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Assessment of local solar resource measurement and predictions in south Louisiana

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Abstract

Background: The accessibility of reliable local solar resource data plays a critical role in the evaluation and development of any concentrating solar power (CSP) or photovoltaic (PV) project, impacting the areas of site selection, predicted output, and operational strategy. Currently available datasets for prediction of the local solar resource in south Louisiana rely exclusively on modeled data by various schemes. There is a significant need, therefore, to produce and report ground measured data to verify the various models under the specific and unique ambient conditions offered by the climate presented in south Louisiana.

Methods: The University of Louisiana at Lafayette has been recording onsite high-fidelity solar resource measurements for the implementation into predictive models and for comparison with existing datasets and modeling resources. Industry standard instrumentation has been recording direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), and global horizontal irradiance (GHI), as well as meteorological weather data since 2013. The measured data was then compared statistically to several available solar resource datasets for the geographic area under consideration.

Results: Two years of high-fidelity solar resource measurements for a location in south Louisiana that were previously not available are presented. Collected data showed statistically good agreement with several existing datasets including those available from the National Solar Radiation Database (NSRDB). High variability in year-over-year monthly DNI due to cloud cover was prevalent, while a more consistent GHI level was observed.

Conclusions: The analysis showed that the datasets presented can be utilized for predictive analysis on a monthly or yearly basis with good statistical correlation. High variability in year-over-year monthly DNI due to cloud cover was prevalent, with as much as a 70 % difference in monthly DNI values observed in the measured data. A more consistent GHI level was observed since the GHI is less susceptible to cloud cover transients. Collected data showed statistically good agreement with several existing datasets including those available from the NSRDB when forecasting was for monthly and yearly intervals.

Background

As an integrated part of the University of Louisiana at Lafayette (UL Lafayette) Solar Technology Applied Research and Testing (START) Lab, local solar resource measurements have been conducted onsite since the summer of 2013. The compilation of short- and long-term solar resource data has been conducted for performance evaluation of the onsite solar energy technologies as well as the generation and validation of reliable solar resource models [1, 2]. The primary solar energy asset during the period of investigation presented here has been a pilot scale (650 kWth) parabolic trough solar thermal power plant, constructed and operated by UL Lafayette, for which knowledge of the solar resource was critical. The results of the solar resource study relative to the operation of this power plant will therefore be presented. In general, there are several important roles that accurate solar resource evaluation and forecasting plays in solar power applications. In the project planning stages, understanding the quality and quantity of the resource is essential to accurately predict system performance and financial viability of any future project and

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can be broken down into three areas of study [3]. Site selection, predicted annual plant output, and short-term temporal performance and operating strategy will all be grossly affected by the local short- and long-term resource availability and fluctuation [4]. Additionally, accurate measurement and dissemination of resource data to determine short- and long-term plant performance is vital to optimize performance once operation is underway. Reliable resource measurement will therefore remain vital to the plant's efficient operation throughout its service life.

From the initial planning stages, site selection will typically be based on datasets of historical solar resource data involving changes in weather affecting ground-level insolation from year-to-year, and therefore, more years of data are advantageous for constructing a representative annual dataset [5]. Reliable long-term (25 year) historical datasets are rarely available. Typical meteorological year (TMY) datasets, available from several sources, including the National Renewable Energy Laboratory, can be efficiently used to compare the solar resource at alternative sites and to predict a range of annual performance values of a proposed solar energy plant. Data from individual years are useful in illuminating year-to-year variability that can be expected for the specific locale which assists in the sizing of components of solar systems accurately [6, 7].

Introduction

The available solar resource is typically measured as a combination of several components of the solar radiation that reaches the ground [8]. Extra-terrestrial radiation can be transmitted, absorbed, or scattered by an intervening medium in varying amounts depending on the wavelength and interactions of the Earth's atmosphere. For purposes of usefulness with solar energy conversion techniques, solar radiation measurements result in three fundamental components of interest. Direct normal irradiance (DNI) is the direct or beam radiation available from the solar disk that reaches the surface with no change in direction. Diffuse horizontal irradiance (DHI) is the scattered diffuse radiation from the sky dome. Global horizontal irradiance (GHI) is the total hemispheric irradiance reaching the

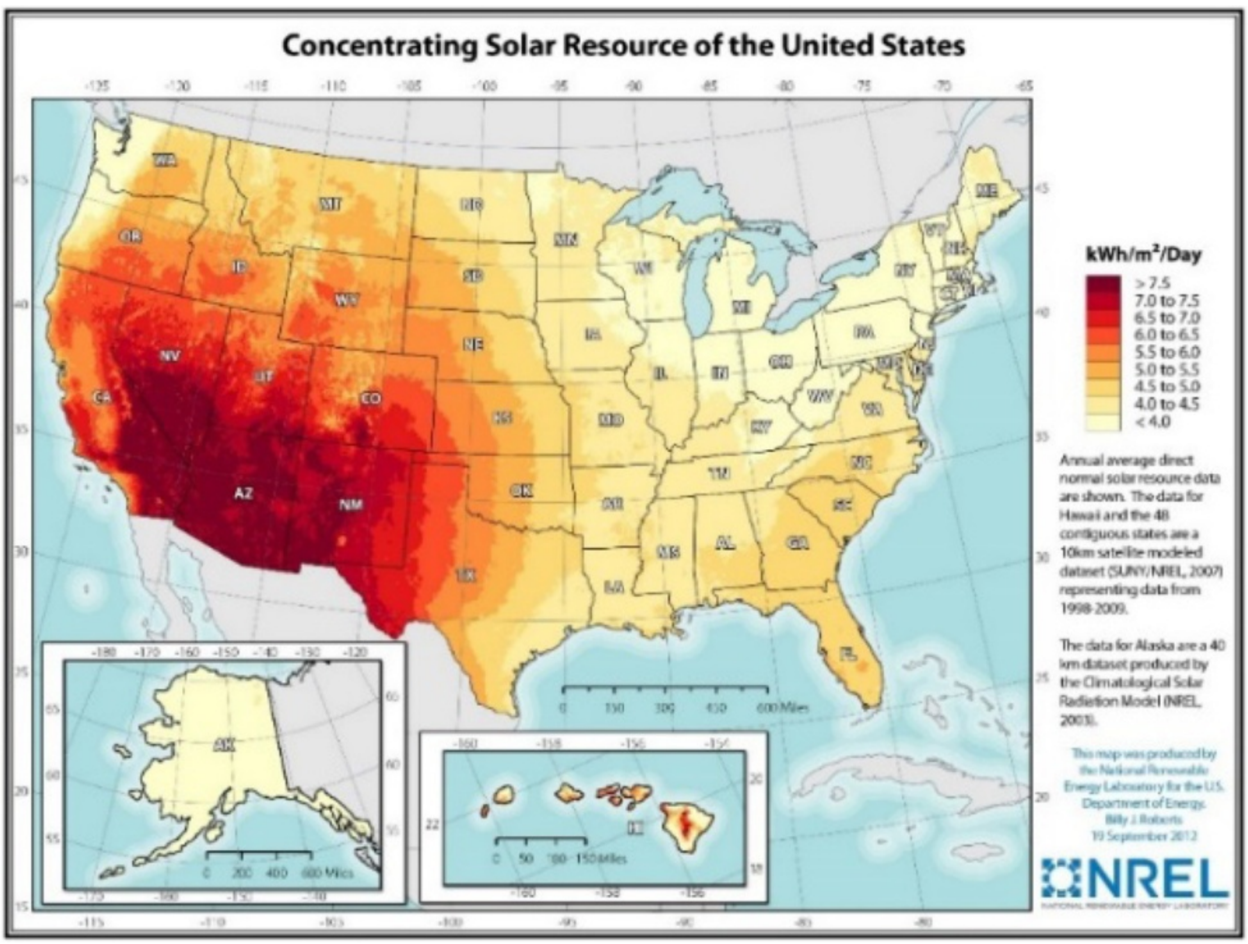

Fig. 1 Concentrating solar resource of the USA. Source: National Renewable Energy Laboratory solar data center

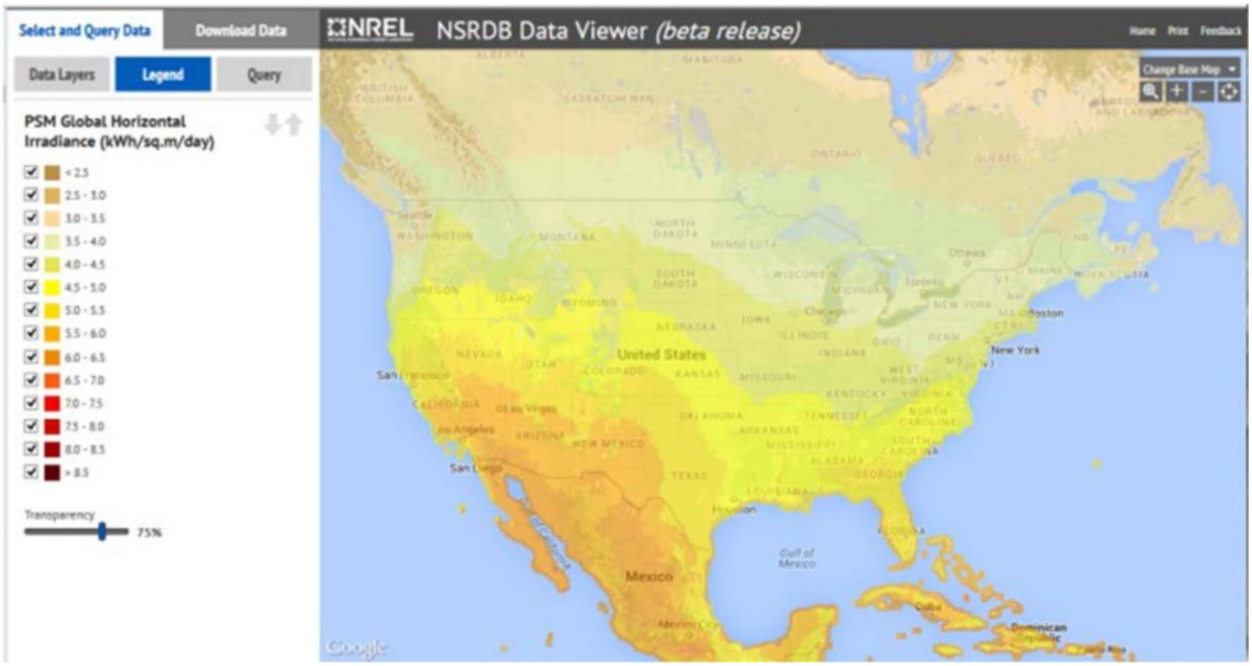

Fig. 2 Screen capture of NREL NRSDB data viewer with GHI displayed. Source: NREL solar data center

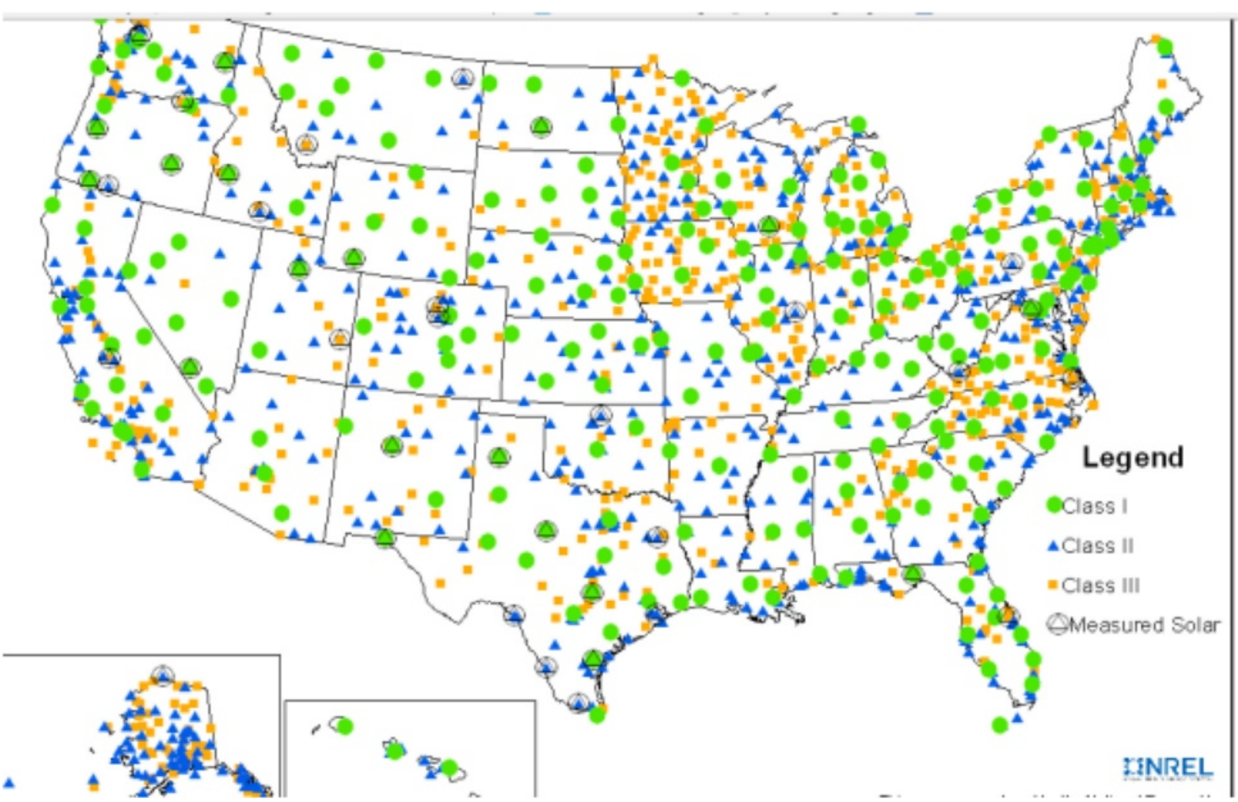

Fig. 3 NREL NSRDB stations

ground which can be determined from the geometric sum of the DNI and DHI [3]:

$$\mathrm{GHI} = \mathrm{DNI} * (\cos(\mathrm{zenith})) + \mathrm{DHI} \quad (1)$$

where zenith is the topocentric solar zenith angle measured in degrees. The DNI is of particular interest to concentrating solar power (CSP) projects since the DNI is the component of the solar radiation which can be concentrated and therefore of particular interest to this study for the operational performance analysis of the solar thermal power plant at UL Lafayette. Likewise, the GHI is of particular interest to photovoltaic (PV) projects as most PV installations are non-concentrating and are not dependent on direct beam radiation but of the total hemispherical radiation intercepted on the plane of the array.

Louisiana resides in an area of the USA where the solar resource is substantially less than that of the current commercial scale CSP installations of the Southwestern United States [9]. Figure 1 shows a map of the US Concentrating Solar Resource developed by the National Renewable Energy Laboratory (NREL), while Fig. 2 is a screen capture of the NREL NRSDB viewer displaying the GHI resource. Economical utilization of the solar resource in this region would significantly increase the footprint of viable areas for commercial development. According to the NREL model, Louisiana receives an average solar DNI resource between 4 and 5 kWh/m^2/day. NREL Typical Meteorological Year (TMY3) data [7] resulted in a median peak DNI for the 6 months beginning in April of 688 W/m^2 for the Lafayette area, with a 15 % error band. While these levels are substantially lower than those of the Southwester Unites States, the insolation still represents a significant level of energy. Indeed, based on the existing installed power capacity of Louisiana [10], one square mile of installed CSP projects would generate about 1 % of the current capacity, based on a solar-to-electric efficiency of 20 %. While there are currently several datasets available for prediction of the solar resource in Louisiana, these datasets almost exclusively rely on modeled data for their output [3, 6, 7, 11]. There is a significant need, therefore, to produce ground measured data to validate the various models under the specific and unique ambient conditions offered by the climate presented in south Louisiana. The work described in this paper provides the first available measured data in the geographic area under consideration and offers the first validation of available solar resource models for south Louisiana.

Available models

A few of the models available for predicting local solar resource will be discussed here for comparison with the data collected onsite in Louisiana. The National Solar Radiation Database (NSRDB) is widely available from several websites and is in the care of NREL. The NSRDB contains three versions of historical TMY data based on ground site models referencing cloud cover and other available information. Figure 3 is a map of the site locations used in the construction the database. Nearly all of the solar data in the original and updated versions of the NSRDB are modeled.

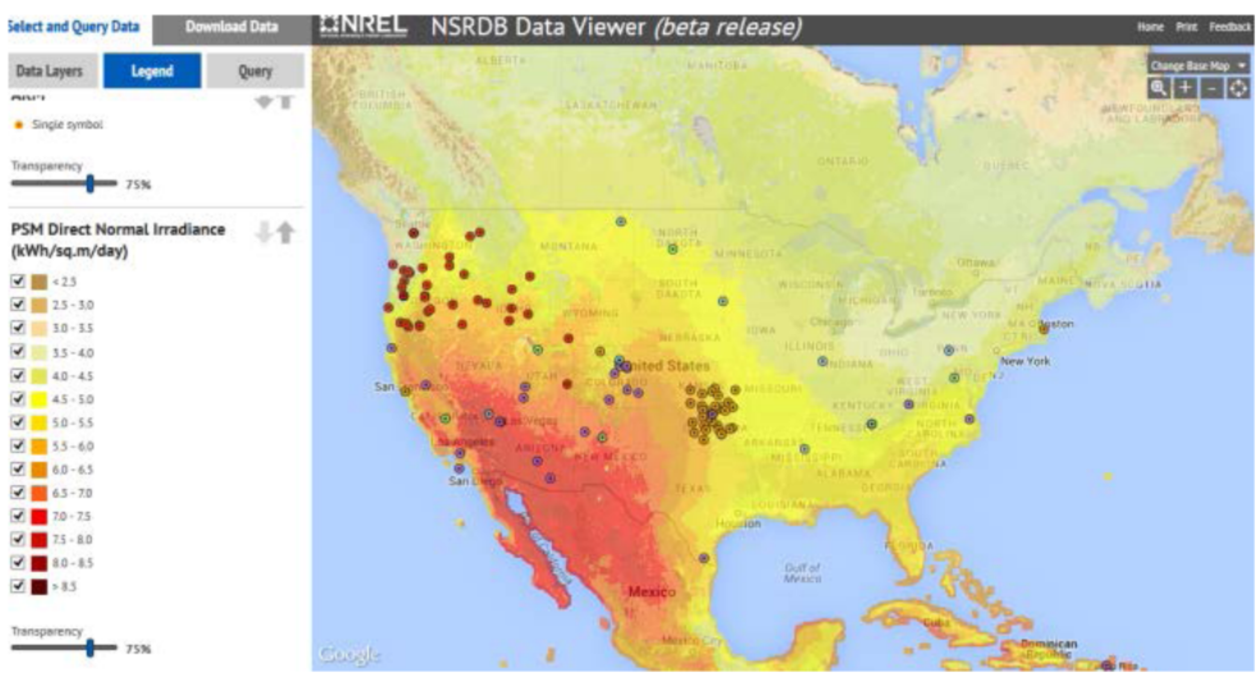

Fig. 4 Map of the TMY NSRDB ground measurement sites

The intent is to supply hourly values that, in the aggregate, will provide a statistical representation that closely approximate those of the measured solar data over the period of a month or year [6, 7]. The NSRDB does employ limited measured solar radiation and meteorological data. Figure 4 is a screenshot of the NSRDB viewer with the measurement sites identified. As can be seen, there are few measurement sites operating in the region of the country that Louisiana resides in. Two models that were used to complete the NSRDB datasets are the SUNY (State University of New York) model and the meteorological-statistical (METSTAT) model. The SUNY model, developed by Perez et al., is an operational model based on satellite imagery [12]. Available commercially from SolarAnywhere® through Clean Power Research, hourly resource data was also provided via SolarAnywhere® (SA) to NREL for free for the years 1998 through 2005. METSTAT is a hybrid operational-empirical model employing the METEOSTAT and GOES stationary satellites. The NASA surface radiation budget (SRB) is a freely available operational dataset developed from a cloud cover-based dataset and developed by Whitlock et al. [13] and providing 3 h, daily, or monthly averages and referencing a 22 year average [3].

The most recent NSRDB data, shown in the NSRDB data viewer utilizes the latest version of the SUNY model. This data provides monthly average and annual average daily total solar resource averaged over surface areas of 4 km in size. The data are generated using the PATMOS-X algorithms for cloud identification and properties, the MMAC radiative transfer model for clear sky calculations and the SASRAB model for cloud sky calculations [14]. The data are averaged from hourly model output over 8 years (2005–2012) with each year downloadable from the website for any user identified location. For all of the models, it should be noted that physics-based solar radiation models grounded in measurements can be no more accurate than the data used to generate the model and cannot be validated or verified to a level of accuracy greater than that of the measurements [15].

Fig. 5 Radiometer setup at the UL Lafayette START Lab

Methods

Weather station setup

Solar radiation measurements were taken onsite by a weather station consisting of a Kipp and Zonen SOLYS 2 Sun Tracker with CHP1 pyreheliometer and CMP10 pyranometers (Figs. 5 and 6). The SOLYS 2 sun tracker provides fully automated year-round two-axis tracking of the position of the Sun with a pointing accuracy of less than 0.1°. It has Baseline Surface Radiation Network (BSRN) levels of performance and reliability. Mounted on the SOLYS 2 is a CHP1 pyrheliometer which fully complies with the most current ISO and World Meteorological Organization (WMO) performance criteria for First Class Normal Incidence Pyrheliometer with a World Radiometric Reference (WRR) calibration certificate. For a first-class pyrheliometer, the WMO limits maximum errors to 3 % for hourly radiation totals. In the daily total, an error of 2 % is expected because some response variations cancel each other out for longer integration periods. Kipp and Zonen, however, anticipate maximum uncertainty of 2 % for hourly totals and 1 % for daily totals for the CHP1 pyrheliometer [16]. The CHP1, installed in July of 2013, provides a measure of the DNI or the direct beam portion of the solar spectrum which can be concentrated for conversion to thermal energy. The CMP10 Secondary Standard pyranometer was then installed in November of 2014 to measure the global horizontal irradiance, a measure of the total (diffuse + direct) radiation reaching the surface. For a "high-quality" pyranometer, the WMO expects maximum uncertainty error for the hourly radiation totals of 3 % and errors in daily totals less than 2 % [17]. Also installed is a second CMP10 pyranometer to give a direct

Fig. 6 Radiometer setup at the UL Lafayette START Lab

measurement of the diffuse potion of the spectrum, installed in December, 2014. A Campbell Scientific CR1000 provides data logging and wireless data streaming to the nearby Cleco Alternative Energy Center. Until now, the closest proximity measured data available for local solar resource measurement and prediction was in Lake Charles, LA, about 100 miles to the west. For measurement of the ambient conditions, a Davis Vantage Vue wireless meteorological weather station is also located within the START Lab. The Vantage Vue provides all the necessary meteorological data for proper evaluation of the solar technologies on site and wirelessly steams and logs the data within the Cleco Alternative Energy Center. Data including ambient temperature, humidity, barometric pressure, wind speed, wind direction, rainfall, and dew point are constantly monitored and recorded. This method of collecting and combining meteorological data from a weather station with DNI from a tracking pyrheliometer and DHI and GHI from pyranometers is an industry standard. Similar active sites can be examined through the NREL Measurement and Instrumentation Data Center (MIDC) website [18].

Data comparison

The data presented here represents about 2 years of collected DNI data at the Louisiana START Lab with about 6 months of collected GHI data. Here, we shall discuss the results of these measurements and their statistical relationship with some available modeled data. Figure 7 gives the results of hourly averaged DNI values aggregated into monthly averages for all available measured

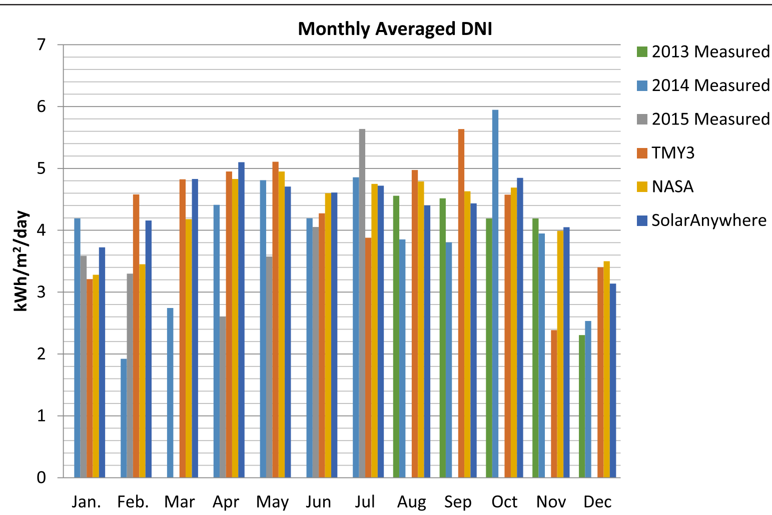

Fig. 7 Hourly averaged DNI values aggregated into monthly averages for measured and modeled data

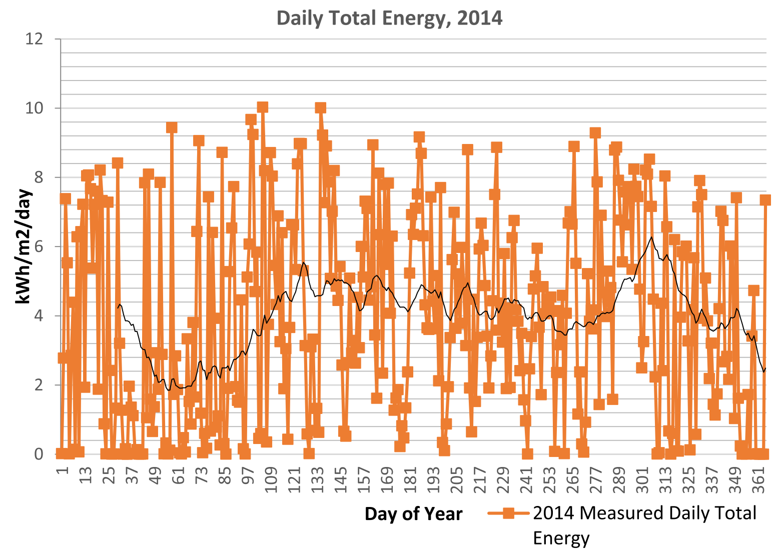

Fig. 8 Daily direct beam energy totals for the 2014 calendar year

and modeled data. The modeled datasets include the TMY3 dataset, the SA dataset, and the NASA SRB dataset. The figure highlights the seasonal variability over the model year as well as the climatic variability year-to-year. As can be seen for the February daily average from the 2 years of measured data, the local weather variations can generate large fluctuations in short-term solar availability. Figure 8 shows the actual daily direct beam energy totals for the 2014 calendar year. Included is a 30-day trend line to relate the daily data points to the monthly averages. The variability in daily totals illuminates the difficulty in short-term resource predictions, as well as the number of days with virtually zero solar availability. The daily minimums play an important role in the operating strategy of a solar plant, especially in the start-up logic.

The annual average solar resource from the measured data was 3.95 kWh/m^2/day while for the TMY3 data, it was 4.31 kWh/m^2/day. However, when excluding February and March, which in 2014 had what appeared to be abnormally low numbers of clear days, the annual averages narrow to 4.255 and 4.24 kWh/m^2/day for the measured and modeled data, respectively. When examining the inter-annual variability, we should see a stabilization to a long-term value as the number of years of data is averaged. This was shown by Gueymard and Wilcox [19] for annual resource data, but should also hold true for monthly resource data. The monthly averaged daily GHI totals are plotted in Fig. 9 for

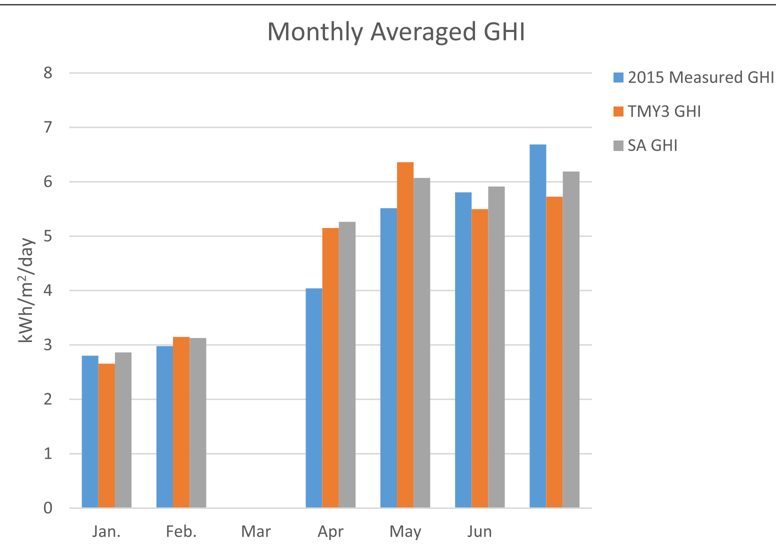

Fig. 9 Modeled and measured monthly averaged daily GHI totals

Table 1 Statistical metrics for comparison of various modeled DNI data with measured data

DNI	TMY3 hourly (W/m^2)	SA hourly (W/m^2)	TMY3 daily (kWh/m^2/day)	SA daily (kWh/m^2/day)	TMY3 monthly (kWh/m^2/day)	SA monthly (kWh/m^2/day)	NASA monthly (kWh/m^2/day)
RMSE	379.482	392.9972	3.6315	3.7868	1.3958	1.0216	0.8980
NRMSE	0.3814	0.3950	0.3564	0.3717	0.2347	0.1718	0.1510
MAE	247.08	258.82	2.9477	3.0805	1.1972	0.7596	0.7479
MBE	15.0	18.72	0.3541	0.4489	0.3821	0.4585	0.3686
K-S test	0.0000		0.0050	0.0020	0.5180	0.5180	0.5180

the measured data and the TMY3 dataset for available months in 2015. It should be noted here that the month of March along with a short period in February were not available due to maintenance of the weather station. The measured and modeled GHI show much better agreement, which is to be expected since the GHI has less dependency on hourly cloud clover variations.

There are currently several statistical metrics which have been proposed to quantitatively correlate and validate the measured and predictive solar radiation data [4, 10, 20–22]. The root-mean-squared error (RMSE) provides a global error measure across an entire forecasting period and is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{\mathrm{mod.},i} - I_{\mathrm{meas.},i}\right)^2} \tag{2}$$

where $I_{\mathrm{mod},i}$ is the modeled irradiance value at time step i, $I_{\mathrm{meas},i}$ is the measured irradiance value at time step i, and N is the number of values under investigation. The normalized RMSE (NRMSE) is normalized by the maximum value for each measurement period and allows a relative comparison across the sampling period. The mean bias error (MBE) provides a measure of the average forecast bias, defined as:

$$\mathrm{MBE} = \frac{1}{N}\sum_{i=1}^{N}\left(I_{\mathrm{mod.},i} - I_{\mathrm{meas.},i}\right) \tag{3}$$

Additional correlation coefficients include the mean absolute error (MAE), to indicate the forecast performance:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|I_{\mathrm{mod.},i} - I_{\mathrm{meas.},i}\right| \tag{4}$$

Finally, the Kolmogorov-Smirnov test (K-S test) is a nonparametric test to determine if two independent datasets are significantly different, determining an absolute difference of the cumulative distribution functions, and employing a confidence level to test a null hypothesis. In this case, the null hypothesis is that the modeled data are well correlated to the measured data. For a K-S result of greater than 0.05, the hypothesis is assumed true. The results of all of the measures are tabulated below (Tables 1 and 2):

Results and discussion

When considering the global error metrics, it is convenient to compare the error relative to the quantities being analyzed. For reference, the maximum values pertaining to each case (hourly irradiance, daily and monthly average insolation) of DNI and GHI measurement are provided in Table 3, where the reference values used to calculate the NRMSE can be found and also used for similar relative comparisons of MAE and MBE. The TMY3 data outperformed the SA data for the hourly and daily case when considering DNI; however, the NASA database was the most accurate with the TMY3 data providing the least accurate forecast, when considering the data collected over the 2-year period. The MBE is a measure of the bias, in terms of over or under predicting the resource. In every instance, the MBE indicated that the model slightly over-predicted insolation. The bias was small, especially when comparing each MBE as a percentage of the MAE, a global error metric that is not as influenced by extreme weather events as the RMSE. The K-S test shows that prediction on an hour-to-hour and day-to-day basis proves difficult for the DNI case; however, a month-to-month prediction gives statistically well-correlated results with the measured data. For the GHI case, a daily prediction is possible because of the lower reliance on predicted cloud

Table 2 Statistical metrics for comparison of various modeled GHI data with measured data

GHI	TMY3 hourly (W/m^2)	SA hourly (W/m^2)	TMY3 daily (kWh/m^2/day)	SA daily (kWh/m^2/day)	TMY3 monthly (kWh/m^2/day)	SA monthly (kWh/m^2/day)
RMSE	202.3308	346.8822	2.1496	2.0313	0.7089	0.5905
NRMSE	0.1900	0.3257	0.2671	0.2524	0.1060	0.0883
MAE	110.9713	222.8374	1.5233	1.4737	0.5898	0.4321
MBE	4.8751	11.3210	0.0961	0.2231	0.1175	0.2662
K-S test	0.0000		0.6370	0.8110	1.0000	1.0000

Table 3 Maximum quantities of irradiance and insolation for different cases

	Hourly (W/m^2)	Daily (kWh/m^2/day)	Monthly (kWh/m^2/day)
DNI	995	10.189	5.95
GHI	1065	8.048	6.687

cover. Overall, there was good correlation between each of the models and the measured data.

For reference, Djebbar et al. [22] reported DNI average hourly MBE and RMSE of 28.5 and 133.7 W/m^2 (67.2 %) for SUNY V3 beta models from an averaged result of three sites across Canada. Here, the percentage data can be taken as equivalent to the NRMSE. Also reported were the daily results of 8.4 MBE and 30.4 RMSE (52.1 %) and monthly results of 8.5 MBE and 15.1 RMSE (25.8 %) (all in kWh/m^2/day). Additionally, values were computed for GHI average hourly MBE and RMSE of 5.6 and 86.5 W/m^2 (27.8 %) for SUNY V3 beta models from an averaged result of 18 sites across Canada. Also reported were the daily results of 0.1 MBE and 0.5 RMSE (15 %) and the monthly results of 0.1 MBE and 0.2 RSME (6.7 %) (all in kWh/m^2/day). Virtually, all the results from the Louisiana location models compare favorably to the results obtained by Djebbar for the Canadian location.

Impact to CSP operation

A primary concern for the UL Lafayette START lab is the predicted performance of the pilot solar thermal power plant located at the facility. The single-axis tracking parabolic troughs are oriented on a north-south axis and therefore will invoke a cosine error to the solar incidence. The cosine effect adjustment has been calculated utilizing the NREL solar position algorithm (SPA) and applied to the measured and modeled DNI for 2014 [23, 24]. Figure 10 shows the monthly averaged output as well as the monthly averaged cosine effect adjustment, as a percentage of the full DNI. It can be seen that the spring and fall months are the most advantageous in terms of cosine effect adjustment.

Based on operating experience of the solar thermal power plant, a minimum DNI level of 400 W/m^2 is preferred prior to the start-up of the facility. Based on a requirement of at least 1 h of the minimum DNI for operation, there were 273 actual days of possible operation in 2014, resulting in 1719 h with an average DNI of 679 W/m^2. Figure 11 plots the predicted daily energy delivered by the solar thermal power plant based on the TMY3 dataset, the cosine adjustment, estimated efficiency, and aperture area (1050 m^2), while Fig. 12 gives the monthly total energy output, a more stable predictor. Due to experimental and testing operations, the solar thermal power plant has not yet operated during every available resource day, preventing the generation of measured data to compare to the modeled data over the course of months or a year. However, based on the statistical quality of the solar resource data, the predicted plant values can be reliably employed.

Impact to PV operation

The current primary generating method for solar energy in Louisiana is through PV conversion. This generation is through residential and commercial rooftop installations, as there are currently no industrial scale installations of solar power plants of any kind in Louisiana. The implications of the solar resource data with regards to PV residential and

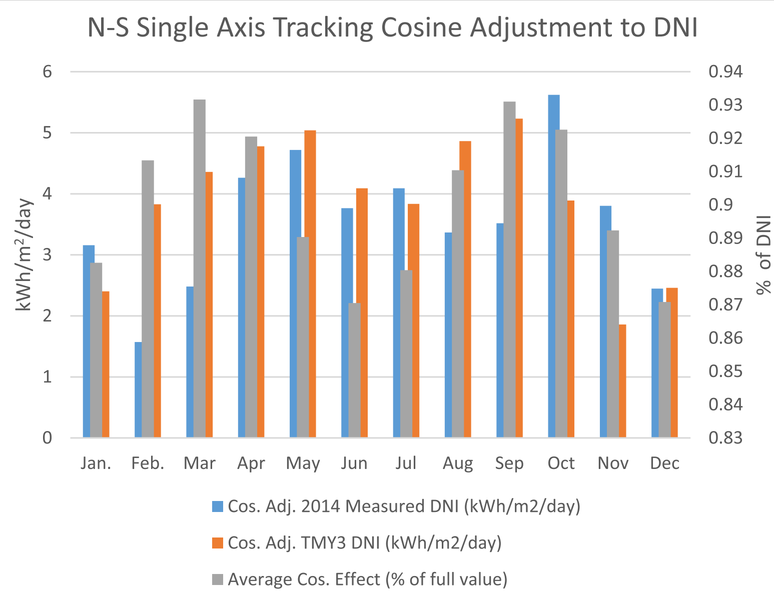

Fig. 10 Cosine adjustment to DNI, N-S tracking single axis concentrator

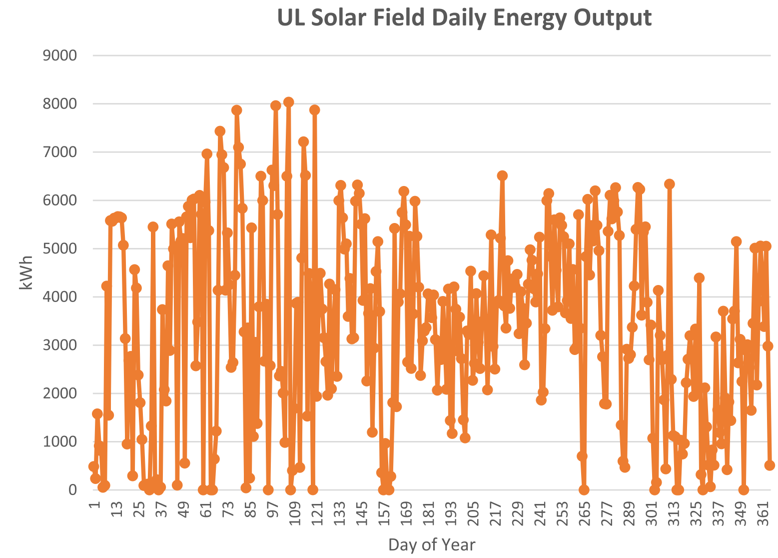

Fig. 11 Predicted daily energy delivered, TMY3 dataset

commercial installations lie with the GHI metric. As most PV installations are non-concentrating, the GHI component of the solar resource is the primary source of comparative data. The GHI values for south Louisiana vary less from the higher solar resource areas of the Southwestern United States than the DNI values, due to the fact that the GHI is less sensitive to transient cloud cover. For example, based on NSRDB data, the ratio of Louisiana DNI to that of the most solar-rich areas of the country is about 0.6, while the ratio of GHI for the same areas is about 0.75. For this same reason, there should be less variance from year-to-year for a given month in a given location. The results of the comparison of modeled to measured values have limited efficacy due to the limited data acquired thus far, yet it can be clearly seen that the GHI modeled data provides a better forecast than the DNI, when comparing the NRMSE, MAE, and the K-S test. There was a positive MBE, indicating a slight over-prediction of solar resource by the models; however, the bias was small.

PV does not require a minimum radiation level for start-up; therefore, the power produced is primarily a function of the system efficiency, the insolation and panel orientation. Actual PV production data was not available at the time of this study; however, it will be presented in future work.

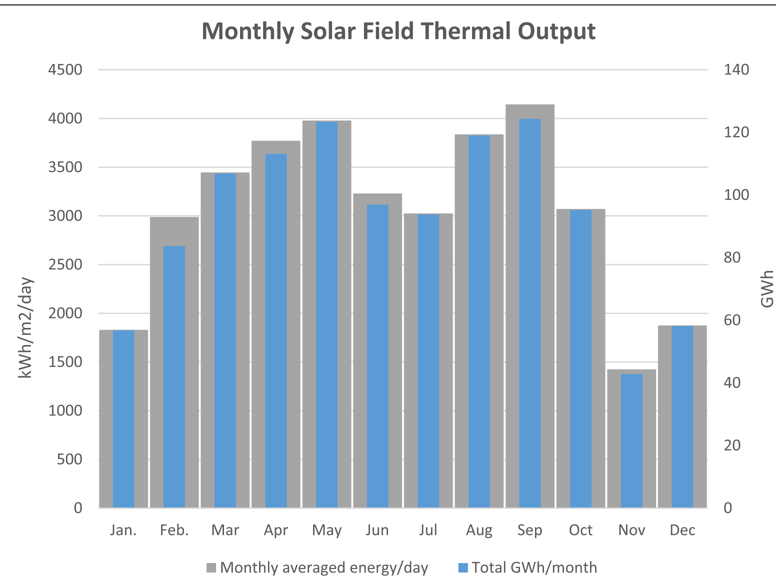

Fig. 12 Predicted monthly energy delivered, TMY3 dataset

Conclusions

This paper has provided the results of 2 years of high-fidelity solar resource measurements for a location in south Louisiana that was previously not available. The data was compared to modeled data from various sources. The measured data showed that high peak irradiance values were available for single days (10 $kWh/m^2/day$) and monthly averages (6 $kWh/m^2/day$), higher than the maximums produced by models available for the same location. In addition, high variability in year-over-year monthly DNI due to cloud cover was prevalent, with as much as a 70 % difference in monthly DNI values observed in the measured data. When comparing the measured data to the modeled data, an over 100 % difference could be seen in the expected DNI. A more consistent global horizontal irradiance (GHI) level was observed since the GHI is less susceptible to cloud cover transients. Collected data showed statistically good agreement with several existing datasets including those available from the National Solar Radiation Database (NSRDB) when forecasting was for monthly and yearly intervals.

The measurements presented here were made in Crowley, LA, and therefore, the radiation measurements are relevant to that location only. The size of the area to which the measurements are relevant is limited by the variance in local weather conditions and will fluctuate with weather patterns, which would dictate a need for a unique station for each commercial or industrial scaled deployment of solar power in order to capture real-time performance. Over longer time scales (months and years), larger areas between stations can be allowed while maintaining fidelity and definition of measurement.

Future work

Additional seasonal comparisons can be made to determine the stability of long-term seasonal predictions which can be important in operational strategies. Furthermore, due to the inherent variability in the year-to-year data, the question of how many years it will take before the solar radiation components stabilize and converge to their long-term value is an appropriate one. This question was addressed by Gueymard and Wilcox [19] among others, and as data is added to the START lab database, an evaluation of this metric can be made accurately. It was found that for the Eugene, Oregon, area the DNI anomaly levels only converged within ±10 % after 5 years of data and approached ±5 % after 10 years of data. The GHI anomaly was within 5 % after 2 years of data and was within 2 % after 15 years of data availability. Also addressed by Gueymard and Wilcox was the magnitude of the inter-annual variation, which was found to fluctuate from region to region. Additionally, a relationship between the monthly averaged expected DNI values and the clear sky days will be investigated along with other cloud cover data to gain a better understanding of the local weather influence on anticipated solar resource. Finally, long-term data on actual solar thermal collector and PV array output will be aggregated and correlated with predicted values for the further validation and refinement of operational models.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

The article was jointly prepared by all authors. All authors read and approved the final manuscript.

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