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Comparative Analysis of Long-Term Solar Resource Databases for Global Horizontal Irradiance Prediction

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Abstract. The short measurement periods of local solar resource measurement campaigns limit the representativeness of these measurements in long-term energy production estimates for solar projects. This study aimed to characterize the main long-term solar resource databases and correlate them with data provided by meteorological stations, with the purpose of identifying the database that best predicts solar radiation at specific locations. Seven long-term databases were used (PVGIS, SOLARGIS, SOLCAST, NASA POWER, NSRDB, HELIOCLIM, ERA5). Measured data from meteorological stations at various locations in Portugal, Saudi Arabia, and Brazil were correlated with the long-term databases available for each location. Different methodologies for evaluating these correlations were tested, including R², MSE, MBE, and MAPE. The analyses revealed that the SOLCAST and SOLARGIS databases highlighted in predicting global horizontal irradiance (GHI) in the Arabia region. In Portugal, the NSRDB was the most accurate in predicting GHI, while in Brazil, SOLCAST showed the highest accuracy in forecasting GHI.

Key words. Solar resource, local measurements, long-term databases, error metrics

1. Introduction

The search for alternative energy sources has been driven by the environmental risks associated with fossil fuels and the potential for their depletion. On the other hand, the costs of renewable energies have decreased significantly, with notable reductions in the costs of photovoltaic and wind energy [1]. Due to the variable nature of the solar resource, the planning and implementation of solar energy projects require detailed knowledge of the spatial and temporal variability of solar irradiance [2]. The detailed design of the project, as well as the assessment of its economic feasibility, are directly related to the magnitude and variability of the local solar resource, making its characterization in different temporal resolutions imperative [3]. Therefore, the temporal resolution of solar radiation data can have a significant impact on the feasibility analysis of a solar energy project [4].

The characterization of long-term solar resource data is a crucial step in the design of a solar power plant. The pace at which these projects have been developed over the past decade has limited the duration of local solar resource measurement campaigns, which rarely exceed two years. This fact restricts the representativeness of these measurements in long-term energy production estimates for the project. The use of time-series radiation data with greater temporal coverage and its correlation with radiation measurement data from local stations presents a methodology for identifying the long-term database that best predicts solar radiation at the location under analysis, serving as a tool that can improve risk management associated with solar energy projects.

2. Methodology

For this study, five measurement stations in Portugal (P1 to P5), nine in Saudi Arabia (A1 to A9), and eleven in Brazil (B1 to B11) were selected, aiming to cover a broad range of orographic characteristics and available solar resource (Table I). One-year measurement campaign periods were chosen for each station. Additionally, seven long-term databases (LTD), both free and paid, were selected: NASA POWER, ERA5, and SOLCAST, which are available for all three countries under study; NSRDB for Portugal and Brazil; PVGIS and HELIOCLIM for Brazil; and SOLARGIS for Saudi Arabia and Brazil.

For each geographic location under study, the measured Global Horizontal Irradiance (GHI) data from local meteorological stations were correlated with data from the different available LTDs, using linear regression between the simultaneous data periods. Various error

metrics were employed to assess the quality of the linear prediction model fits [5-7.:
Coefficient of Determination (R^2), which represents the percentage of data variance that is explained by the model;
Mean Bias Error (MBE), which measures the average bias of forecasts compared to observed values;
Mean Squared Error (MSE), which gives greater weight to larger errors, making it sensitive to outliers;
Mean Absolute Percentage Error (MAPE), which shows the percentage of error relative to the actual values.

Two main tests were used to verify these metrics:
Levene's test, which verifies the equality of variances, and the **Kolmogorov-Smirnov** test, which verifies the normal distribution of the data [8, 9].
When the Levene test showed unequal variances and the Kolmogorov-Smirnov test showed a non-normal distribution, the **Kruskal-Wallis** test was used to check for differences in group medians. If the Kruskal-Wallis test showed no significant differences, the analysis ended. If significant differences were found, **Dunn's** test was used to find out which groups had different medians [10].

Table I. – Generic information for each measurement station.

Country	Met Mast	Characteristics of the surroundings	Measurement period
Saudi Arabia	A1	Arid desert area	jun22-may23
	A2	Arid desert area	jun22-may23
	A3	Arid desert area	jun22-may23
	A4	Arid desert area	jun22-may23
	A5	Arid desert area	jun22-may23
	A6	Arid desert area	nov22-oct23
	A7	Arid desert area	nov22-oct23
	A8	Arid desert area with some dispersed ground vegetation	nov22-oct23
	A9	Arid desert area	nov22-oct23
Portugal	P1	Low vegetation and some medium-sized shrubs	jun22-mar23
	P2	Agricultural land on an island in the Azores	mai-22-apr23
	P3	Rural area on an island in the Azores	sep22-aug23
	P4	Agricultural land with some buildings on an island in the Azores	aug22-jul23
	P5	Coastal agricultural land on an island in the Azores	dec22-nov23
Brazil	B1	Low vegetation and some medium-sized shrubs	jun15-may16
	B2	Low vegetation and some medium-sized shrubs	oct19-sep20
	B3	Agricultural land with some dispersed vegetation	aug15-jul16
	B4	Area with some large vegetation and buildings	aug15.jul16
	B5	Densely wooded area	jan18-dec18
	B6	Low vegetation and some medium-sized shrubs	jan16-dec16
	B7	Area with ground vegetation	aug17-jul18
	B8	Area with ground vegetation	aug18-jul19
	B9	Area with medium-sized vegetation	sep16-aug17
	B10	Agricultural land	dec19-nov20
	B11	Area with some large vegetation	sep19-aug20

3. Results

Correlations between GHI data measured at local meteorological stations and data from different LTDs available for each study site were obtained. In Table II the obtained results for R^2 of each linear model obtained for Saudi Arabia, Portugal and Brazil were presented**.** The best values are shaded in green and the worst in orange.
For Arabia, all databases generally showed high R^2 values above 90%. SOLCAST and SOLARGIS had the best R^2 values, with very small differences between them, except at station A5. ERA5 had the lowest R^2 values, except at station A7. NASA POWER, although not having the highest correlations, showed R^2 values close to those of SOLCAST and SOLARGIS, which are paid services.

Table II. – Coefficient of Determination for GHI in Arabia (**A**), Portugal (**P**) and Brazil (**B**)

Stations	NASA POWER	PVGIS	ERA5	NSRDB	HELIOCLIM	SOLARGIS	SOLCAST
A1	0.9812	-	0.9712	-	-	0.9870	0.9858
A2	0.9845	-	0.9746	-	-	0.9866	0.9866
A3	0.9762	-	0.9611	-	-	0.9849	0.9830
A4	0.9911	-	0.9854	-	-	0.9932	0.9942
A5	0.9856	-	0.9734	-	-	0.9884	0.9916
A6	0.9824	-	0.9640	-	-	0.9886	0.9885
A7	0.9072	-	0.9793	-	-	0.9903	0.9906
A8	0.9795	-	0.9623	-	-	0.9832	0.9856
A9	0.9683	-	0.9489	-	-	0.9839	0.9850
P1	0.9579	-	0.9420	0.9668	-	-	0.9755
P2	0.9029	-	0.8683	0.9170	-	-	0.8781
P3	0.8180	-	0.7806	0.8653	-	-	0.7821
P4	0.7786	-	0.7441	0.8338	-	-	0.7457
P5	0.8932	-	0.8519	0.8916	-	-	0.8545
B1	0.9442	0.9380	0.9340	0.9537	0.9421	-	0.9736
B2	0.9311	0.9350	0.8957	0.9169	0.9694	-	0.9800
B3	0.9683	0.9506	0.9374	0.9544	-	0.9741	0.9780
B4	0.9558	0.9426	0.9239	0.9674	0.9778	-	0.9796
B5	0.9506	0.9438	0.9142	0.9753	-	0.9715	0.9756
B6	0.9615	0.9276	0.9174	0.9591	0.9678	-	0.9701
B7	0.9352	0.9133	0.9011	0.9568	-	0.9598	0.9521
B8	0.9536	0.9379	0.9270	0.9649	-	0.9681	0.9656
B9	0.9441	0.9455	0.9080	0.9294	0.9686	-	0.9573
B10	0.9542	0.9306	0.9197	0.9771	0.9709	-	0.9799
B11	0.9484	0.9385	0.9100	0.9617	0.9636	-	0.9760

For Portugal, it was found that the LTDs used have difficulty in predicting GHI data at stations P2 to P5, which are located on the islands, with R^2 values lower than 90% in most stations. Despite the unsatisfactory results, NSRDB had the highest R^2 values while ERA5 had the lowest correlations across all stations. In Brazil, SOLCAST had the best correlations, while ERA5 had the lowest across all stations. NSRDB performed well among the free databases, with R^2 values above 95% in most stations.
The results for the MSE, MBE and MAPE were presented in Table III to V.
For Arabia, SOLCAST and SOLARGIS showed the least bias, with SOLCAST slightly higher at station A7. NASA POWER exhibited the largest overestimations, while ERA5 had the smallest variation in MBE values. SOLARGIS and SOLCAST presented lower MSE and MAPE values, indicating more accurate predictions.
The results obtained for Portugal, showed negative MBE values for most LTDs indicating GHI underestimation,

with NSRDB showing the least bias. ERA5 and SOLCAST had higher MSE values, while NSRDB had the lowest, suggesting better accuracy. Regarding MAPE, in general the values are high, above 10%, in all LTDs.

For Brazil, the results for those error metrics showed that SOLCAST had the lowest MSE and MAPE values, providing the most accurate predictions across most stations, while ERA5 had the highest MAPE and MSE values.

Table III. - Mean Bias Error, Mean Squared Error and Mean Absolute Percentage Error for GHI in Saudi Arabia

Error metrics	LTD	A1	A2	A3	A4	A5	A6	A7	A8	A9
MSE (Wh^2/m^4)	NASA POWER	3747.34	2926.26	4243.24	2804.48	2123.08	3620.68	13107.11	2484.44	3522.03
	ERA5	4430.96	3672.93	5517.47	4061.47	3693.11	4916.70	4510.44	4382.26	5741.81
	SOLARGIS	2263.46	2263.46	2359.07	1796.49	1647.07	2277.33	1612.77	2123.22	1916.53
	SOLCAST	2473.70	2473.70	2881.68	1544.31	1080.68	1933.41	2347.33	2030.40	2039.90
MBE (Wh/m^2)	NASA POWER	22.24	19.81	21.72	12.11	10.71	25.72	34.34	7.82	0.39
	ERA5	15.65	12.87	13.21	10.33	12.44	14.01	19.74	7.94	8.01
	SOLARGIS	14.48	14.55	12.87	2.14	9.43	19.53	13.83	10.44	7.80
	SOLCAST	14.83	7.61	16.55	2.47	2.64	15.24	23.04	13.37	13.26
MAPE (%)	NASA POWER	10.00	8.68	9.16	7.67	6.19	11.00	18.81	7.38	8.90
	ERA5	9.00	8.42	8.51	8.18	7.97	9.00	9.00	9.22	10.09
	SOLARGIS	7.00	7.09	7.00	5.25	5.42	8.00	6.44	6.74	6.47
	SOLCAST	7.00	6.10	8.00	5.24	4.23	7.00	8.82	7.57	7.54

Table IV. - Mean Bias Error, Mean Squared Error and Mean Absolute Percentage Error for GHI in Portugal

Error metrics	LTD	P1	P2	P3	P4	P5
MSE (Wh^2/m^4)	NASA POWER	6599.84	7543.64	12730.22	15431.37	7666.46
	ERA5	7511.88	9467.42	14158.35	17195.60	9584.71
	NSRDB	4430.02	6657.21	8177.17	10808.51	8044.26
	SOLCAST	3799.44	8858.19	14329.85	17626.08	9533.86
MBE (Wh/m^2)	NASA POWER	24.79	-19.47	-37.10	-45.71	-28.91
	ERA5	22.33	-10.30	-32.71	-44.34	-23.92
	NSRDB	18.95	-13.93	-21.10	-32.78	-24.04
	SOLCAST	17.44	-12.80	-34.81	-47.22	-25.41
MAPE (%)	NASA POWER	16.31	12.56	14.31	15.74	10.97
	ERA5	15.99	16.22	17.24	17.92	14.71
	NSRDB	12.57	12.74	13.58	14.61	14.68
	SOLCAST	12.44	15.36	16.77	17.75	14.25

Table V. - Mean Bias Error, Mean Squared Error and Mean Absolute Percentage Error for GHI in Brazil

Error Metrics	BD	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
MSE (Wh^2/m^4)	NASA POWER	5932.41	6504.24	3577.00	4762.73	4947.84	4538.22	7050.90	5541.59	6087.57	4934.50	5354.21
	ERA5	6938.22	9772.70	7146.34	8219.02	8686.87	9354.90	10749.60	8742.12	10087.81	8595.91	9300.64
	NSRDB	6055.80	8826.53	5779.49	4003.69	3024.18	4846.89	4789.24	4628.41	8382.34	2532.51	4452.40
	PVGIS	7328.33	6614.46	6065.76	6878.51	6228.91	8176.15	9821.95	7465.33	6015.05	7762.35	6927.18
	HELIOCLIM	6032.76	2848.33	-	2464.52	-	3565.91	-	-	3451.09	3150.18	3874.68
	SOLARGIS	-	-	3001.28	-	2838.49	-	4393.41	3866.59	-	-	-
	SOLCAST	2779.40	1862.74	2479.37	2187.57	2435.75	3306.68	5254.05	4145.68	4741.75	2146.72	2602.70
MBE (Wh/m^2)	NASA POWER	-7.97	-7.15	-4.03	1.38	-5.28	7.80	1.17	2.14	-3.32	3.95	-6.48
	ERA5	-3.04	-4.15	10.98	7.11	-5.98	12.19	3.42	10.55	0.82	6.03	-0.51
	NSRDB	-18.88	-14.16	-12.63	-11.28	-14.82	-10.33	-5.59	-14.06	-13.59	-5.60	-12.96
	PVGIS	-13.78	-10.75	-8.65	4.07	-9.79	-0.92	-3.69	-6.67	2.06	-0.77	-9.99
	HELIOCLIM	-0.43	0.46	-	7.76	-	2.94	-	-	5.50	4.02	-4.51
	SOLARGIS	-	-	7.95	-	-0.74	-	3.78	8.03	-	-	-
	SOLCAST	-4.10	-3.88	3.13	2.33	-1.37	0.11	5.29	8.41	-6.30	-2.15	-8.16
MAPE (%)	NASA POWER	11.93	11.00	8.81	10.49	9.69	9.74	11.09	11.30	11.24	9.23	9.70
	ERA5	13.01	15.00	13.39	14.26	12.33	13.86	13.59	14.58	14.96	12.15	12.70
	NSRDB	12.19	15.00	10.90	9.33	8.15	8.00	8.35	9.20	12.94	5.56	8.96
	PVGIS	13.86	12.00	11.98	12.29	12.62	12.03	14.12	13.10	12.35	12.18	11.47
	HELIOCLIM	10.94	8.00	-	7.93	-	7.07	-	-	9.33	6.84	8.53
	SOLARGIS	-	-	8.58	-	8.40	-	9.24	9.55	-	-	-
	SOLCAST	8.45	6.00	7.93	7.27	7.46	7.12	10.62	9.91	10.00	5.78	7.48

After verifying the non-normality of the data, the Kruskal-Wallis test for GHI errors (MBE, MSE, MAPE) applied across nine Saudi Arabia stations revealed statistically significant differences in most groups (Table VI). Chi-squared test results further indicate that larger values provide stronger evidence of significant differences between group medians. The Dunn's post-hoc test further demonstrated that, in most Saudi Arabia stations, these differences were statistically significant, with the exception of specific cases such as ERA5–NASA POWER and SOLARGIS–SOLCAST at station A4. In

Portugal, the Kruskal-Wallis test for GHI errors also indicated significant differences in the majority of groups, with the exception of station P3, where MSE and MAPE did not show statistical significance (Table VII). Dunn's test further corroborated these discrepancies, with SOLCAST yielding estimates analogous to those of other methodologies, thereby suggesting stability. In Brazil, Kruskal-Wallis results demonstrated statistically significant GHI discrepancies across methodologies, particularly at stations B6 and B10 (Table VIII). Dunn's test further substantiated these discrepancies, with SOLCAST frequently exhibiting no substantial differences from other methodologies, signifying consistent performance with models like SOLARGIS in specific regions.

Table VI. - Kruskal-Wallis test for GHI in Saudi Arabia

Kruskal-Wallis Test						
Stations	MBE_GHI		MSE_GHI		MAPE_GHI	
	Chi-square	Sig.	Chi-square	Sig.	Chi-square	Sig.
A1	260.43	<0.01	274.72	<0.01	292.92	<0.01
A2	546.10	<0.01	400.62	<0.01	379.28	<0.01
A3	256.62	<0.01	231.67	<0.01	225.96	<0.01
A4	875.13	<0.01	619.42	<0.01	612.95	<0.01
A5	1093.10	<0.01	964.19	<0.01	887.97	<0.01
A6	399.30	<0.01	371.08	<0.01	385.00	<0.01
A7	746.89	<0.01	1580.61	<0.01	1424.60	<0.01
A8	91.27	<0.01	175.31	<0.01	169.74	<0.01
A9	149.95	<0.01	175.94	<0.01	3411.70	<0.01

Table VII. - Kruskal-Wallis test for GHI in Portugal

Kruskal-Wallis Test						
Stations	MBE_GHI		MSE_GHI		MAPE_GHI	
	Chi-Square	Sig.	Chi-Square	Sig.	Chi-Square	Sig.
P1	174.68	<0.01	152.90	<0.01	222.37	<0.01
P2	298.40	<0.01	5075.70	<0.01	132.23	<0.01
P3	16.11	<0.01	8.76	0.067	7.18	0.127
P4	49.56	<0.01	60.40	<0.01	50.43	<0.01
P5	233.42	<0.01	85.66	<0.01	60.54	<0.01

Table VIII. - Kruskal-Wallis test for GHI in Brazil

Kruskal-Wallis Test						
Stations	MBE_GHI		MSE_GHI		MAPE_GHI	
	Chi-Square	Sig.	Chi-Square	Sig.	Chi-Square	Sig.
B1	506.11	<0.01	420.22	<0.01	386.54	<0.01
B2	371.97	<0.01	1065.3	<0.01	986.94	<0.01
B3	803.27	<0.01	385.52	<0.01	355.10	<0.01
B4	769.31	<0.01	671.56	<0.01	628.19	<0.01
B5	545.32	<0.01	471.92	<0.01	447.07	<0.01
B6	1135.10	<0.01	865.56	<0.01	861.96	<0.01
B7	484.63	<0.01	666.95	<0.01	669.25	<0.01
B8	799.42	<0.01	541.54	<0.01	509.84	<0.01
B9	424.45	<0.01	145.58	<0.01	130.26	<0.01
B10	912.25	<0.01	1423.20	<0.01	1413.30	<0.01
B11	548.09	<0.01	306.03	<0.01	297.76	<0.01

4. Conclusion

This study evaluated long-term solar databases (LTDs) and their correlation with measured solar irradiance in multiple regions, including Portugal, Saudi Arabia, and Brazil. In Saudi Arabia, SOLCAST and SOLARGIS outperformed, with R^2 values exceeding 90%, while ERA5 showed the poorest correlation, NASA POWER was competitive, albeit slightly below the top databases. Selecting premium databases like SOLCAST and SOLARGIS enhances solar resource estimation accuracy in Saudi Arabia.

In Portugal, GHI was less accurately predicted by LTDs, particularly at island-based stations (P2 to P5), where R^2 values were below 90%. NSRDB was the most reliable database, outperforming other datasets in terms of correlation and error metrics. ERA5 consistently underperformed.

For Brazil, SOLCAST was found to be the most accurate LTD, yielding the lowest MBE, MSE and MAPE across most stations. NSRDB also exhibited strong correlations, particularly among the free databases, while ERA5 consistently delivered the least accurate predictions. This suggests that SOLCAST can be a robust tool for energy planning and risk assessment in the region.

Statistical analyses confirmed significant differences between the LTDs' predictive capabilities. SOLCAST and SOLARGIS provided more consistent and statistically significant results compared to other databases in most cases, particularly in Saudi Arabia and Brazil. This further validates the reliability and usefulness of these databases for solar energy assessments. LTDs have some limitations, such as the availability and representativeness of local stations, variations in atmospheric conditions, topography and climate patterns, which may influence database performance. Future research should explore hybrid models using additional datasets and machine learning to enhance accuracy. Adaptive correction methods may help in areas where deviations are more pronounced, and the implications of this study are relevant for solar energy forecasting and photovoltaic system design and yield predictions. This research identifies the most reliable LTDs for different regions and can contribute to developing consistent solar resource assessments worldwide.

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