Methods for Site-Adaptation of Satellite-Based DNI Time Series: Application to Brazilian Northeast

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Abstract

The standard procedure today in solar industry is the acceptance of solar irradiance estimates via satellite images (normally time series longer than 15 years) and its adaptation to the site where the solar power plant will be. The adaptation was done by correlating the long time series via satellite with a short time series (1 year) of good quality devices (first class pyrheliometer and standard secondary pyranometer) for measurements on terrestrial surface. The purpose of this work was the development as well as the demonstration of four computational techniques (simple regression, multiple regression, ANN and SVR) which allowed the correction/mitigation of this bias. The estimators developed were applied for Patos, city in the Northeast of Brazil, and allowed a significant decrease of the bias through the root mean square deviation (RMSD) of the originally estimated values obtained from a satellite database. Bias correction for the employed metrics provided low bias values or very close to zero according to some metrics. Regarding the RMSD, the simple, multiple and ANN (MLP) linear regression algorithms produced slight improvements over the raw data from satellite, respectively of 2.5, 8.0 and 4.3%. When using the SVR, the resulting improvement was remarkable for the RMSD. In this case, the improvement was about 57.9%. The results obtained showed the capacity of SVR for a reliable adjustment with precision for the estimation of DNI via satellite, provided with high quality terrestrial data.
Keywords: DNI, MOS, Site Adaptation, Multiple regression, ML-SVR, Brazilian Northeast

1. Introduction

The knowing of total and direct solar irradiance is of fundamental importance for planning, analysis of feasibility and design of a solar power plant. Within the uncertainties of a solar enterprise, the greater impact in the financial risk (seen isolated) is by the inaccurate knowledge of long-term solar resources (15-25 years). Currently in the world there are very few terrestrial measurements with long time series of DNI or GHI solar irradiance. Although not ideal, the standard procedure today in solar industry is the acceptance of solar irradiance estimates via satellite images (normally time series longer than 15 years) and its adaptation to the site where the solar power plant will be. The adaptation is performed correlating the long time series via satellite with a short time series (1 year or less) of good quality (first class pyroheliometers and standard secondary pyranometer), measured on terrestrial surface.

A series of scientific works have already been done on the subject. Gueymard et al.(2012) did an extensive work and proposed two methods for the correction of solar irradiation data obtained from satellite images. The first method combined a clear sky model with local aerosol data. The second, known as MOS (Model Output Statistics), consisted in the removal of the bias of solar irradiation with high quality local terrestrial data. The conclusion is that the method improves with the increase of the measurement period and reaches its optimum with 01 year duration. The adjustment was performed by a multiple regression. Cebecauer and Suri (2011), Cebecauer et al. (2011) and Polo et al. (2016) demonstrated that the bias can be removed by determining the correction factor between the terrestrial and satellite data. Cebecauer et al., (2011), Vernay et al. (2013) and Polo et. al. (2014) proposed improvements by correcting aerosol values used in satellite modeling. Nonlinear correction methods and correction using the cumulative probability distribution function were proposed by Mieslinger et. al. (2014) and Cebecauer et. al. (2012). Finally, Polo et al. (2016) performed an extensive and complete review on the subject, resulting from the Task Group of the International Energy Agency Solar Heating and Cooling Program, Task 46 “Solar Resource Assessment and Forecasting”. That paper concluded the need to maintain the quality of the various existing algorithms and the local adaptation of atmospheric and topographic conditions, and in general, environmental conditions.

By keeping that context in mind, this work aimed to verify the operation of traditional algorithms (linear and multiple regression) as well as proposing new ones based on artificial neural networks (ANN) and machine learning (ML), by means of a Multilayer Perceptron (MLP) and a Support Vector Machine applied to regression (SVR). As a secondary goal, verify and test such algorithms, particularly in the semi-arid region in Northeast of Brazil, a place with much abundance of solar resources, although poorly known.

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2. Material and Methods

Model Output Statistics - MOS modeling will take under consideration two time series, $Gsat(t)$ and $Gobs(t)$, time series of solar irradiance observations via satellite and time series of the terrestrial station, respectively. From the previous series, the solar irradiation prediction error was defined as:

$$E(t) = Gsat(t) - Gobs(t) \qquad (1)$$

where, $E(t)$ is a function of local meteorological and/or physical variables.

2.1. Simple Linear Regression

The simplest method is called the quotient method and it is a process of scale correction. DNI or GHI solar irradiance suffers a correction of the bias (systematic deviation) in a way that the time series via satellite and the terrestrial surface measurement overlap for the period considered (Gueymard and Wilcox, 2009; Polo, J et. al, 2015). It is the application of Minimum Squares Method, such that the coefficients A and B of the linear expression bellow are estimated:

$$E(t) = y(t) = \mathrm{A.x(t)} + \mathrm{B}$$

The input data for this model, since there is a single input variable, x(t), will be the satellite irradiance measurement, while the output data will be the values of E(t), that is, the differences $Gsat(t) - Gobs(t)$ for each observation in the instant t of the time series.

It is important to observe in the models that will be succeeded in this text, that there is the clear goal of bias removal E(t) insofar through its estimator $< E(t) >$, obtained by the model in question. Further in each model, it will be subtracted from the $Gsat(t)$ output from the satellite.

2.2. Multivariate Linear Regression

Approaches based on multivariate linear regression have been used in literature within the field of solar resources assessment (Clack, 2017). In the present case, the adopted model considers the output variable, $E(t)$, as a function of a linear relation of several input attributes. Then, the expression that follows with four inputs was used for modeling the bias:

$$E(t) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \qquad (2)$$

where,

X_1: Temperature(sat), in Celsius degrees
X_2: relative humidity (sat), in %
X_3: GHI(sat), total irradiance, in kW/m²
X_4: DNI(sat), direct irradiance, in kW/m²

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2.3. Artificial Neural Network (ANN) and Machine Learning (ML) approaches: MLP and SVM(R)

Machine Learning (ML) and Artificial Neural Networks (ANN`s) have proven their capabilities in providing solutions when dealing with regression problems. In particular, ML and ANN, have also been broadly used to estimate irradiances, as can be found in the work of Ameen at al. (2019) to estimate GHI. Both, ML's and ANN's, have their own algorithms with different architectures associated with weight distribution/adjustment and loss function concepts. Besides, they have different tuning parameters that allow, while reducing the output error and searching for a global minimum, build and optimize their respective models. All previous approaches can then be compared according to some metrics in order to classify each model that was built. In terms of ANN's, a Multilayer Perceptron (MLP) was chosen and with respect to ML's, the Support Vector Machine (SVM) was selected, regarded that they would be applied to the regression case.

The ANN Multilayer Perceptron used here was conceived with the architecture depicted in Fig 1. In the input layer (X) there are 6 neurons, one for each input. There are also 3 hidden layers with 10 neurons, each. One single neuron is in the output layer (Y). The sigmoid type activation function was the hyperbolic tangent. An amount of irradiance data in 220 days were randomly selected to be used in the training stage, 75% in a total of 293 days. To the test stage, the remaining 73 days (25%) were applied. And the difference, i.e., 365-293 days, were not used once that at least one of the two conditions were satisfied in those days: Kt < 0.5 or irradiances were less than 50W/m². Those conditions will be covered later in the text.

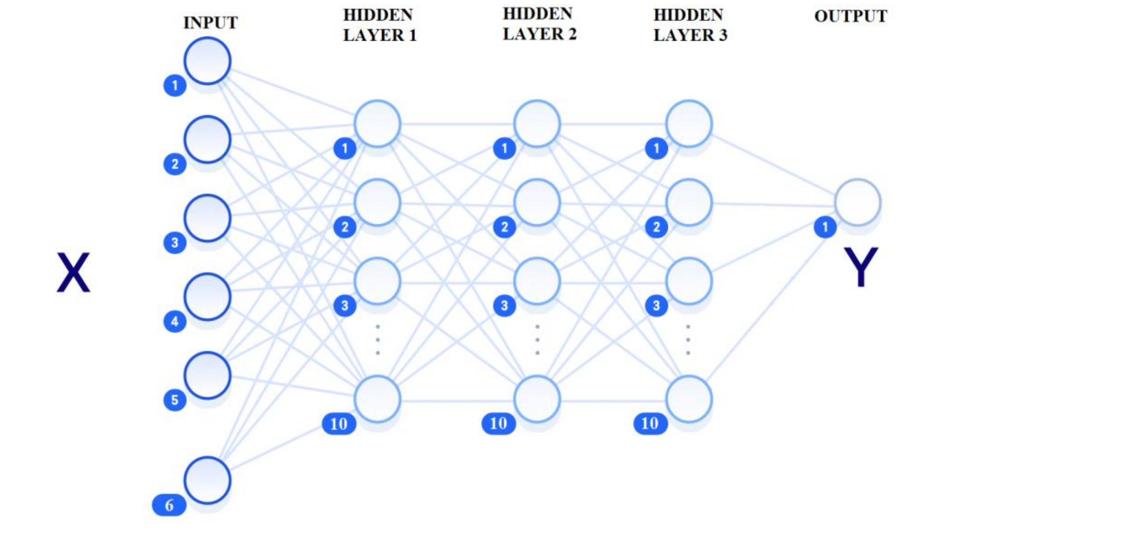

Fig. 1 - Multilayer Perceptron (MLP) ANN

Support Vector Machine or SVM is a supervised learning technique that has been established within the concept of machine learning (ML). Basically, the SVM is a linear machine (HAYKIN, 2002). It is a tool that has been used extensively and successfully in problems that require classification or even, with some needed changes in the algorithm, regression. It has its bases based on the theory of statistical learning developed by Vapnik (1998;1999a). The application of this technique has presented results that are comparable and often superior to those obtained by other learning algorithms, such as Artificial Neural Networks (ANNs). The SVM has some characteristics that deserve to be emphasized:

- Well defined theory. The SVM's have, within the areas of Mathematics and Statistics, a well-established theoretical formulation;
- Convexity of the objective function. The use of SVM means optimizing a quadratic function that has only a global minimum. This is an advantage, for example, over artificial neural networks, where it is possible to have local minimums in the objective function, minimization target;
- Good generalization capacity. The classifiers resulting from SVMs generally have good generalization capabilities, considering that the efficiency of a predictor is measured through data that does not belong to the training set. In this way, overfitting is avoided, in which the predictor becomes very specialized in the training set, but presents poor performance against new standards;
- Robustness in large dimensions. SVM's are robust when applied to large objects such as images, for example. Other types of classifiers commonly generate overfitting in the presence of such data.

When working with a regression problem, SVM is commonly known as SVR, given that SVR is a SVM with some modifications in the algorithm to attend the regression case. An important step to build a SVR model is done by choosing a kernel, a mapping technique accomplished in order to achieve a better curve fitting. Indeed, whatever would be a solution in respect to classification (SVM) or regression (SVR), a radial basis kernel function is often selected among other possible choices. So, a radial kernel was then the choice that reached the best results in the SVR model. Finally, the refinement of the input parameters in SVR model is usually done through heuristic methods or guides for optimization of such model (C.W., C.C. e C.J, 2019). That cited guide was useful for adjusting the parameters of the SVR model, especially for optimizing the parameters called cost and gamma.

It is worth to say that the algorithm LIBSVM (Chang, 2011) is embedded in the library used in Python language to implement the SVR, which also incorporates an algorithm named SMO (Fan, Chen and Lin, 2005), an abbreviation for sequential minimal optimization (Platt, 1998), to get more efficiency.

In MLP as well as SVR, the (satellite) measured input variables to use in the models were:

- X_1: Temperature
- X_2: Relative humidity
- X_3: GHI;

- X_4: DNI;
- X_5: Atmospheric pressure;
- X_6: Day of year

The development of the entire software with the modeling algorithms was done through Python programming language, widely used nowadays.

2.4. Metrics Adopted

Three metrics were established to assess the performance of the methods for bias removal or mitigation, that is, the minimization of the error variable defined by the previous section such as $E(t)$.

MBD – Mean Bias Deviation:

$$MBD = \frac{1}{N}\sum_{t=1}^{N} E(t) = \frac{1}{N}\sum_{t=1}^{N}(Gsat(t) - Gobs(t))$$

The usefulness of this measure reflects the total mean deviation considering all the occasional deviations observed in the instant t.

MBD_{abs} – Absolute Mean Bias Deviation:

$$MBD_{abs} = \frac{1}{N}\sum_{t=1}^{N} |E(t)| = \frac{1}{N}\sum_{t=1}^{N}|(Gsat(t) - Gobs(t))|$$

RMSD –Root Mean Square Deviation:

Besides the previous metrics, there is another one commonly used to measure the deviation from the desired values:

$$RMSD = \sqrt{\frac{1}{N}\sum_{t=1}^{N} E(t)^2} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Gsat(t) - Gobs(t))^2}$$

2.5. Dataset

The satellite dataset was obtained for 2013 with a one minute resolution for the city of Patos (Latitude 07º 01' 28" S and Longitude 37º 16' 48" W), elevation of 254m above the sea level. The city of Patos is in the Northeast of Brazil, in the state of Paraiba (PB). The long time series via satellite (Direct Normal Irradiance, DNI, and Global Horizontal Irradiance, GHI) was purchased from Solargis. The spatial resolution provided is 250m. Besides, the output from the database Solargis (v2.1.17) was calculated from GOES satellite data (© 2018 NOAA) and from atmospheric data (© 2018 ECMWF and NOAA) by Solargis method. Besides, it is important to note that the satellite dataset was referred to the same coordinates as the ground station.

The solarimetric station on the ground was formed by a class 1 pyrheliometer, standard secondary pyranometers and other meteorological instruments compliant with WMO standard (2015). The Fig. 2 shows where the ground station was mounted. The localization of the ground station can also be seen online through the internet link:
https://solargis.info/imaps/#tl=Google:hybrid&bm=satellite&loc=-7.079722,-37.277222&c=-7.079722,-37.277222&z=14

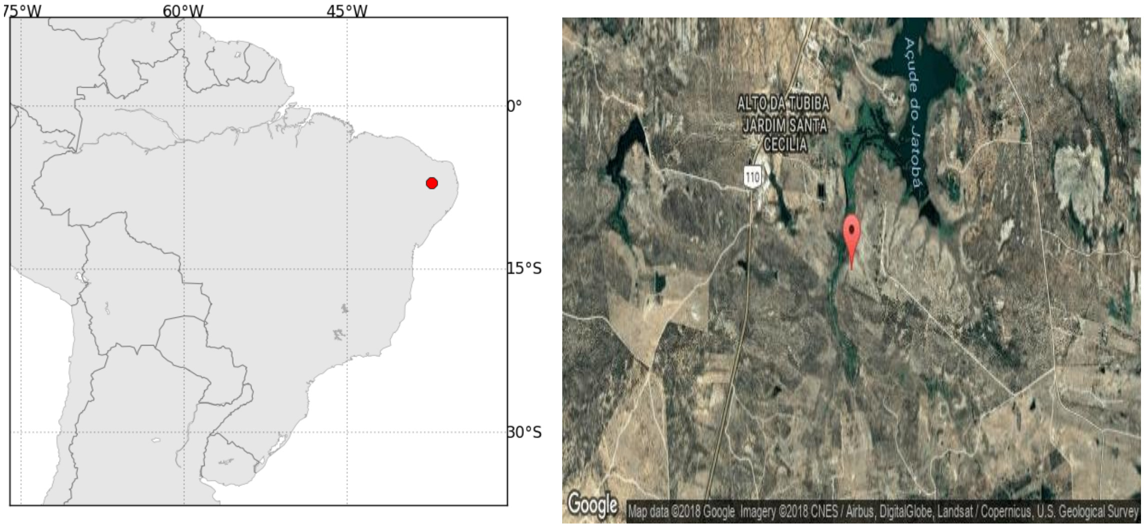

Fig. 2 – Localization of the ground station.

3. Results and discussions

Several techniques were implemented through the software developed for the scientific purpose of investigation and research about the DNI – Direct Normal Irradiance – measured by satellite in relation to data obtained on terrestrial surface. Parameters such as MBD and RMSD were presented in form of algorithms and placed as instruments for the measurement of results for each adjustment model chosen. Particularly, the analysis through artificial neural-network involved, as usual in this technique, refinements of external parameters of the programming libraries of the neural-networks with the purpose of obtaining better performance of the selected models (Tiba et. al., 2018).

3.1 Raw and filtered data for Patos city

Initially, an algorithm was created to perform the reading and synchronizing in time two databases originated from different sources: satellite and terrestrial solarimetric station. In Fig. 3a can be seen the hourly raw data for Patos city, shown in ordered pairs (DNIsup ; DNIsat) in a system of Cartesian coordinates.

To reduce scattering, clear sky days were filtered so that the transmittance index (Kt) is higher than 0.5 and the DNI is higher than 50W/m² (Polo et al., 2016). By filtering the raw data, the result will be the graphic showed in Fig. 3 on the right.

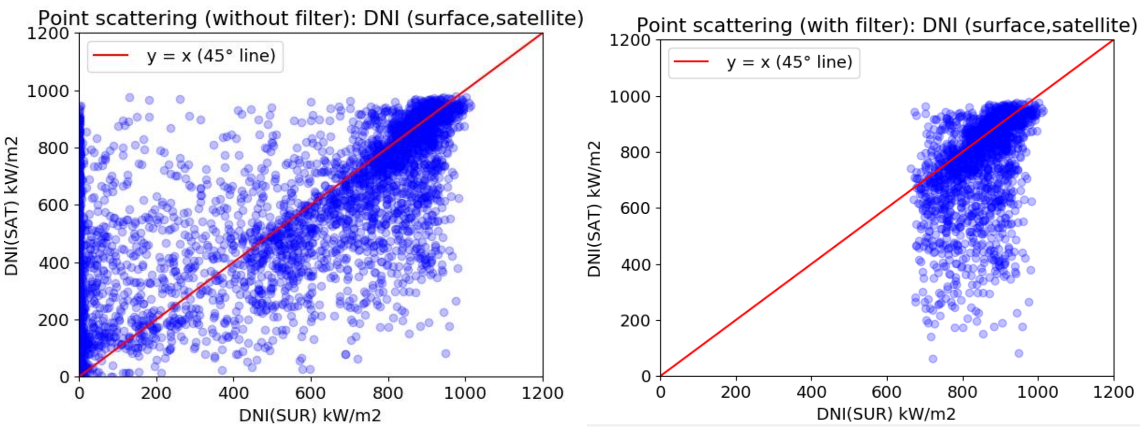

Fig. 3 – Graphics of avg. hourly irradiance: raw data (left) and filtered data (right).

3.2 Linear Regression

Using the filtered dataset the simple regression between terrestrial and satellite solar irradiation results in the equation, regarding a daily average basis of DNI irradiance:

$$E(t)=\Delta(DNI_{SAT} - DNI_{GROUND}) = 0.058DNI_{SAT}-0.220$$

And the Gsat(t) value may be adjusted by the subtraction of E(t), that is, by the removal of the bias:

$$Gsat_{adj}(t) = Gsat(t) - E(t) = Gsat(t) - (0.058\, Gsat(t) - 0.22)$$

That is,

$$Gsat_{adj}(t) = 0.942Gsat + 0.22 \quad (\text{kWh/m}^2)$$

The Fig 4 shows a graphic overlay for Patos city regarding satellite e ground based DNI irradiances along the year, before (left) and after (right) the site adaptation process by linear regression method.

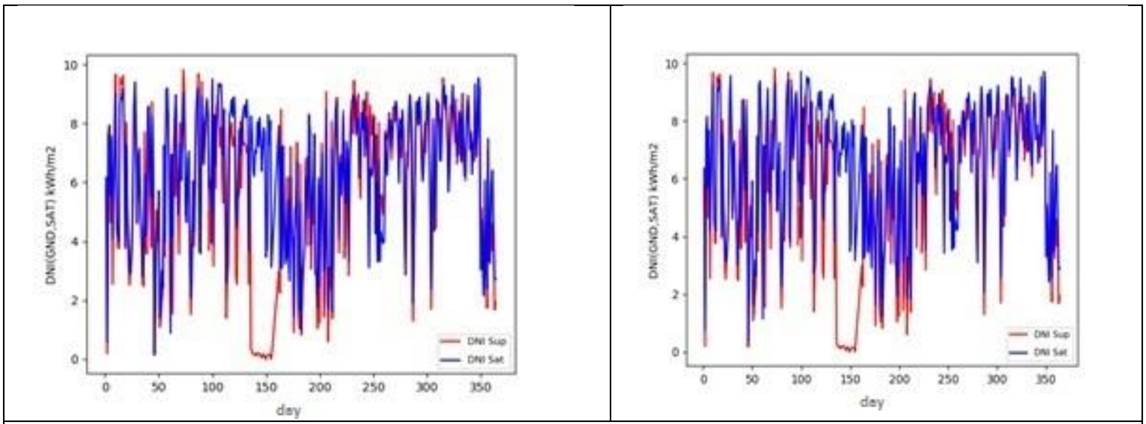

Fig. 4 – Graphic overlay for Patos, before (left) and after (right) the linear regression method.

On the other hand, the Fig. 5 shows the graphic scattering of points before (on the left) and after (on the right) the adjustment between the satellite and observed irradiance data in surface, regarding a daily average basis. The previously filtered pointes were included in those graphics in spite of not being modeled.

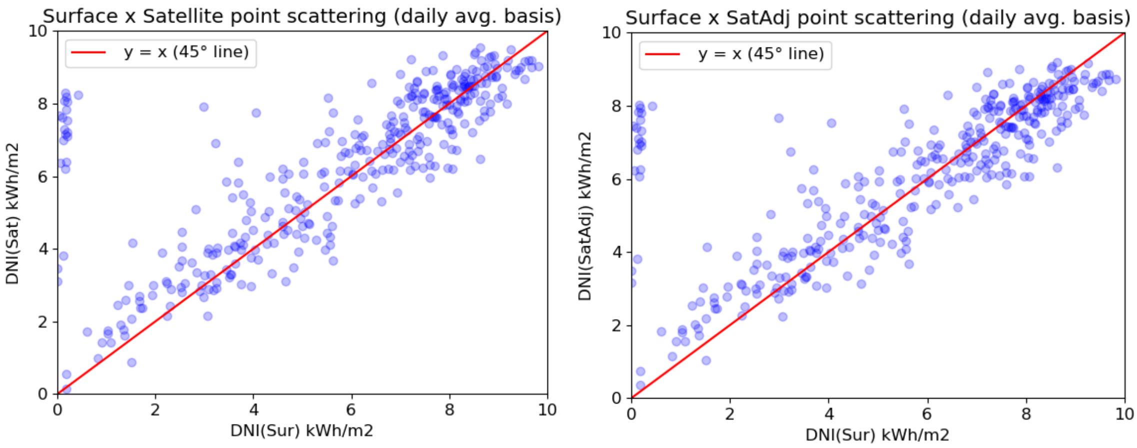

Fig. 5 – Graphics of avg. hourly irradiance: before (left) and after (right) linear regression approach.

3.3 Multiple Linear Regression

The model considered the output variable, $E(t)$, as function of a linear relation of various input attributes.

$$E(t) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

In the cases of Multiple Linear Regression, the (satellite) measured input variables to use in the models were:

X_1: Temperature(sat), in Celsius degrees
X_2: Relative humidity(sat), in %
X_3: GHI(sat), total irradiance, in kW/m²
X_4: DNI(sat), direct irradiance, in kW/m²

where, E(t) is the bias, Xi are the variable obtained by satellite, respectively from the environmental temperature (^{0}C), relative humidity (%), total irradiance (kW/m²) and direct irradiance kW/m². The data processing for this model provided the following results for the β_i coefficients seen in the expression above:

β_0: -8.5746, β_1: 0.2295, β_2: 0.0556, β_3: -0.3720, β_4: 0.2538

The Fig. 6 shows a graphic overlay for Patos city regarding satellite e ground based DNI irradiances along the year, before (left) and after (right) the site adaptation process by multivariate linear regression method.

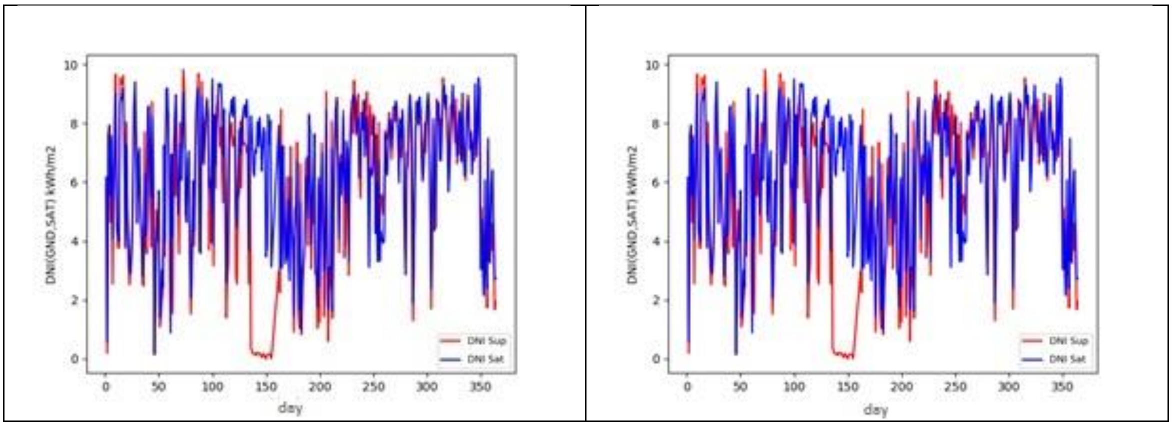

Fig. 6 – Graphic overlay, before (left) and after (right) the multivariate linear regression method.

To compare the scattering results of the multivariate approach, the Fig. 7 shows the results in terms of the points before (on the left) and after (on the right) the adjustment between the satellite and observed irradiance data in surface. The previously filtered pointes were again included in those graphics.

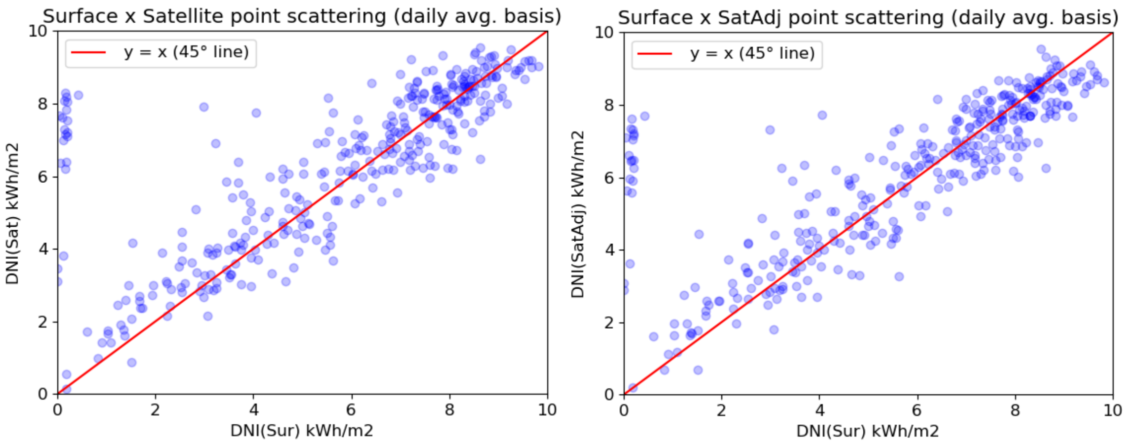

Fig. 7 – Graphics of avg. hourly irradiance: before (left) and after (right) multivariate regression approach.

3.4 MLP and SVM(R) Algorithms

In order to test the bias mitigation by an ANN approach, the satellite data for Patos city were submitted to a Multilayer Perceptron (MLP). There was a lot of agreement with the results previously obtained, what can be seen in Tab. 1 and Tab. 2. Only the MDB bias had not reduced as could be expected by comparing with the past methods employed. This is partially due to the technical construction of the neural network model in which 75% of the samples were took randomly and used exclusively in the training of the MLP and, therefore, 25% of the samples were reserved and presented to the MLP just in the later stage of testing and evaluation of results. Finally, the MBD, MBDabs and RMSD metrics were calculated over all samples, i.e., including the values returned from the training and testing stage.

The Fig. 8 shows a graphic overlay for Patos city, regarding satellite e ground based DNI irradiances along the year, before (left) and after (right) the site adaptation process by the ANN-MLP method.

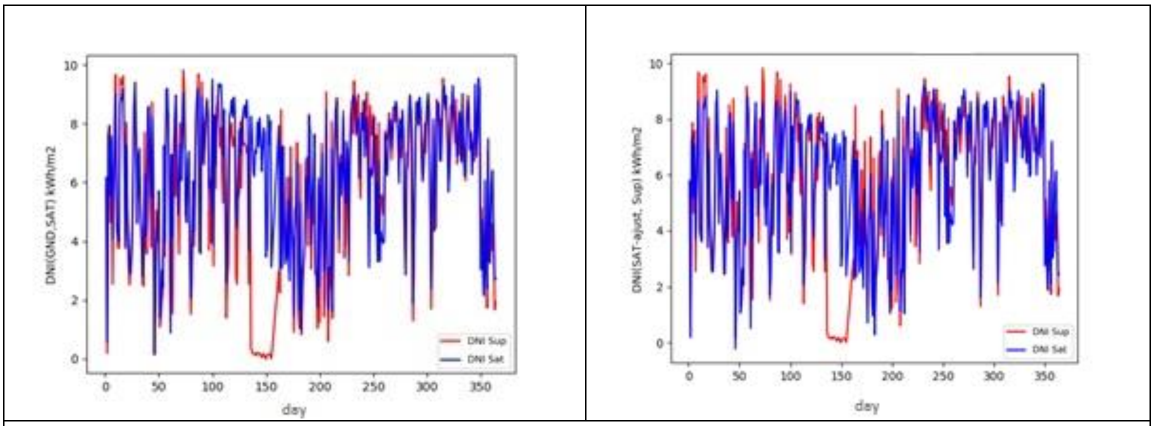

Fig. 8 - Graphic overlay, before (left) and after (right) the ANN-MLP method.

With the aim of comparing the scattering results of the MLP approach, the Fig. 9 shows the results in terms of the points before (on the left) and after (on the right) the adjustment between the satellite and observed irradiance data in surface. The previously filtered pointes were once again included in those graphics.

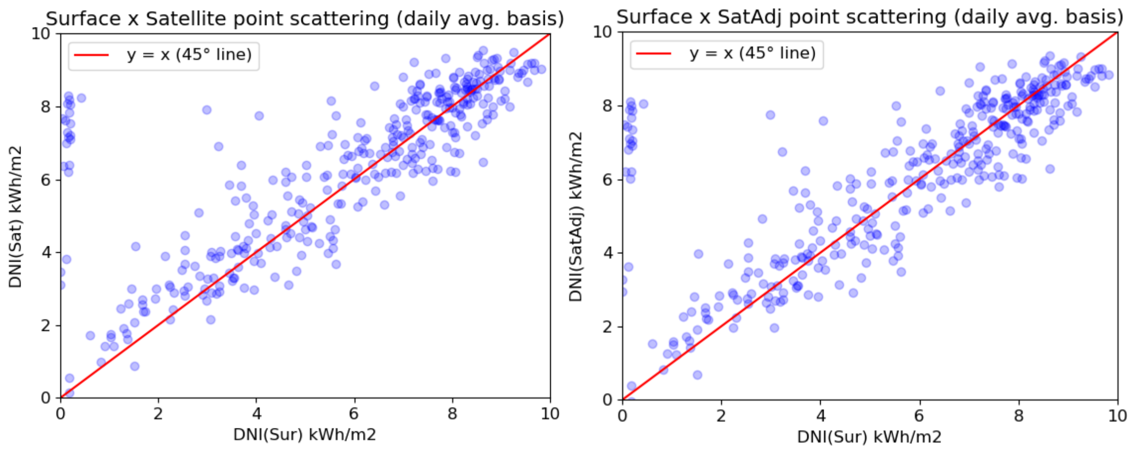

Fig. 9 – Graphics of avg. hourly irradiance: before (left) and after (right) MLP approach.

By using the same inputs (and split ratio) for train and test stages as in the MLP method, a SVR machine learning approach was built. As a result, it was found a significant improvement over the past algorithms. The Fig. 10 shows a graphic overlay for Patos city for the SVR method in a similar way as done before.

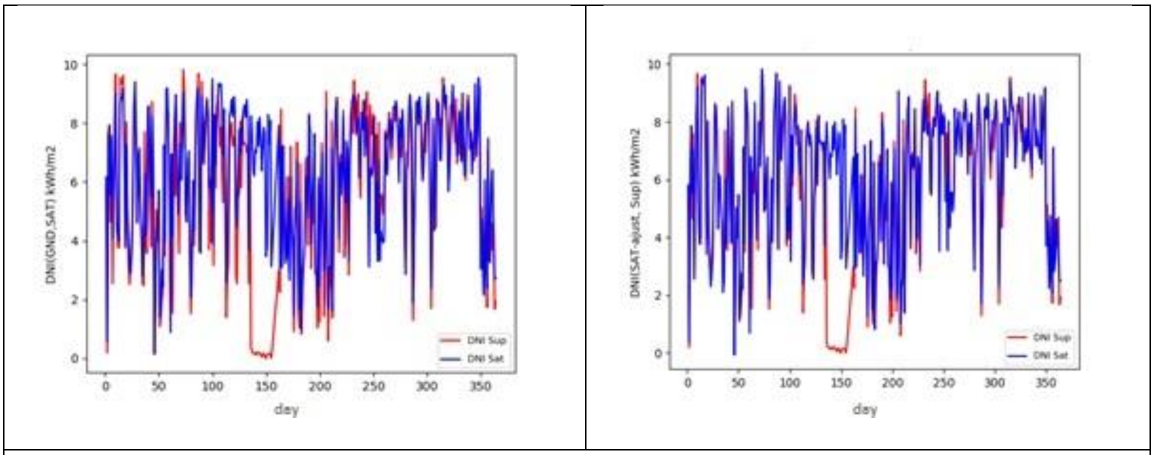

Fig. 10 – Graphic overlay, before (left) and after (right) the SVR method.

To compare the scattering results of the SVR approach, the Fig. 11 shows the results in terms of the points before (on the left) and after (on the right) the adjustment between the satellite and observed irradiance data in surface. The previously filtered pointes were once again included in those graphics.

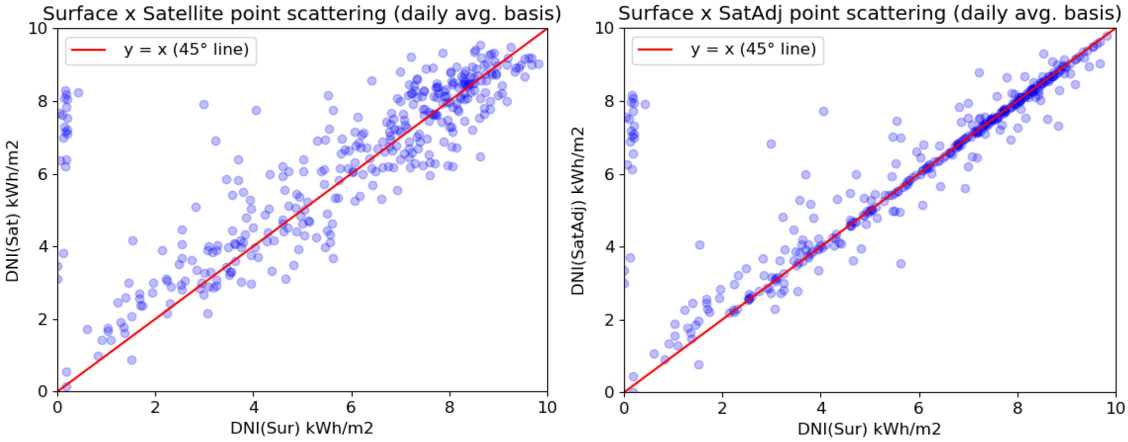

Fig. 11 – Graphics of avg. hourly irradiance: before (left) and after (right) SVR approach.

Finally, to summarize the results, a comparison among the 04 algorithms employed here is shown in Tab. 1 and Tab. 2. All the methods performed the correction of the bias adequately. With respect to the RMSD metric, the simple, multiple and ANN (MLP) regression algorithms yielded a slight improvement regarding the satellite data adjustment, respectively of 2.5, 8.0 and 4.3%. When using SVR, the improvement of the results was remarkable. The RMSD, in particular, reduced 57.9% from its initial value. It is important to emphasize that the regions with the restrictions, i.e., the filtering procedure, were not modeled, what means that the models did not take those points into account.

Tab. 1 – Performance metrics for Linear and Multiple Regression (daily average values in kWh/m^2)

Method and metric	Linear Regression			Multiple Regression		
	MBD_{abs}	MBD	RMSD	MBD_{abs}	MBD	RMSD
Before adjust.	0.693	0.178	0.932	0.693	0.178	0.932
After adjust.	0.680	0	0.909	0.645	0	0.858

Tab. 2 – Performance metrics for MLP and SVR methods (daily average values in kWh/m^2)

Method and metric	ANN (MLP)			ML (SVR)		
	MBD_{abs}	MBD	RMSD	MBD_{abs}	MBD	RMSD
Before adjust.	0.693	0.178	0.932	0.693	0.178	0.932
After adjust.	0.671	0.038	0.892	0.184	0.008	0.392

3.5 Conclusions

In the present work, different methods were analyzed for the performing of site adaptation of direct solar irradiance data estimated by satellite with high quality experimental terrestrial data. It was demonstrated that the methods that use linear regression, multiple regression and ANN-MLP produce discreet improvements in the statistical indictors MBD and RMSD The use of the SVR method produced a MBD measurement close to zero and a RMSD, at least, 54.3% lower than other methods. The obtained results show the ability of SVR machine learning for reliable and precise adjustment of the estimations by satellite of the DNI with high quality terrestrial data. Further improvements may be expected when using in SVR method the adjustment with local terrestrial variable, such as: precipitable water, aerosol optical depth, cloud index and clear sky solar radiation measurements. Such variables may be derived upon existing empirical expressions that relate them with conventional terrestrial station data (temperature, relative humidity, atmospheric pressure GHI and DNI). With that, the adjustment between the terrestrial and satellite data will be performed with a larger number of common physical variables.

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