Observed Recent Trends in the Solar Resource across North America: Changing Cloud-cover, AOD and the Implications for PV Yield

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Abstract — This study was prompted by recent low-resource years in the eastern US observed in the SolarAnywhere[®] dataset. Herein, we investigate 20-year trends in GHI and clear-sky GHI for every latitude/longitude pair in the continental United States. Metrics we calculate are 20-year rate-of-change, means, and interannual variability. We also look at the changes in GHI attributable to changes in AOD over this time-period. Thanks to accurate remote sensing, we can now provide this useful information. Our analysis also provides a solar industry perspective by quantifying the trends in potential kWH_{AC}/kW_{DC} for PV across the same regions; trends influenced largely GHI but also by temperature. These trends are not only important to understand from a bankability and performance assessment perspective for solar energy applications but also for future planning.

Index Terms —solar resource, bankable data, future planning, performance assessment, trends, climate change.

I. INTRODUCTION

Surface-level downward shortwave radiative flux at any given location on the planet is contingent on a number of deterministic and stochastic factors: the rotation of the earth around the sun and about its own tilted axis, variability of the extraterrestrial solar resource, cloud thickness driven by macro- meso- and micro-scale weather phenomena, the atmospheric optical depth (AOD) and water vapor content in the upper atmosphere. In this paper, we investigate the macro- and meso-scale trends in global horizontal irradiance (GHI) and clear-sky global horizontal irradiance GHI_{CLR} at the annual timescale across 20 years, from 1998 through the end of 2019. GHI_{CLR} is reflective only of the radiative transfer attenuation stemming from AOD and water vapor while GHI is reflective of both of these plus the attenuation from clouds.

SolarAnywhere's (SA) satellite-based hourly-interval irradiance dataset is sampled across 832 1°x1° tiles arrayed evenly across the ConUS. During the considered 20-year period, mean and extreme temperatures have moved upward – one of the many global warming trends observed worldwide. Here we explore whether this documented thermal trend is matched by changes in surface and clear-sky solar resource over the same period. This question is of interest to PV financiers, developers and asset managers to assess the risks associated with any predicted future cashflows.



Figure 1: 365-day moving average of GHI (W/m²) at Eureka, California. Red line shows annual averages while blue line and shaded region shows linear trend with 90% confidence interval.

II. CASE STUDY: EUREKA, CALIFORNIA

As an example to demonstrate the method we will use to investigate trends across the ConUS, consider Eureka, CA. 365-day moving average irradiance at this site is pictured in Figure 1. GHI's inter-annual variability exhibits a standard deviation of 6.7 W/m² about a mean of 163 W/m² (+/-3.9%). While this does not jump out as particularly drastic, a linear trend (fit using QR decomposition to solve the linear least-squares equation) indicates a rate of change of roughly +14 W/m² or +9.2% across 20 years. If a PV project developer selected the long-term average as a benchmark to forecast project revenue, the +9.2% in yield across this period, if persistent, would drive +6.4% increased yield across its (30-yr) lifetime. A welcome surprise.

This method of calculating 20-year rate-of-change is applied to every site across the ConUS for both GHI and CHI_{CLR}.





III. REGIONAL TRENDS ACROSS THE CONUS

Over the last 20 years, we indicate the typical insolation in W/m^2 across the ConUS in Figure 2. As expected, the areas of the country with the highest insolation (with the exception of Hawaii) are concentrated in the southwest, owing to their desert climatology. Correspondingly, Figure 3 shows the long-term average of GHI_{CLR} across the ConUS. The distribution follows a similar spatial distribution as GHI but the magnitude is much greater owing to the removal of cloud reflection and absorption implicit in this metric.



Figure 3: Average Clear Sky Insolation: 20-year mean GHI_{CLR} (W/m2) across the ConUS interpolated to 0.1° from 1° SA data.

In the lower left corner of both Figures, the mean for each parameter is listed, as is the spatial standard deviation. As evident both visually and by way of these parameters, cloud absorption and reflection diminishes solar flux by an average of 24% past what is already reduced from the impact of AOD and water vapor. These meteorological factors also introduce 62% more spatial resource heterogeneity than present in the resource before such effects are accounted for.



Figure 4: Inter-annual variability: standard deviation of annual average GHI relative to 20-year mean GHI (%) across 20 years and the ConUS interpolated to 0.1° from 1° SA data.

Figure 4 illustrates the inter-annual variability in GHI relative to the 20-year mean pictured in Figure 2. As previously documented by several authors, the regions experiencing the highest amount of inter-annual variability fall in the pacific northwest and in the eastern half of the continental US where mesoscale cloud formations are most pronounced: cyclonic storms to the east and marine layers to the west. By contrast, the southwest of the US, with its high desert climate, correspondingly sees much less year-on-year change in insolation.

Correspondingly, Figure 5 illustrates the same inter-annual variability metric but for GHI_{CLR} . Variations evidenced by this metric follow a similar spatial distribution but with far lower mean and standard-deviation.



Figure 5: Inter-annual Clear Sky variability: standard deviation of annual average GHI_{CLR} relative to 20-year mean GHI (%) across 20 years and the ConUS interpolated to 0.1° from 1° SA data.



Figure 6: 20-year rate-of change in average GHI relative to 20-year mean GHI (%) across the ConUS interpolated to 0.1° from l° SA data. Contours identify regions whose 20-year change exceeds mean inter-annual variability.

Figure 6 highlights the 20-year rate-of change inferred through linear regression from annual mean GHI values. Cooler colors represent areas which are trending towards less insolation while warmer colors represent areas which are generally receiving more insolation. 20-year change in GHI is distributed heterogeneously though there are some regionally notable trends. The trends range from -4% in the northern Rocky Mountains to +4% along the west coast and New England. Correspondingly, Figure 7 highlights the 20-year change in GHI_{CLR} across the same region.



Figure 7: 20-year rate-of change in average GHI_{CLR} relative to 20-year mean GHI_{CLR} (%) across the ConUS interpolated to 0.1° from 1° SA data. Contours identify regions whose 20-year change exceeds mean inter-annual variability.

Trends in GHI_{CLR} are more homogeneously distributed across the region. Clearly evident upon examination of Figure 7, the area to the East of the Mississippi has generally seen an increase in this metric to the order of 0-1% while the area to the West of the Mississippi has seen a trend in the opposite direction of roughly equal magnitude.

Generally, one would have confidence in the trends pictured in Figure 6 and Figure 7 if they exceed the corresponding interannual variability metric shown in Figure 4 and Figure 5. If this significance thresholding is performed, only the changes in GHI along the West coast of North America and the New England Regions are noteworthy. For GHI_{CLR}, if this same thresholding is used, the trends across larger regions of the continental US are deemed significant. Contours on Figures 6 and 7 geographically highlight regions deemed significant by this metric.

IV. IMPACTS OF TRENDS ON PV SYSTEM YIELD

As a utility-scale PV developer, one is typically involved in a power-purchase agreement with an off-taker; a commercial entity or utility. Historical irradiance, typical meteorological year data or typical global year data are all used to assess risk and establish probabilistic bounds around expected yield. What impacts do these evidenced trends in GHI have on yield for a PV system? In Figure 8, we show the difference in 30year yield in kWhAC/kWDC if the identified trends persist over this time period relative to if mean GHI remains stable. As can be seen, if the rates of change identified in Figure 4 persist, a system owner will see between -3.5% and 4% difference in yield depending on location. By contrast, system capacity degradation, typically 0.5% per year for c-Si systems will drive a cumulative lifetime drop in yield of roughly 7.4%—relative to if the system did not degrade. Figure 8 shows that over the past 20 years, in the northern Rocky Mountains, long-term trends in irradiance have had an effect on yields to the same order of magnitude as crystalline-silicon degradation.



Figure 8: Deviation in cumulative kWh_{AC} output for a 1 kW_{DC} horizontal system over 30 years driven by observed trends in irradiance relative to if irradiance remained stable.

Correspondingly, systems along the West Coast of the United States will have seen an increase in yield of a magnitude that roughly halves the effect of system degradation.

V. EFFECTS OF CHANGING AOD ON INSOLATION

After cloud cover, AOD is the next most important factor affecting the radiative transfer of insolation through the atmosphere. Federal environmental regulations have driven a dramatic decrease in air pollution in the last four decades, with the impact being most pronounced in Eastern region as evidenced by Figure 7. To further quantify the impact of changes in AOD on the solar resource, we developed three irradiance data models that vary by only the AOD input: (1) static AOD based on historical climatological averages (year to year); (2) monthly timeseries AOD derived from SURFRAD measurements; (3) monthly timeseries AOD derived from MERRA-2. The difference between the first and second datasets as a percentage of annual insolation is shown in figure 9. The difference represents the change in insolation attributable to changes in AOD.



Figure 9: Contribution of changes in AOD to average annual insolation for 3 West and 4 East SURFRAD locations.

Using this methodology, in the East region, we observe an increase in annual GHI_{CLR} of 1.4% when comparing 2015present from a baseline of 2000-2005. In the West, where changes in pollution are less pronounced and are potentially offset by increased emissions from wildfires, the change is - 0.4%. The results were validated by calculating the accuracy of each data model using SURFRAD-measured GHI as a reference. The dynamic AOD input of models (2) and (3) perform better and result in negligible bias across the two decades of record, effectively eliminating a trend of increasing low bias observed in the static model in the East region.

VI. CONCLUSIONS

We looked at trends in GHI and GHICLR across the ConUS region using twenty two years of hourly data (1998-2019) from SolarAnywhere. We used the inter-annual variability metric (standard deviation of inter-annual changes) in GHI and GHI_{CLR} as a significance threshold to identify regions which exhibit a persistent long-term change outside the interannual noise. For GHI, we found that the regions of New England, northern Rocky Mountains, coastal Carolina and Pacific coast all met this criteria. We used these modeled linear trends to determine the 20-year change and calculate corresponding impacts on PV system revenue which ranged between -3.5% in the Northern Rockies to +4% along the Pacific coast. Trends in GHICLR meanwhile, indicative of systemic changes in AOD ranged between -1% for almost the entire region west of the Mississippi to +1% for nearly the entire region east of the Mississippi.

The geographical homogeneity of regions demonstrating significant change indicate a probable geophysical driver. The retirement of coal assets in the eastern half of the US and the increase in wildfire activity are two drivers that are hypothesized to drive this change in AOD and hence GHI_{CLR}.

Finally, we used time-synchronous AOD data to identify what impact changes in AOD had on horizontal irradiance at the surface. AOD was shown to decrease across the Eastern US and increase across the Western US driving opposite trends in GHI at SURFRAD sites. These trends match those shown in Figures 6 & 7. Significant outliers include the majority of the Pacific Coast which has increased in GHI despite decreasing in GHI_{CLR}. It is hypothesized that this is due to reductions in impacts of the coastal marine layer. A less striking example over on the East coast is visible along the Carolina coast. Further study of long-term trends and the geophysical processes driving these changes is warranted. REFERENCES

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