THE ROAD TO BANKABILITY: IMPROVING ASSESSMENTS FOR MORE ACCURATE FINANCIAL PLANNING

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ABSTRACT

This paper discusses and demonstrates methods for significantly reducing production estimation errors and bias by combining satellite derived irradiance values with available short-term surface observations. Results show how combining micro-scale site information, such as aerosol optical depth measurements and local irradiance observations, with long-term satellite irradiance data significantly improves the accuracy of solar resource estimations and provides more confidence in financial planning. Problems associated with the popular use of TMY data are also discussed.

1. INTRODUCTION

Solar resources are highly variable, both spatially and temporarily. In the latter case, it is possible to separate the short-term basis (e.g., due to the passage of clouds) and the long-term basis (e.g., due to natural climatological cycles, resulting in “good years” and “bad years”). For the U.S. in particular, Gueymard in 2011 [1] provided an in-depth analysis of both the spatial and interannual variability in the main irradiance components for solar energy applications: direct normal irradiance (DNI), global horizontal irradiance (GHI), and global tilted irradiance (GTI). The interannual variability in GHI and DNI constitutes the focus of the present contribution.

Once a promising site for solar development is identified, a more in-depth analysis is required to better quantify the long-term availability of the solar resource, to design technical aspects of the project, and to secure the upfront capital for construction. This is particularly true for large solar projects, since the risks associated with the servicing of debt during “bad years” must be assessed and validated.

2. LONG-TERM VARIABILITY

Year-to-year variability has a significant impact on annual energy production. For example, Figures 1 and 2 show the annual variability for two sites: Carpentras, France and the Marshall Islands, respectively. These graphs show that at both locations for either GHI or DNI there will be years that are above the long-term mean and years that are below. This is true even in areas known to have a strong solar resource, where solar projects are actively developed, such as the southwest U.S., north and south Africa, India, and Australia. Recognizing this variability and building it into financial modeling *before* making any significant investments or breaking ground is key to the commercial success of a project.

Using long time series of high-quality measured or modeled data, it is possible to analyze the interannual irradiance variability, as was shown in [1]. There are various causes for this variability, and various ways to analyze it. Here, the annual total of GHI and DNI are simply divided by their long-term mean to obtain an annual anomaly in percent of the mean. For sites with significant cloudiness, and therefore low potential for concentrating solar projects (but still good potential for flat-plate collectors, whose resource is characterized by GTI), it is observed that a relatively high variability exists for both GHI and DNI, mostly due to natural variations in cloudiness. This is shown in Fig. 3 for Eugene, Oregon, using measured data from the University of Oregon’s network. At this location the long-term daily mean GHI and DNI are 3.8 and 3.7 kWh/m^2, respectively.

At sites with a somewhat clearer atmosphere, such as Burns, Oregon, the variability results from a combination of cloudiness and aerosol load (Fig. 4). In both Figures 3 and 4, the yellow area indicates a range of ±5% around the long-term mean (4.6 kWh/m^2 for GHI and 5.5 kWh/m^2 for DNI), and the two upward arrows indicate the intense volcanic eruptions of El Chichon and Pinatubo. Note the different anomaly patterns between the two stations. Even though they are only 330 km apart, they are not in the same climate zone.

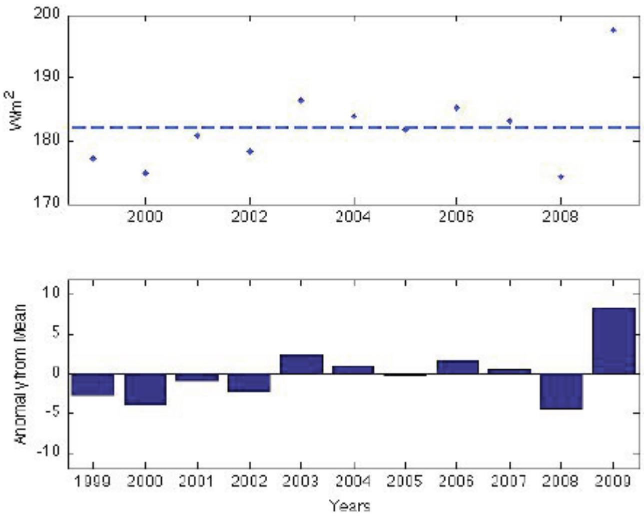

Fig 1: Variability of global irradiance at Carpentras, France. The blue dashed lines show long-term averages from ground observations while the blue dots indicate the individual annual averages. The annual total GHI varies between -5% and +8.9% of the long-term mean.

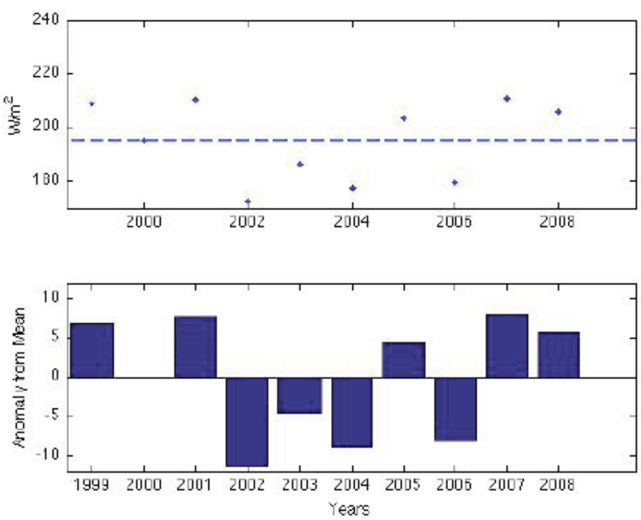

Fig 2: Same as Fig. 1, but showing DNI at the Marshall Islands. The variability in the annual total here is between -12% and +8% of the long-term mean.

Comparatively long series of radiation measurements are currently not available for sites in arid areas, where many large solar projects are currently being projected. This is unfortunate, but it can be argued that the variability there would be mostly caused by natural changes in aerosol concentration, which has a large seasonal variability [2].

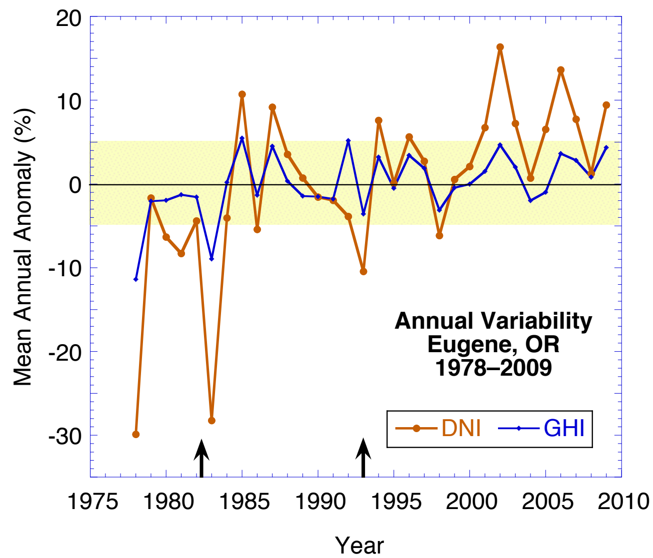

Fig. 3: Variability of GHI and DNI at Eugene, OR.

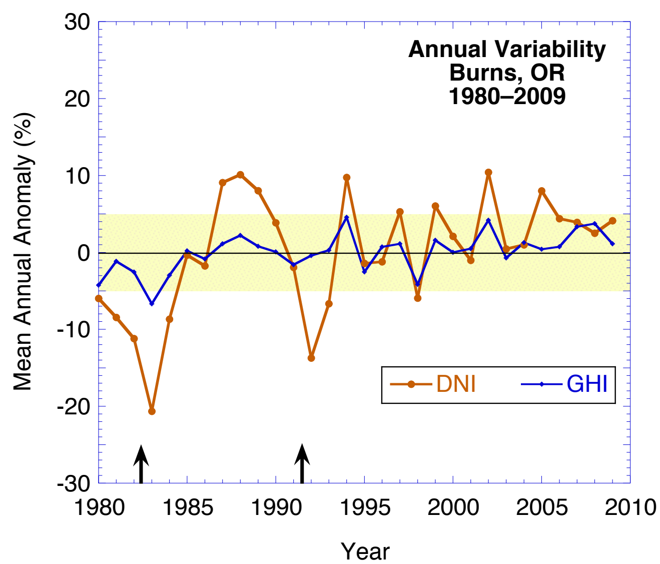

Fig. 4: Variability of GHI and DNI at Burns, OR.

Many financial and rating institutions, as well as internal certification organizations, require 1-year P90 exceedance probability values to assess the economic feasibility of a project. A 1-year P90 value indicates the production value that the annual solar resource will exceed 90% of the time. A 1-year P90 value (as opposed to a 10-year P90 value) is typically mandatory because most solar projects have a lending structure that requires them to service debt one to four times a year, not one to four times every 10 years. If power production decreases significantly in a given year due to solar variability, debt on the project is at risk of being defaulted—which is precisely what financiers are trying to avoid. The only way to determine 1-year P90 values acceptable to funding institutions is with long-term continuous data at the proposed site.

3. TYPICAL METEOROLOGICAL YEAR (TMY)

At the design stage of most solar systems, it is customary to use design tools (such as NREL's PVWatts and Solar Advisor Model software) or more complex system simulation software (such as TRNSYS) to obtain information on the system's operation, estimate its power output, optimize its design, and prepare financial projections. Most of these design tools are built to use hourly data from a Typical Meteorological Year (TMY), i.e., a single synthetic year specially developed to provide 8760 hourly values of the most important variables (including GHI and DNI). Statistical methods are used to select the most "typical" month out of a series of 30 years of actual (measured or modeled) data. This approach is appealing to all designers since they can do hourly simulations of complex systems 30 times faster than if they had to do that over 30 "real" years.

Although the TMY approach has many advantages, it must be noted that it is not a perfect tool. Since "extreme" years are intentionally excluded from consideration in the construction of TMYs, these datasets should not be used for financial projections of debt servicing. The risk of "bad years" and the amount of power that can actually be produced under adverse circumstances is precisely what needs to be assessed. TMYs are specifically constructed so that their frequency distribution of all variables approaches their long-term counterpart. Because of the inherent variability in GHI and DNI, a TMY frequency distribution may not always be appropriate to represent the solar resource, particularly during bad years. This is demonstrated in Fig. 5, where actual DNI cumulative frequency distributions from 15 individual years (1991–2005) of measured data at Golden, Colorado are compared to that obtained from the corresponding TMY3 file developed and distributed by NREL. Note that this period does not include any major volcanic eruption. The actual spread for a 30-year period, such as 1981–2010, would therefore be much larger.

NREL's TMY2 files are constructed from modeled GHI and DNI data throughout the period 1961–1990, which encompasses the El Chichon eruption. The mean daily DNI for each year deviates more or less from the TMY2 value. The distribution of these 30 yearly totals at Boulder, Colorado appears in Fig. 6. The TMY2 mean DNI is 5.5 kWh/m^2, whereas the individual annual totals vary from 4.34 to 5.99 kWh/m^2. For that specific location, the TMY2 value corresponds quite exactly to the 50th percentile (P50 or median) of the distribution. The P90 and P95 probabilities of exceedance correspond to much lower values, 11% and 16% below the TMY2 value, respectively. This confirms why TMY data should not be used to derive bankable reports of financial projections.

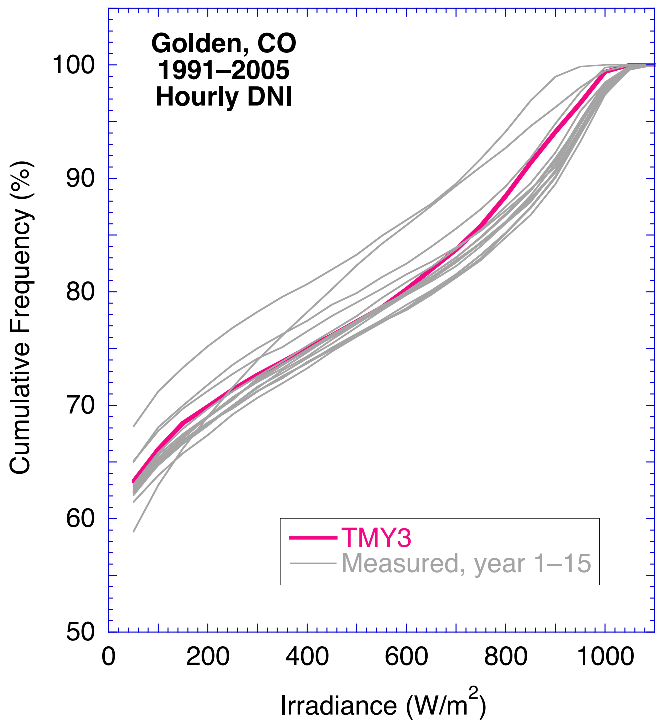

Fig. 5: Cumulative frequency distributions of hourly DNI at Golden, CO from 15 years of measured data and from the TMY3 file for that site.

4. AEROSOLS

Micro-scale site information, such as aerosol optical depth measurements, can also be incorporated into the analysis to significantly improve the accuracy of solar resource estimates and further reduce uncertainty and enhance bankability.

The radiative effects of aerosols are a function of different variables. The most important one is called the aerosol optical depth (AOD), which varies widely with wavelength. For precise DNI modeling, values of AOD at various wavelengths would be required each hour at any location, which is currently a nearly impossible challenge. The prediction of GHI is less of a problem, since it is much less sensitive to AOD than DNI. Since many large solar projects use concentrators, they must rely on DNI as their only fuel, and hence must also cope with the inherent uncertainties in DNI caused by difficulties in obtaining consistent and accurate AOD data for the duration of the whole time series.

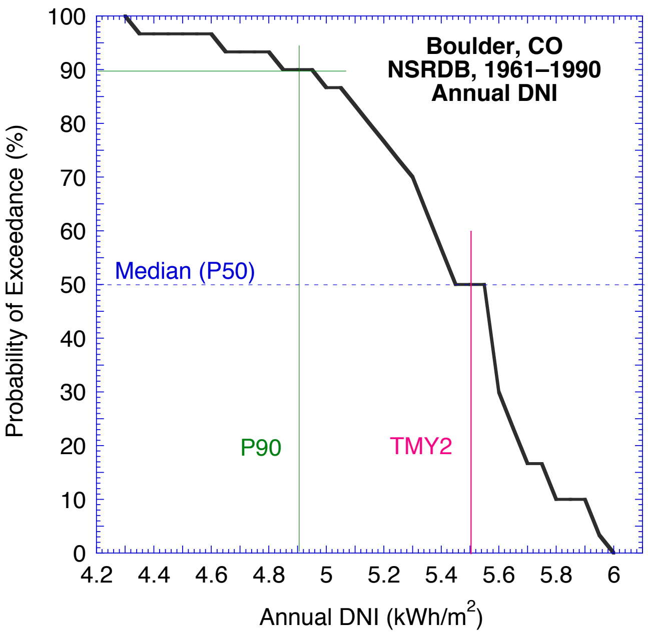

Fig. 6: Annual DNI's probability of exceedance over the period 1961–1990 at Boulder, CO vs. the TMY2 value.

As shown in a recent study [2], relatively good DNI predictions are generally obtainable for sites in southern Europe. Serious problems, however, are found at various sites in North Africa and the Middle East. Most of these problems appear linked to inadequate AOD data used by the models, and to the dust storms from the Sahara that regularly, and strongly, modify the aerosol regime. That study introduced a proposed method that can potentially correct these problems, or allow for model benchmarking based on a reference aerosol database. Without model inputs based on high-quality AOD data in areas subjected to highly variable and frequently strong aerosol episodes. When using irradiance data for financial projections, it is strongly recommended that the effects of aerosol optical depth be analyzed to ensure a proper understanding of the variability and uncertainty of the solar resource.

5. ASSESSMENT PRACTICES

A combination of short-term ground measurements and long-term satellite-derived irradiance modeled values is ideal for assessing variability and project risk.

If collected properly, surface observations can provide very accurate measurements of solar radiation at high temporal resolution, but few developers want to wait the 10+ years required to develop a 1-year P90 value. In addition, the present global network of solar surface observations does not provide adequate information to quantify solar resources at most potential sites. This is because a vast majority of surface observations only provide a limited short-term record of the resource (months to a few years), are rarely located near proposed sites, and are often plagued with measurement errors or substantial periods of missing data.

In order to calculate the variance of production values, it is necessary to have a long-term record of solar irradiance estimates. Just like TMY data is not sufficient to understand interannual variability, an *average* annual irradiance value simply does not provide sufficient data to determine accurate annual exceedance probabilities. Therefore, it has become an accepted practice to calculate the long-term surface solar irradiance values at a site using geostationary satellite data [3]. Within the global atmospheric science community, satellite-derived data is known to be the most accurate measurement of ground irradiance beyond ≈25 km of a ground station [4].

Satellite modeling uses visible satellite imagery to calculate the level of cloudiness at the Earth's surface. The resulting time series of cloudiness (or 'cloud index') is then combined with other information to model the amount of solar radiation at the Earth's surface. The result is a long-term record that provides hourly estimates of surface irradiance (GHI, DNI, and Diffuse Horizontal Irradiance) and can be consistently replicated for all of the Earth's landmass. The spatial resolution needed from the dataset is dependent on the spatial variability of the terrain at any specific project site. (Spatial irradiance variability over the U.S. is addressed in [1].)

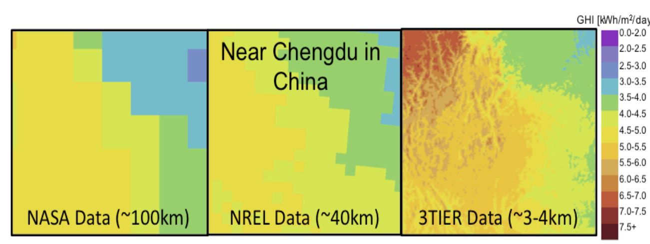

Fig. 7: In regions of low spatial variability, use of low-resolution resource maps (e.g., 100 x100 km) is acceptable for preliminary design. Conversely, in regions of high spatial variability, only high-resolution maps (10 x10 km or better) should be used.

Satellite-derived irradiance values can accurately provide a long-term, hourly time series of data without the expense and wait associated with measurements. However, satellite data cannot always capture the micro-scale features that often affect a specific site, such as highly variable elevation or surface albedo. Therefore a combination of short-term ground measurements and long-term satellite derived irradiance values is ideal for assessing resource variability and project risk.

One method of combining short-term ground measurements with longer-term satellite data is a technique known as *model output statistics* (or MOS). 3TIER's MOS algorithm can significantly reduce error and bias by statistically correcting the modeled satellite data to the environmental context of a particular site based on available surface observations—particularly GHI and/or DNI.

MOS is a multi-variate linear regression analysis between a prescribed set of predictors and the surface observational data. This method has been used successfully in many meteorological applications since the 1970's [5]. In this case the set of predictors includes the raw satellite-derived irradiance data, as well as meteorological variables from a Numerical Weather Prediction (NWP) simulation. A subset of the predictors is chosen using multiple statistical criteria to maximize the explained variance of the surface observational data. The primary result from the MOS algorithm is a multi-linear regression equation that is designed to remove bias and adjust the variance of the raw satellite-derived data as compared to the surface observational data. Since the MOS equation does not depend on the surface observational data directly, the MOS correction may be applied to the full time series of satellite-derived data.

Figure 8 shows an example of where MOS correction was able to improve a systematic bias in the satellite record. At Desert Rock, Nevada in 2008 there was a 2% low bias in the satellite record as compared to ground observations from NOAA's SURFRAD network. Using one year of actual ground data (2008), the MOS method allows to statistically correct for the bias and to apply this correction across the 10-year satellite record. Since this correction is dynamic, its magnitude varies from year to year. The important result is that, after correction, the time series has virtually no bias compared to actual measurements.

For applications in solar project development MOS corrections can be done using either GHI or DNI values depending on what observations were taken and whether the final project is a flat-plate photovoltaic or concentrating project. The observations have a direct impact on how well the statistical model corrects for local conditions, which makes quality observations key to the process. A year of ground observational data is preferred for training MOS in order to get a picture of seasonal patterns. However, corrections can be done with less data with some success at six, or even four, months, if seasonal variability in AOD is not too large.

Being able to correct for local conditions is important when using satellite-derived data as the long-term record because of deficiencies in satellite imagery. These include the tendency of satellite image interpretation algorithms to resolve bright areas or snow cover as clouds, the effects of microclimates, and the inability to resolve much of the effects of aerosols at a local level. Statistical corrections, such as MOS, can correct for most known satellite-related problems with the use of high-quality local observations. A long-term MOS-corrected time series is valuable for understanding the inter-annual variability of the solar resource, and thus also helps to reduce the uncertainty when making financial projections

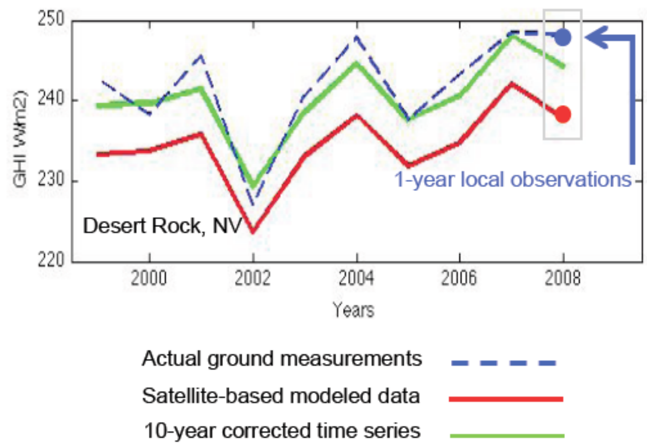

Fig. 8: Variability of GHI at Desert Rock, Nevada. The blue dashed line shows annual averages from ground-based surface measurements, the solid red line indicates 10 years of satellite-derived GHI estimates for that location, while the green line shows MOS-corrected satellite data using one year of surface observations in 2008.

6. CONCLUSION

The development of solar projects has expanded significantly and appears to have a promising future. However, even the best locations are not immune to normal year-to-year variations in solar irradiance, which have a corresponding impact on power production and the ability of the project to service its debt. Long-term records of 10 years or more, not TMYs, are necessary to understand annual variability and are often required by financial institutions.

While on-site observational data is able to capture the localized nuances of solar irradiance at a particular location, they typically do not provide the long-term perspective that is required. Satellite derived solar datasets accurately capture year-to-year fluctuations, but may miss micro-site effects at the project site such as the effects of aerosols. A solar resource assessment, performed by an experienced analyst, combining both on-site observations and long-term satellite derived data greatly reduces uncertainty, and provides the "bankable" production estimates that are typically required to secure funding for a project.

7. REFERENCES

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