek MS
GHI: Solar radiation anomaly (2003-2015)
Sioux Falls SD
NSRDB
Surface Measurement
Solar radiation anomaly (%)
Year

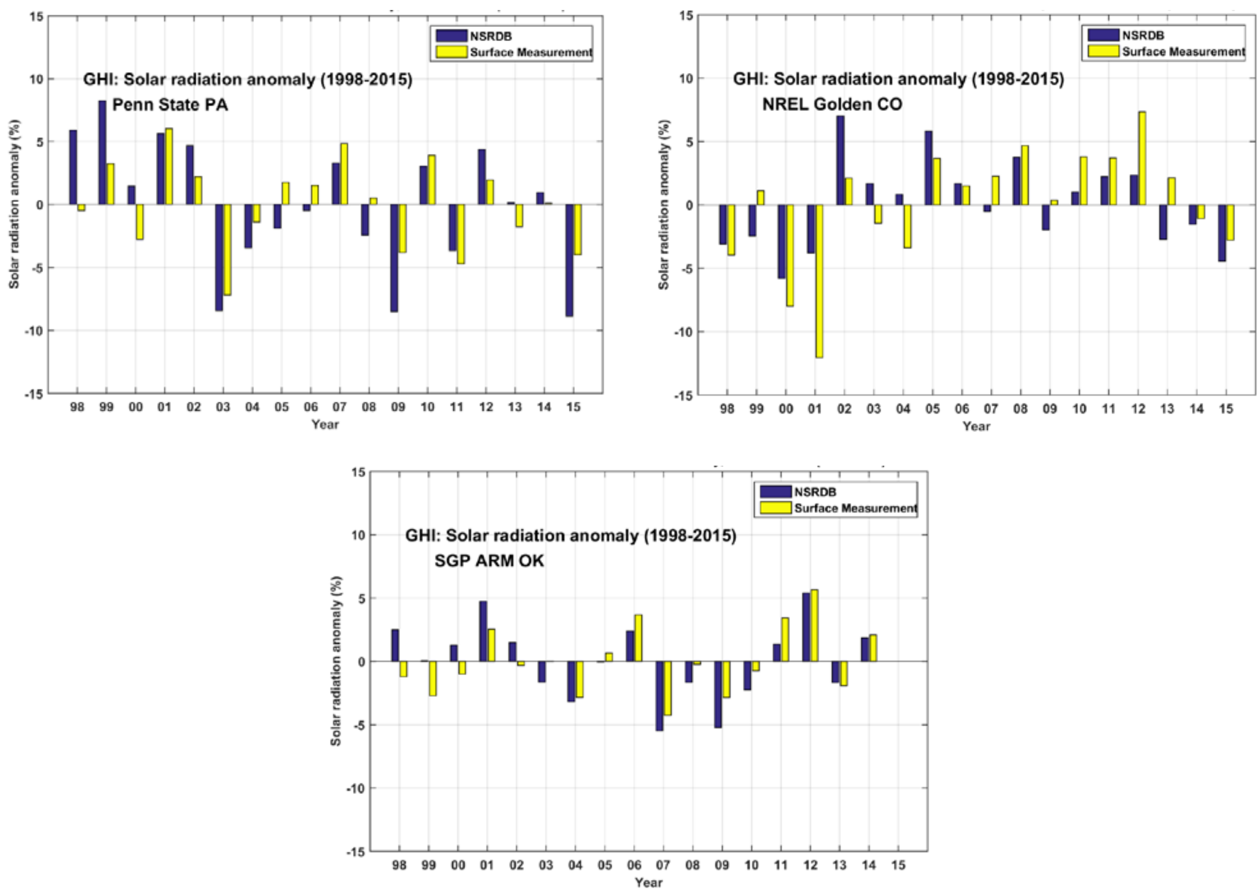


Figure 9. NSRDB and surface measurement solar radiation anomaly

As shown in Figure 9, the NSRDB data compare well from one year to another to the surface-measured data set in estimating the solar radiation anomalies. In most cases, both data sets have similar anomalies in terms of directions and magnitudes of percentages. This provides confidence in using the NSRDB (1998–2015) data to understand solar resource anomalies.

4 Summary

Implementing a comprehensive approach for applying available solar resource information is essential when discussing bankable data for all phases of solar energy conversion projects, from the conceptual phase to routine solar power plant operation. This validation study provided insight on the performance of the NSRDB (1998–2015) data set. This latest version of the NSRDB is based on PSM estimates of solar irradiance from satellite data for each half-hour over a 4-km by 4-km gridded cell. In most cases, the comparisons of the PSM data to the ground-based data demonstrated similar statistical outcomes (+/- 5% for GHI MBE, +/-10% DNI MBE), thereby providing confidence to users of the reliability of the NSRDB (1998–2015) data set. Further, a comprehensive uncertainty estimate demonstrated the performance characteristics of the NSRDB (1998–2015) when including all sources of uncertainty at various time-averaged periods, a protocol that is not often used in model evaluations. However, readers are advised to carefully interpret the higher RMSE observed because these higher RMSE values are attributed to the spatial and temporal differences between the satellite pixel and the ground measurement and the parallax issue. Also, the study analyzed the interannual and climate anomaly of solar radiation. There was less than 5% interannual variability in the GHI and DNI for both the NSRDB (1998–2015) and surface-measured data sets. This provides confidence that the NSRDB represents the surface measurement when annual estimates of solar radiation are considered. Climate anomalies due to extreme events are essential information for policymakers, financiers, project developers, and grid integration studies. This information will assist in accurately determining solar project risks and better planning for such projects. For instance, the year 2015 appeared to have a 5%–10% reduction in solar irradiance (GHI) compared to other years for the central and southern plains.

Additional work is planned for the NSRDB (1998–2015) data set to investigate why the PSM overestimates solar radiation by approximately 5% under clear-sky conditions. This could be related to the underestimation of aerosol optical depth when considering monthly averaged data. In an attempt to mitigate this problem, future updates of the NSRDB will use high temporal and spatial resolution aerosol data sets derived from the National Aeronautics and Space Administration's Modern Era Retrospective Reanalysis (MERRA-2) data sets. Distinguishing clouds from snow or vice versa continues to present significant challenges. High-reflecting surfaces—such as areas with light sand, playas, and water bodies—also pose problems. We will investigate this issue by acquiring an accurate temporal albedo input data set that would help detect and characterize such surfaces. Capturing the intra-hourly variability is a unique challenge for any satellite-derived data set; however, the problem could be solved with the deployment of the Geostationary Operational Environmental Satellite-R Series (GOES-R) satellite, which will provide higher temporal and spatial resolution data. Future work will focus on addressing and identifying the sources of uncertainty in the NSRDB (1998–2015) and developing methods to reduce those uncertainties.

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Appendix A: Statistical Result for Varying Time Averaging for both NSRDB and Surface Measurement

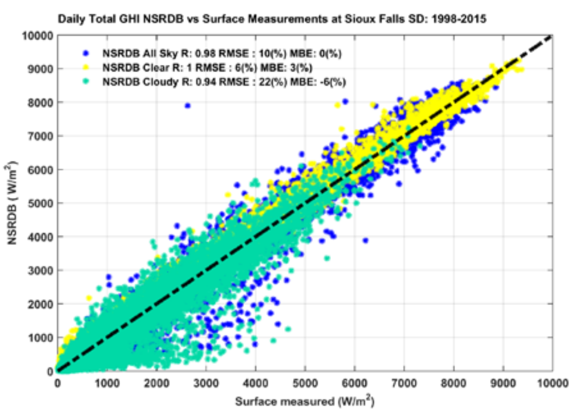
As stated in various sections of the report, understanding the statistical differences under varying time averaging is essential for various phases of solar energy projects. The table below shows MBE, MAE, and RMSE differences for both GHI and DNI data sets.

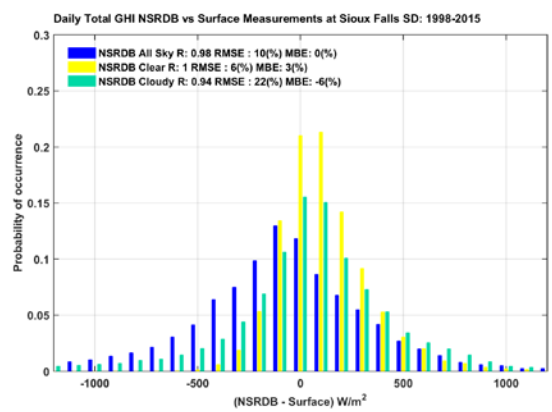
Table A.1. Statistical Results of the Comparison between the NSRDB and Surface Measurements

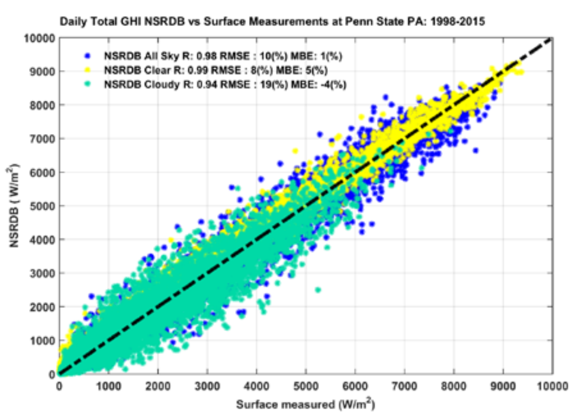
		GHI							DNI						
Station	Time Avg.	No. Obs.	MBE (W/m²)	MBE (%)	RMSE (W/m²)	RMSE (%)	MAE (W/m²)	MAE (%)	No Obs.	MBE (W/m²)	MBE (%)	RMSE (W/m²)	RMSE (%)	MAE (W/m²)	MAE (%)
	Hourly	66,685	7.65	1.95	115.27	24.35	85.06	21.71	52,803	37.70	8.31	206.46	37.12	145.39	32.05
	Daily	6,565	77.70	1.95	481.64	10.49	331.85	8.34	6,545	319.75	8.18	946.89	19.12	719.26	18.40
	Monthly	216	76.47	1.92	247.25	5.71	181.34	4.56	213	326.49	8.49	418.60	10.38	360.34	9.37
BON	Annually	18	76.47	1.92	139.52	3.51	107.48	2.70	18	325.58	8.46	340.59	8.82	325.58	8.46
	Hourly	66,322	-7.08	-1.30	106.23	17.29	82.84	15.19	63,264	-3.55	-0.48	170.91	21.71	107.99	14.73
	Daily	6,467	-72.65	-1.30	314.22	5.20	209.54	3.75	6,467	-35.70	-0.50	701.41	9.02	533.10	7.41
	Monthly	214	-73.01	-1.31	117.23	1.97	97.28	1.74	214	-34.62	-0.48	218.86	2.95	176.26	2.45
DRA	Annually	18	-73.44	-1.31	86.10	1.54	76.09	1.36	18	-35.36	-0.49	110.92	1.54	79.44	1.11
	Hourly	66,233	-14.09	-3.19	115.58	22.28	71.56	16.20	56,840	-25.79	-4.57	213.24	32.07	141.63	25.11
	Daily	6,568	-142.12	-3.19	554.30	11.26	370.28	8.31	6,567	-226.23	-4.58	904.68	15.69	664.15	13.45
	Monthly	216	-143.62	-3.23	241.71	5.11	182.70	4.11	216	-226.20	-4.58	337.74	6.68	275.21	5.57
TBL	Annually	18	-143.62	-3.23	171.57	3.86	143.62	3.23	18	-226.20	-4.58	247.64	5.01	226.20	4.58
	Hourly	65,157	-16.92	-4.44	120.92	26.70	87.17	22.87	51,553	23.77	4.60	207.14	34.18	141.02	27.28
	Daily	6,556	-168.20	-4.44	618.06	13.90	393.97	10.40	6,537	182.70	4.18	843.11	15.66	620.77	14.19
	Monthly	216	-170.52	-4.51	418.26	9.81	268.24	7.10	216	200.17	4.71	345.33	7.54	276.14	6.50
FPK	Annually	18	-170.52	-4.51	202.72	5.36	170.52	4.51	18	200.17	4.71	227.63	5.35	200.17	4.71
	Hourly	66,162	16.83	3.97	115.89	22.91	87.50	20.62	56,109	42.98	9.07	203.51	35.78	140.89	29.73
	Daily	6,466	172.17	3.97	414.42	8.49	304.33	7.01	6,463	378.42	8.90	935.47	18.05	713.60	16.78
	Monthly	216	171.77	3.96	236.80	5.11	187.35	4.32	216	380.91	9.02	472.34	10.87	394.53	9.34
GWN	Annually	18	171.77	3.96	209.47	4.83	171.77	3.96	18	380.91	9.02	410.41	9.69	380.91	9.02
	Hourly	45,163	2.61	0.66	93.76	19.97	58.58	14.89	36,975	40.04	8.05	175.20	29.40	118.28	23.79
	Daily	4,570	25.79	0.66	542.31	12.07	353.78	9.10	4,556	348.87	8.23	895.97	17.10	651.82	15.38
	Monthly	151	24.26	0.62	325.47	7.64	241.47	6.20	151	334.78	8.01	426.19	9.74	356.45	8.53
SXF	Annually	13	26.23	0.67	86.94	2.23	75.66	1.94	13	323.57	7.70	353.77	8.41	325.87	7.76
	Hourly	64,888	4.10	1.14	122.69	27.62	89.16	24.80	49,740	32.81	8.16	220.71	42.75	156.28	38.86
	Daily	6,370	41.76	1.14	446.36	10.36	326.02	8.90	6,359	267.95	8.02	914.42	20.33	686.60	20.56
	Monthly	211	45.74	1.25	204.00	5.09	149.98	4.11	211	272.46	8.35	365.58	10.56	311.32	9.54
PSU	Annually	18	53.96	1.48	144.36	3.95	106.95	2.93	18	275.81	8.45	300.90	9.18	275.81	8.45
	Hourly	61,452	-1.51	-0.35	149.78	29.08	107.25	24.62	53,429	2.05	0.37	256.98	38.93	171.28	31.13
	Daily	6,217	-14.52	-0.34	555.79	11.57	382.90	8.90	6,217	17.71	0.37	995.14	17.74	710.10	14.95
NREL-	Monthly	206	-15.53	-0.36	257.25	5.60	186.33	4.35	206	17.73	0.37	367.18	7.48	283.47	6.00
SRRL	Annually	18	-19.99	-0.47	150.50	3.50	125.22	2.92	18	17.95	0.38	173.00	3.64	137.98	2.92
	Hourly	63,888	17.53	3.95	83.02	15.97	49.76	11.21	53,117	39.02	7.06	167.23	26.25	110.26	19.95
	Daily	6,052	175.70	3.90	430.76	8.60	290.68	6.45	6,030	340.87	7.14	859.87	15.24	639.18	13.38
SGP-	Monthly	203	176.73	3.93	244.74	5.12	197.43	4.39	203	332.81	6.99	420.57	8.63	344.71	7.24
ARM	Annually	17	177.25	3.94	195.68	4.35	177.25	3.94	17	333.00	7.00	351.87	7.39	333.00	7.00

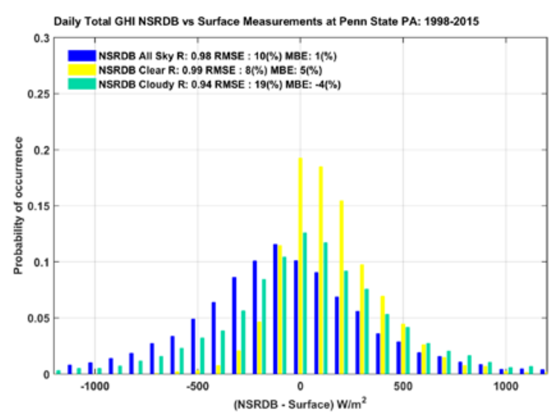
Appendix B: GHI Daily Totals Data Comparisons for Nine Locations

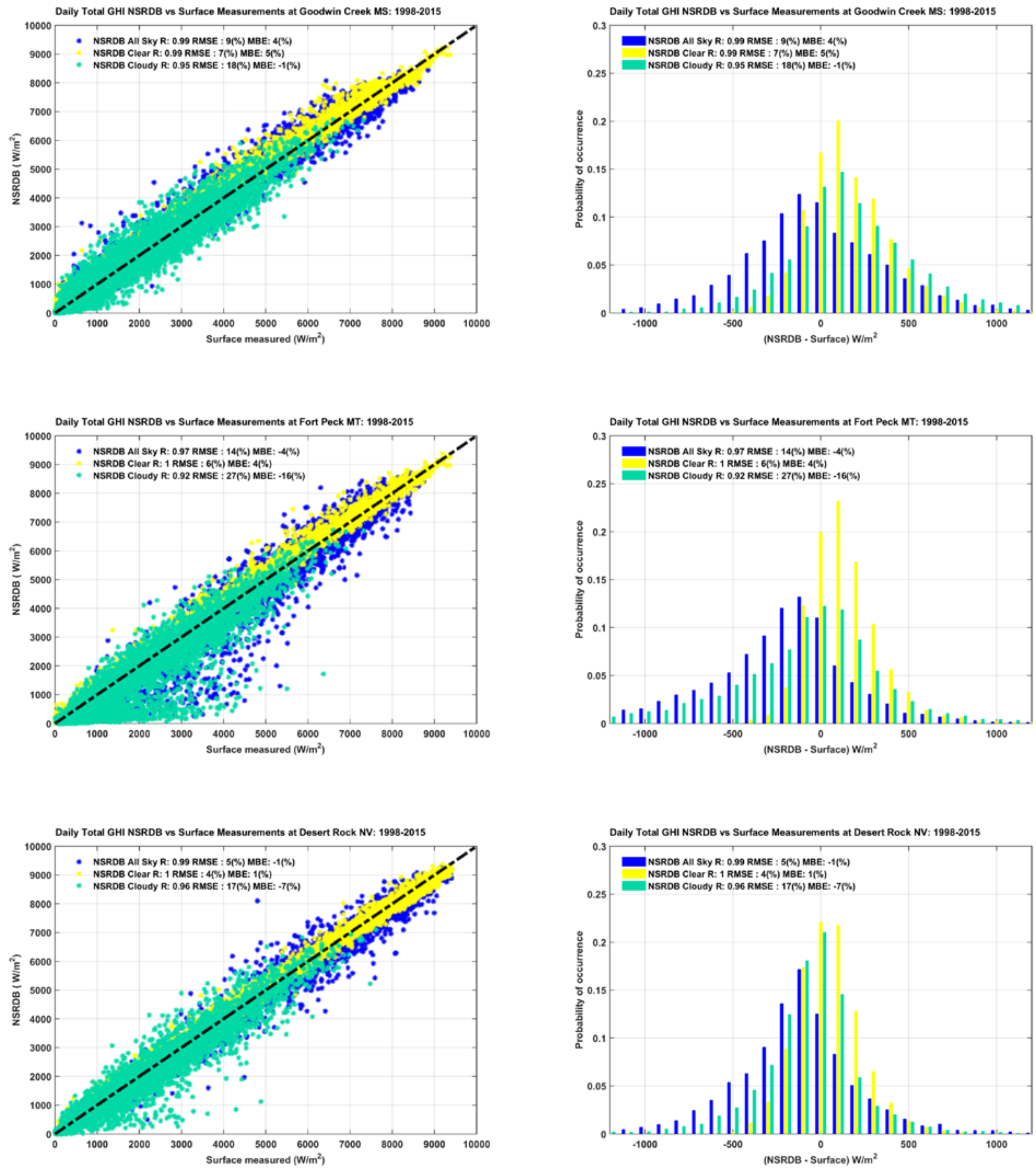
The scatter plots below show the daily totals and probability distributions of the errors for the GHI between the NSRDB (1998–2015) and the surface measurement data set. In the scatter plots, most of the points fall along the 1-to-1 line, and the correlation is more than 0.9 for all the locations. The probability distributions show similarity in the distributions among the stations, and in most cases the distribution is normal. The distributions also show skewed positive bias under clear-sky conditions; however, the baises have less magnitude than the cloudy-sky conditions. The cloudy-sky conditions have heavy-tailed distributions relative to those of the clear-sky conditions.

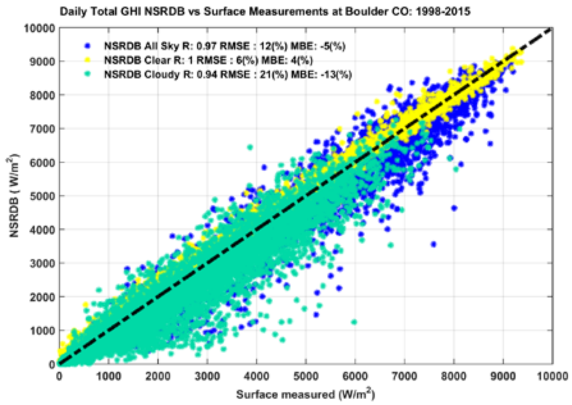


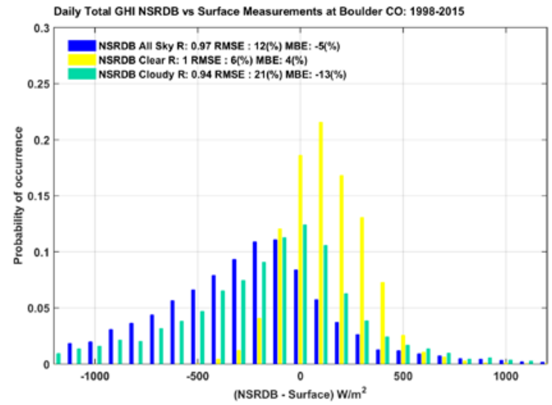


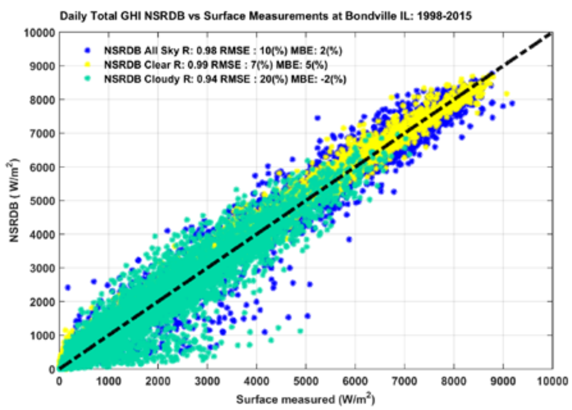


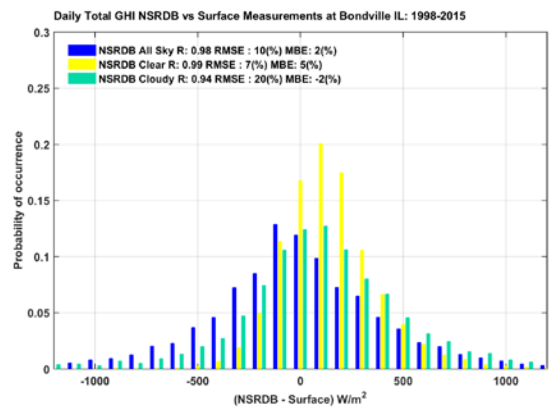


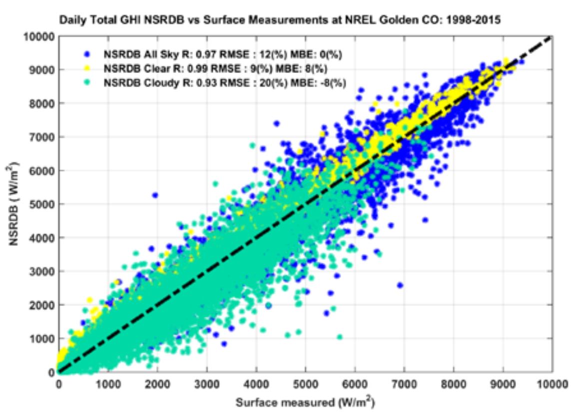

Daily Total GHI NSRDB vs Surface Measurements at Goodwin Creek MS: 1998-2015
NSRDB All Sky R: 0.99 RMSE : 9(%) MBE: 4(%)
NSRDB Clear R: 0.99 RMSE : 7(%) MBE: 5(%)
NSRDB Cloudy R: 0.95 RMSE : 18(%) MBE: -1(%)
NSRDB (W/m^2)
Surface measured (W/m^2)
Probability of occurrence
(NSRDB - Surface) W/m^2
Daily Total GHI NSRDB vs Surface Measurements at Fort Peck MT: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 14(%) MBE: -4(%)
NSRDB Clear R: 1 RMSE : 6(%) MBE: 4(%)
NSRDB Cloudy R: 0.92 RMSE : 27(%) MBE: -16(%)
Daily Total GHI NSRDB vs Surface Measurements at Desert Rock NV: 1998-2015
NSRDB All Sky R: 0.99 RMSE : 5(%) MBE: -1(%)
NSRDB Clear R: 1 RMSE : 4(%) MBE: 1(%)
NSRDB Cloudy R: 0.96 RMSE : 17(%) MBE: -7(%)

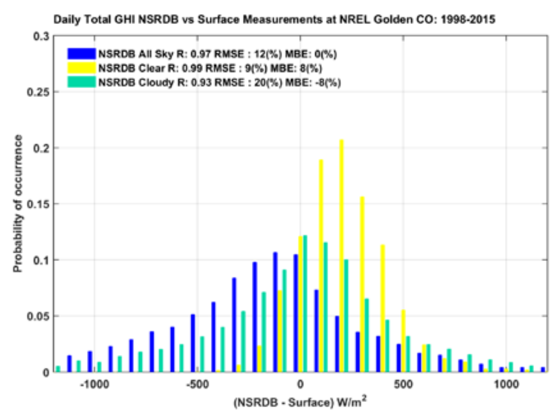

Daily Total GHI NSRDB vs Surface Measurements at Boulder CO: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 12(%) MBE: -5(%)
NSRDB Clear R: 1 RMSE : 6(%) MBE: 4(%)
NSRDB Cloudy R: 0.94 RMSE : 21(%) MBE: -13(%)
NSRDB (W/m^2)
Surface measured (W/m^2)


Daily Total GHI NSRDB vs Surface Measurements at Boulder CO: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 12(%) MBE: -5(%)
NSRDB Clear R: 1 RMSE : 6(%) MBE: 4(%)
NSRDB Cloudy R: 0.94 RMSE : 21(%) MBE: -13(%)
Probability of occurrence
(NSRDB - Surface) W/m^2


Daily Total GHI NSRDB vs Surface Measurements at Bondville IL: 1998-2015
NSRDB All Sky R: 0.98 RMSE : 10(%) MBE: 2(%)
NSRDB Clear R: 0.99 RMSE : 7(%) MBE: 5(%)
NSRDB Cloudy R: 0.94 RMSE : 20(%) MBE: -2(%)
NSRDB (W/m^2)
Surface measured (W/m^2)


Daily Total GHI NSRDB vs Surface Measurements at Bondville IL: 1998-2015
NSRDB All Sky R: 0.98 RMSE : 10(%) MBE: 2(%)
NSRDB Clear R: 0.99 RMSE : 7(%) MBE: 5(%)
NSRDB Cloudy R: 0.94 RMSE : 20(%) MBE: -2(%)
Probability of occurrence
(NSRDB - Surface) W/m^2


Daily Total GHI NSRDB vs Surface Measurements at NREL Golden CO: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 12(%) MBE: 0(%)
NSRDB Clear R: 0.99 RMSE : 9(%) MBE: 8(%)
NSRDB Cloudy R: 0.93 RMSE : 20(%) MBE: -8(%)
NSRDB (W/m^2)
Surface measured (W/m^2)


Daily Total GHI NSRDB vs Surface Measurements at NREL Golden CO: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 12(%) MBE: 0(%)
NSRDB Clear R: 0.99 RMSE : 9(%) MBE: 8(%)
NSRDB Cloudy R: 0.93 RMSE : 20(%) MBE: -8(%)
Probability of occurrence
(NSRDB - Surface) W/m^2

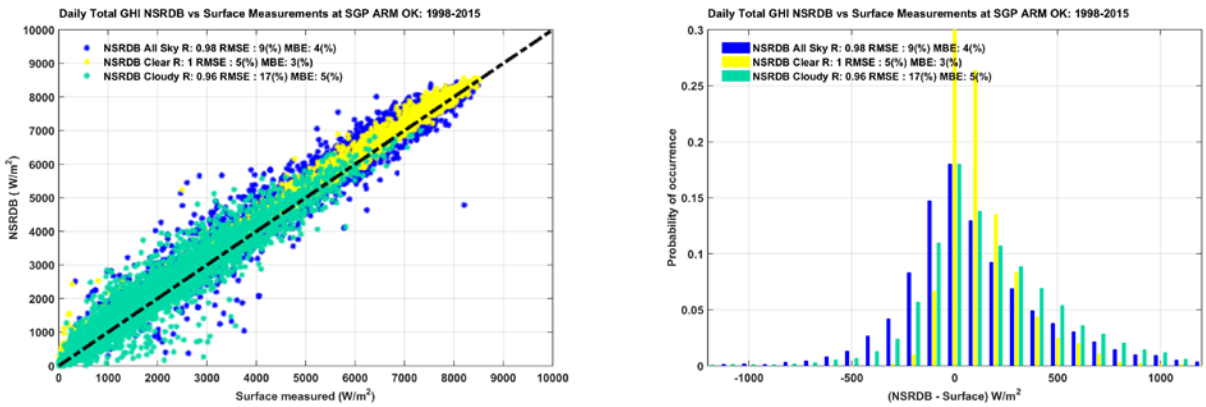
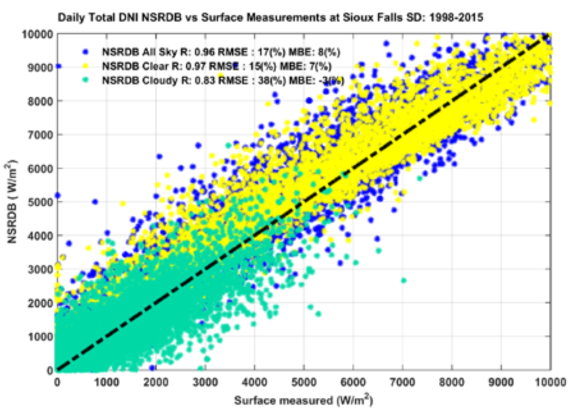
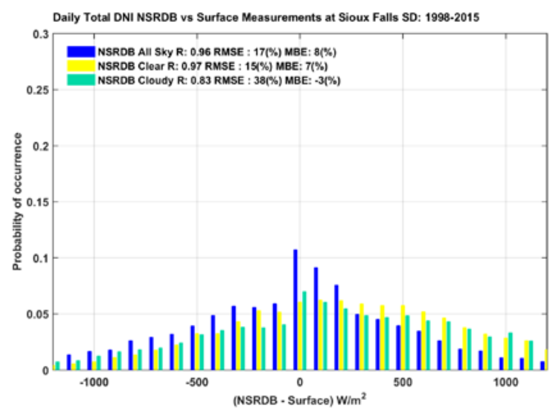


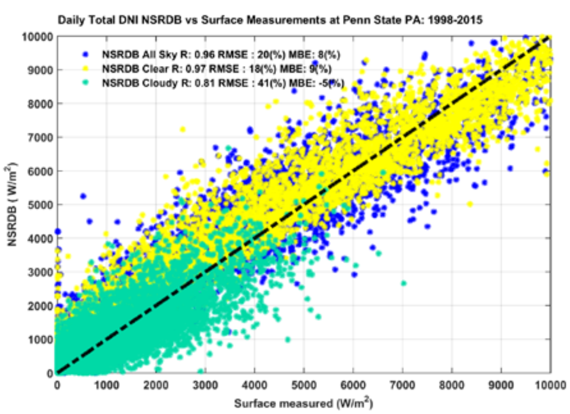
Figure B.1. Scatter plots of the daily totals (right) and probability distributions (left) of the errors for the GHI between the NSRDB (1998–2015) and the surface measurement data set

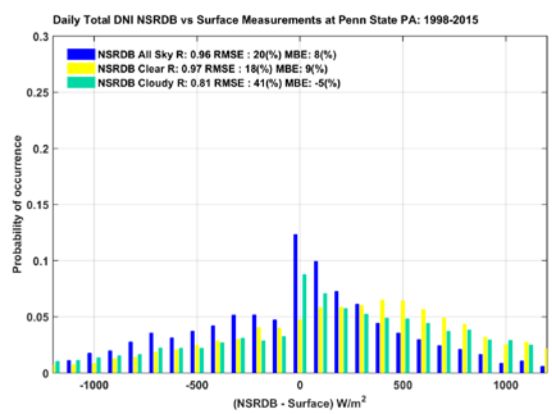
Appendix C: DNI Daily Totals Data Comparisons for Nine Locations

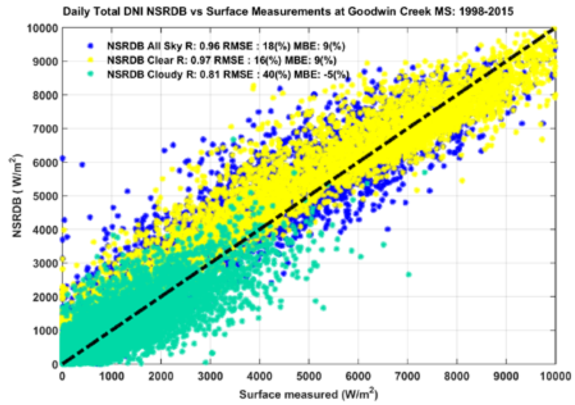
The scatter plots below show the daily totals and probability distributions of the errors for the DNI. As in the GHI data set, most of the points fall along the 1-to-1 line, but these contain more scatter than the GHI data set. The correlation shown is more than 0.9 for all the locations; however, the normal distributions are heavy-tailed compared to the GHI data sets for both clear-sky and cloudy-sky conditions. This is because the DNI is more prone to the subpixel variability, field-of-view differences, and the parallax effect mentioned above compared to the GHI data sets. The clear-sky conditions possess skewed positive bias relative to the cloudy-sky conditions.

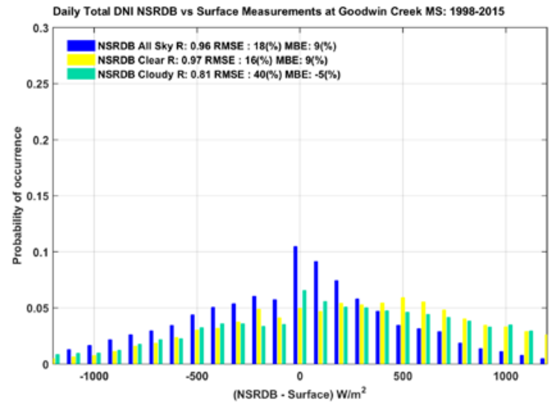


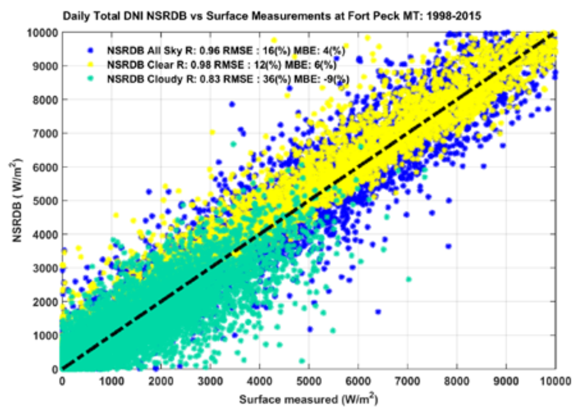


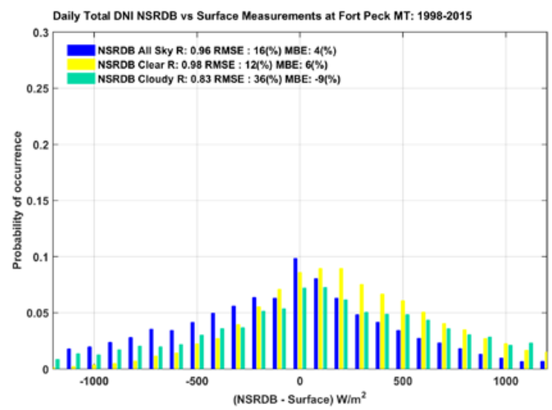


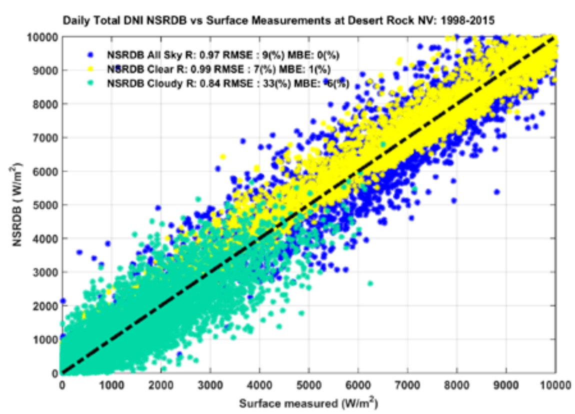


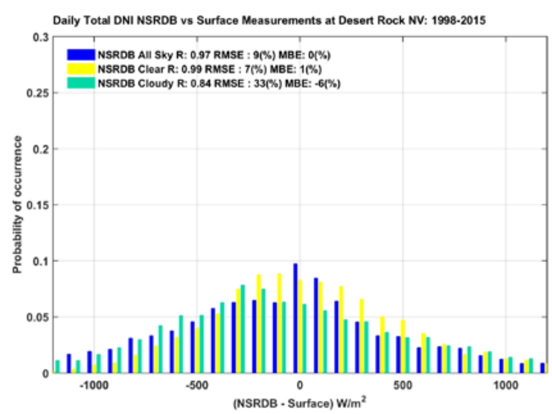

Daily Total DNI NSRDB vs Surface Measurements at Goodwin Creek MS: 1998-2015
NSRDB All Sky R: 0.96 RMSE : 18(%) MBE: 9(%)
NSRDB Clear R: 0.97 RMSE : 16(%) MBE: 9(%)
NSRDB Cloudy R: 0.81 RMSE : 40(%) MBE: -5(%)
NSRDB (W/m^2)
Surface measured (W/m^2)

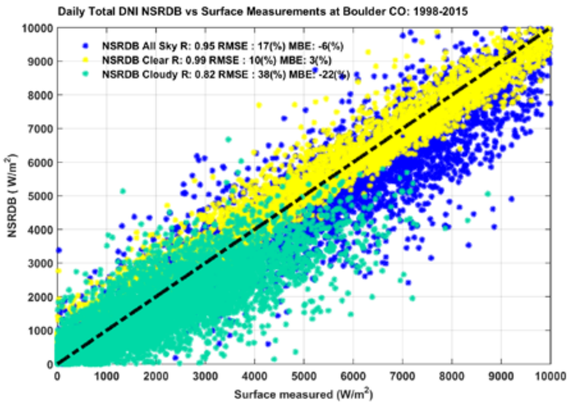

Daily Total DNI NSRDB vs Surface Measurements at Goodwin Creek MS: 1998-2015
NSRDB All Sky R: 0.96 RMSE : 18(%) MBE: 9(%)
NSRDB Clear R: 0.97 RMSE : 16(%) MBE: 9(%)
NSRDB Cloudy R: 0.81 RMSE : 40(%) MBE: -5(%)
Probability of occurrence
(NSRDB - Surface) W/m^2

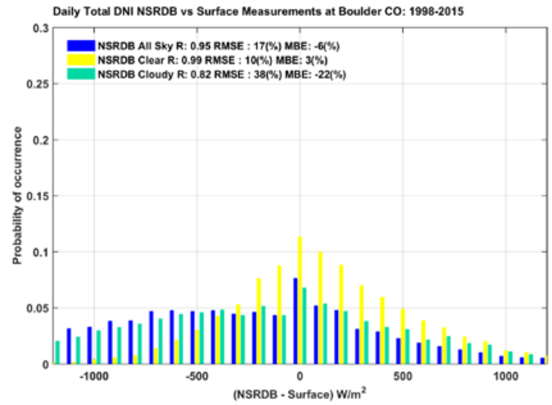

Daily Total DNI NSRDB vs Surface Measurements at Fort Peck MT: 1998-2015
NSRDB All Sky R: 0.96 RMSE : 16(%) MBE: 4(%)
NSRDB Clear R: 0.98 RMSE : 12(%) MBE: 6(%)
NSRDB Cloudy R: 0.83 RMSE : 36(%) MBE: -9(%)
NSRDB (W/m^2)
Surface measured (W/m^2)

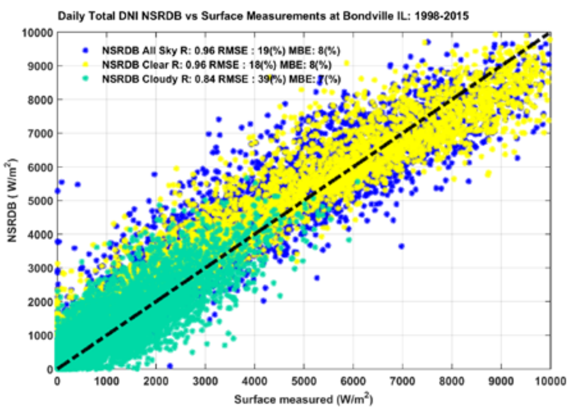

Daily Total DNI NSRDB vs Surface Measurements at Fort Peck MT: 1998-2015
NSRDB All Sky R: 0.96 RMSE : 16(%) MBE: 4(%)
NSRDB Clear R: 0.98 RMSE : 12(%) MBE: 6(%)
NSRDB Cloudy R: 0.83 RMSE : 36(%) MBE: -9(%)
Probability of occurrence
(NSRDB - Surface) W/m^2

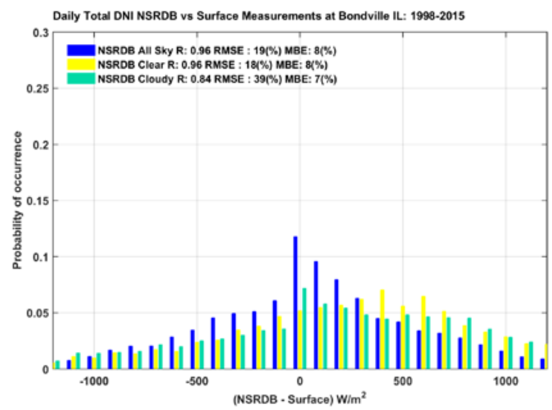

Daily Total DNI NSRDB vs Surface Measurements at Desert Rock NV: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 9(%) MBE: 0(%)
NSRDB Clear R: 0.99 RMSE : 7(%) MBE: 1(%)
NSRDB Cloudy R: 0.84 RMSE : 33(%) MBE: -6(%)
NSRDB (W/m^2)
Surface measured (W/m^2)

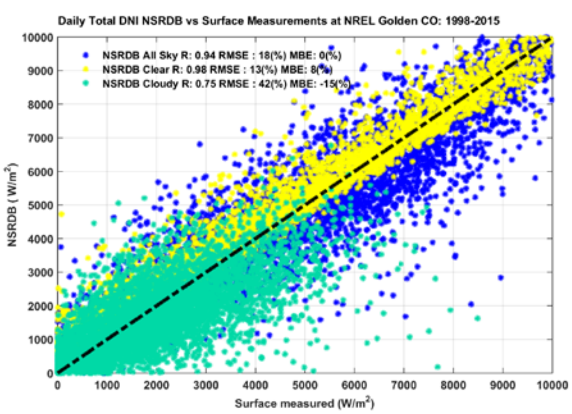

Daily Total DNI NSRDB vs Surface Measurements at Desert Rock NV: 1998-2015
NSRDB All Sky R: 0.97 RMSE : 9(%) MBE: 0(%)
NSRDB Clear R: 0.99 RMSE : 7(%) MBE: 1(%)
NSRDB Cloudy R: 0.84 RMSE : 33(%) MBE: -6(%)
Probability of occurrence
(NSRDB - Surface) W/m^2

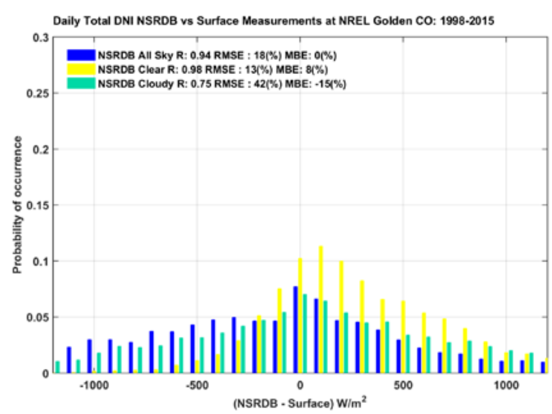

Daily Total DNI NSRDB vs Surface Measurements at Boulder CO: 1998-2015
NSRDB All Sky R: 0.95 RMSE : 17(%) MBE: -6(%)
NSRDB Clear R: 0.99 RMSE : 10(%) MBE: 3(%)
NSRDB Cloudy R: 0.82 RMSE : 38(%) MBE: -22(%)
NSRDB (W/m^2)
Surface measured (W/m^2)


Daily Total DNI NSRDB vs Surface Measurements at Boulder CO: 1998-2015
NSRDB All Sky R: 0.95 RMSE : 17(%) MBE: -6(%)
NSRDB Clear R: 0.99 RMSE : 10(%) MBE: 3(%)
NSRDB Cloudy R: 0.82 RMSE : 38(%) MBE: -22(%)
Probability of occurrence
(NSRDB - Surface) W/m^2


Daily Total DNI NSRDB vs Surface Measurements at Bondville IL: 1998-2015
NSRDB All Sky R: 0.96 RMSE : 19(%) MBE: 8(%)
NSRDB Clear R: 0.96 RMSE : 18(%) MBE: 8(%)
NSRDB Cloudy R: 0.84 RMSE : 39(%) MBE: 7(%)
NSRDB (W/m^2)
Surface measured (W/m^2)


Daily Total DNI NSRDB vs Surface Measurements at Bondville IL: 1998-2015
NSRDB All Sky R: 0.96 RMSE : 19(%) MBE: 8(%)
NSRDB Clear R: 0.96 RMSE : 18(%) MBE: 8(%)
NSRDB Cloudy R: 0.84 RMSE : 39(%) MBE: 7(%)
Probability of occurrence
(NSRDB - Surface) W/m^2


Daily Total DNI NSRDB vs Surface Measurements at NREL Golden CO: 1998-2015
NSRDB All Sky R: 0.94 RMSE : 18(%) MBE: 0(%)
NSRDB Clear R: 0.98 RMSE : 13(%) MBE: 8(%)
NSRDB Cloudy R: 0.75 RMSE : 42(%) MBE: -15(%)
NSRDB (W/m^2)
Surface measured (W/m^2)


Daily Total DNI NSRDB vs Surface Measurements at NREL Golden CO: 1998-2015
NSRDB All Sky R: 0.94 RMSE : 18(%) MBE: 0(%)
NSRDB Clear R: 0.98 RMSE : 13(%) MBE: 8(%)
NSRDB Cloudy R: 0.75 RMSE : 42(%) MBE: -15(%)
Probability of occurrence
(NSRDB - Surface) W/m^2

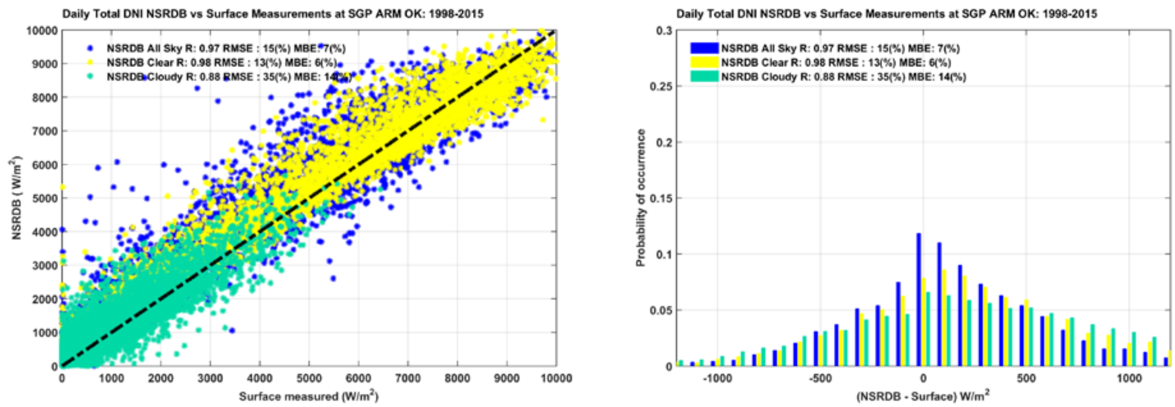


Figure C.1. Scatter plots of the daily totals (right) and probability distributions (left) of the errors for the DNI between the NSRDB (1998–2015) and the surface measurement data set