# ON THE RELATIONSHIP BETWEEN GROUND- AND SATELLITE- BASED GLOBAL HORIZONTAL IRRADIANCE

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#### **ABSTRACT**

Global horizontal irradiance (GHI) plays a significant role in maintaining the earth's ecological balance and generating electricity in photovoltaic systems. While the satellites have more range, they have been shown to over/under-estimate the true values of GHI that are observed at the ground-based stations. Hence, this study aims at analyzing the relationship between these two sources of GHI data in order to better and effectively utilize the reach of satellites for GHI analysis. The paper identifies a near linear relationship between the two and thereby concludes that an approximate mapping from satellite- to ground-based GHI values can be obtained.

*Index Terms*— Solar Irradiance, Renewable Energy, Remote Sensing, Satellite Data, Machine Learning

## 1. INTRODUCTION

Horizontal surface solar irradiance, or global horizontal irradiance (GHI), is the amount of power reaching a horizontal plane on the surface of the earth from the sun. It plays a vital role maintaining the surface energy balance and affects the behaviour and growth of flora and fauna [1]. It also drives various atmospheric and climate phenomenon [2]. Apart from being essential to the very existence of life on the earth, the amount of GHI that reaches the surface of a photovoltaic system determines the amount of electrical energy that it can generate [3]. Hence a correct estimation of its value at the surface of the earth is crucial for multiple research directions.

Primarily, there are two sources for GHI data collection and estimation, i.e., satellite and ground-based sensors. Satellites can cover a larger area, including the remote locations, mountains and oceans, a feat which is not realistic with ground-based sensor systems. However, it has been noted that satellites generally provide biased estimations for the GHI values [4, 5, 6]. Typically low spatial resolution of

the satellites further elevates the problem, making their readings more inaccurate. To this end, this paper<sup>1</sup> analyzes the relationship between the satellite and ground-based sensor readings. The paper further attempts to model ground-based GHI readings from the satellite data.

#### 1.1. Relevant Literature

Estimating surface solar irradiance values from the satellites has been an area of ongoing research [7]. Satellites typically sense the solar energy going into the top of the earth's atmosphere and the energy that is reflected back. These observations are then used to estimate atmospheric constituents and their effects on incoming solar radiations. Post accumulating these estimations the surface solar irradiance is estimated. Being such an indirect process, it becomes very difficult to correctly estimate the true ground-level values from the satellites.

In a comparative analysis, it was noted that the average errors of satellite-derived GHI readings range between -7% to upto 25% in Nigeria [4]. Upto 9.3% overestimation error in satellite-based values was reported in a separate study in Australia [5]. Manara *et al.* [6] analyzed the accuracy of satellite-based GHI over varying altitude levels. It was noted that the results vary with elevation. The values were generally overestimated in low-lying areas whereas they were underestimated at more elevated locations. In general, there was a question on the accuracy and effectiveness of the methods which are being used to estimate GHI from the satellite readings.

#### 2. DATASET

The data was separately downloaded for ground-based stations and the satellite derived readings. The details for both datasets is discussed in the following subsections.

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<sup>&</sup>lt;sup>1</sup>In the spirit of reproducible research, the code related to this paper is available from https://github.com/ydjoel/SolarSatGround.

#### 2.1. Ground-based Sensor Data

We collected the GHI land-based data from the Solcast website [8]. Specifically, the dataset provides total irradiance or GHI that is received on a horizontal surface on the ground. It is the sum of direct and diffuse irradiance components. In this study, we choose Dublin as the city under consideration. By default, Solcast provides data from the nearest available solar farms given the latitude and longitude information.

Seven years worth of data was obtained from 2014 to 2020. The data consists of the timestamp and the GHI readings in  $W/m^2$ . Apart from that, other vital information about the exact location, altitude and time zone is provided in the dataset. To organize the data better, it was separated into lists where data from the same day are kept together similarly days of a month are held together and months of the same year.

### 2.2. ERA5 Data

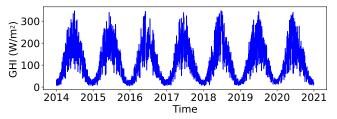
The satellite-based solar irradiance data is compiled from the Climate Data Store (CDS) website which was provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) [9]. The ERA5 dataset provides hourly estimates for many atmospheric, ocean-wave, and land-surface quantities. In this case the estimated surface level GHI values were provided under the name of 'Surface Solar Radiation Downwards' variable.

The data was obtained by making API calls to the CDS Server. A POST request is sent with exact specifications of the variable name, timestamps, and the geographical area to obtain the final response in NetCDF format. In this case, the data was downloaded for the exact same location for which the ground-based data was taken. Since the ERA5 data is the hourly reanalyses data over 3 hours, a shift in sequential data by 2 time-steps was required to match the timestamp of the ground-based sensor data. Furthermore, the raw satellite data was divided by  $3\times3600$  to convert the units from  $Js^{-1}m^{-2}$  to  $Wm^{-2}$  to match the units that were obtained from the ground-based sensors.

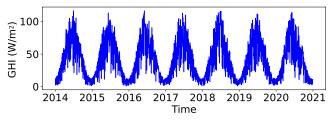
#### 3. METHODS

Both the land and satellite datasets have solar radiation values spaced at successive intervals of an hour. Fig. 1(a) shows the actual GHI values that were obtained from the ground-based sensor dataset, whereas Fig. 1(b) shows the trend of GHI values that were estimated from the satellites.

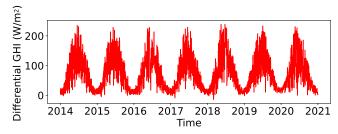
It can be clearly noted that the radiation is high in warmer months of a year but comes down progressively as we get to December and January. This cycle continues each year. The only notable difference between the two plots is the peak value they attain. Ground-based sensors seems to record higher observations than its satellite counterparts. In other words, satellites are generally underestimating the true GHI values in this case. To compare the difference between the



(a) Actual GHI values as obtained from ground-based sources [8]



(b) GHI data estimated from satellites [9]



(c) Difference between ground- and satellite-based observations

Fig. 1: GHI data estimated from ground-based station and satellite data.

readings obtained from the two datasets, a difference curve was plotted by subtracting the satellite readings from the corresponding ground-based sensor readings. The obtained difference plot in Fig. 1(c) confirms that there is considerable difference in the satellite estimations and the actual values of the GHI at the earth's surface.

To further understand the impact of temporal variations on the data, boxplots of daily mean differential GHI were plotted against different months for different years. Fig. 2 shows one such plot for the year 2020. It can be clearly seen from the figure that there is a huge amount of variations across different months. However, on the other hand, there is no such significant difference between in the GHI values of the same month over the years. Fig. 3 shows the boxplots of daily mean GHI values for the August month over the years. Overall, it can be noted that the variation over months is much more considerable than over the years. Hence, the paper attempts to create different models for each month for better accuracy.

While the GHI values are reported for the whole 24 hours in both the datasets, they are 0 (or nearly 0) at nighttime. The length of nighttime also varies across the year as nights are longer in winters but much shorter in summers. However, in

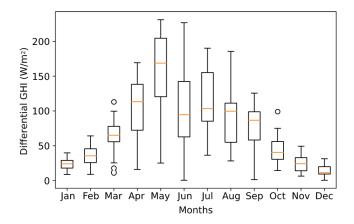
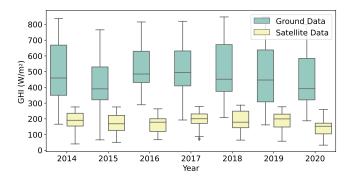
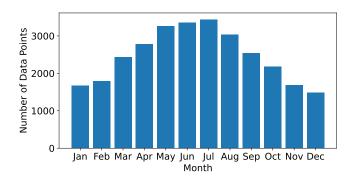


Fig. 2: Daily mean difference between satellite and ground-based sensor data as obtained for different months in 2020



**Fig. 3**: Variation in daily mean GHI values from ground- and satellite- based sources for the month of August from 2014 and 2020

any case, all such timestamps were removed where either of the ground- or satellite-based readings were 0. Fig. 4 show the number of remaining data points (across the years) that were considered for further analysis post this stage. A clear bell-shaped curve can be seen re-emphasising the idea that summers have longer days than winters.



**Fig. 4**: Number of daytime data points that were available for each month accumulated from 2014 - 2020

Once the data has been filtered for relevant values, it is important to identify underlying patterns in the data to establish a mapping from satellite-based readings to true ground-based GHI values. For this case, linear regression was performed. As noted before, for better analysis, individual models must be trained for each month. Consequently, the data was further divided into 12 parts by months over which independent linear regression models were trained. Note that the dataset was combined over the years as no significant variation across the years was noticed.

Since a significant variation in GHI values can be noted across the day, it is important to incorporate the timestamp as input feature to the regression models. Individual components of timestamps (i.e. day of month and hour of the day) were extracted and converted into one-hot encoded vectors. These were then concatenated to result in the final input feature vector. Since different models were created for the different months and each month has similar number of daylight hours, the size of one-hot encoded 'hour' vectors will vary from one month to another as per the number of daylight hours in that particular month. Same goes for the 'days' vector as well. Thus, including the satellite derived GHI readings, atleast 40 features were created for a particular month. Finally each month's data was randomly shuffled and an 80-20 split was made to divide the data into training and test set respectively. Coefficient of determination  $(R^2)$  was used to evaluate the model's performance.

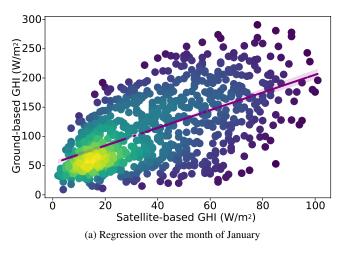
# 4. RESULTS AND DISCUSSIONS

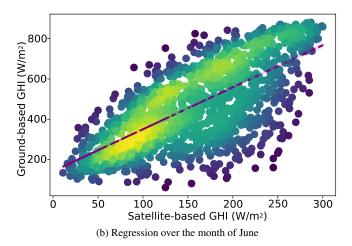
Fig. 5(a) and 5(b) shows the linear regression results on the test set for two sample months of January and June, respectively. The data can surely be seen to be highly correlated and a simple linear regression itself decently approximates the underlying data. However, its still not accurate by a long shot.

To evaluate the fit coefficient of determination  $(R^2)$  metric was used. It gives a goodness-of-fit measure for linear regression model.  $R^2$  explains how much of the variance in dependent variable can the independent variables collectively explain. Fig. 6 shows the obtained  $R^2$  values for all 12 models, where each of them correspond to the respective month in the year. As seen from the figure, the value of  $R^2$  falls between 0.75 and 0.85. This indicates that although linear fit is definitely not the best approximation, it certainly proves that such a mapping is possible with more complex models like neural networks.

#### 5. CONCLUSION & FUTURE WORK

The paper presents a systematic analysis of ground- and satellite- based datasets of global horizontal solar irradiance (GHI). It was noted that satellite estimations are generally significantly off than the true ground-level observations. Not only that, but this disparity varies significantly across the





**Fig. 5**: Scatter plot showing the satellite readings and the corresponding ground-based sensor readings in the test set. The line through the center shows the linear regression fit on the data.

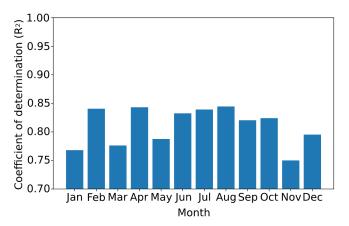


Fig. 6: Coefficient of determination Values for each month

months of the year. As such the paper recommends creating different models for different months of the year in order to find the best mappings from the satellite data to true GHI values. Lastly, it was shown that this mapping is almost linear but a significantly better fit might be obtained by using more complex models than linear regression. In future, the authors would like to analyze the relationship even further and try to model it with better coefficient of determination scores. Additionally, the plan is to study the generalizability of the identified models and/or the approach that is discussed in the paper for different locations on the earth.

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