VALIDATION OF 441 TYPICAL METEOROLOGICAL YEAR (TMY) CREATED WITH INMET/BRAZIL STATIONS DATA

Vinicius Rugeri Borges Bonini – vinicius.bonini@lepten.ufsc.br
Allan Ricardo Starke – allan.starke@lepten.ufsc.br
Leonardo Freire Lacerda Lemos – llacerda@lepten.ufsc.br
Sergio Colle – sergio.colle@ufsc.br
Laboratory of Energy Conversion Engineering and Energy Technology, Department of Mechanical Engineering/ Federal University of Santa Catarina, Florianopolis (Brazil)

Abstract. Renewable energy sources are essential to solve the problem of scarcity of fossil fuels that we will face in the future, without compromising our quality of life. Yet, the deployment of these technology, especially solar energy, requires a detailed yield, economic and risk analysis to secure financing options. To do so, a set of specialized software (or tools) are used, requiring meteorological and irradiation data as input, known as typical meteorological year (TMY). Recently, our group generated 441 TMY files from the data of the largest weather station network in Brazil, operated by the National Institute of Meteorology (INMET). The authors used the BRL-Brazil separation model to estimate the diffuse and direct normal irradiance and applied the Sandia Method to generate the TMY files. Although the authors generated and provided TMY files across Brazilian territory, it lacks a thoroughly analysis of the accuracy of the generated TMY files and the original data of the INMET station. Cross-validation between the irradiance values in the TMY files and the irradiance data provided in the Brazilian Solar Atlas. The TMY were validated comparing the yearly and monthly means of daily GHI totals from the files against the values provide by the Brazilian Solar Atlas. Small differences were found, with TMY yearly means of GHI differing an average 2% in relation to the Atlas, with maximum deviations are not larger than 10%. Regarding the DNI and DIF values from the TMY, the deviations between the TMY and the Solar Atlas were significantly larger than the deviations found for GHI. This can be explained by the inherent uncertainty in DNI and DIF methods of estimations used to generate the TMY files (BRL-Brazil) and in the Solar Atlas (Brasil-SR). After this validation study, it can be said that Brazil has a database with TMY for 441 cities with known uncertainties, all of which can be used to support solar studies on a continental scale.

Keywords: *Typical Meteorological Year, INMET/Brazil, Atlas Brasileiro de Energia Solar*

1. INTRODUCTION

Regardless of if the anthropologic effects of GHG emissions are responsible for the global warming or not, one must acknowledge that fossil fuels are a finite resource. When these resources approach depletion, there will be an imbalance in the supply and demand chain, generating an energy and economic crisis. In the meantime, alternative means should be researched to supply the energy demand required for the human's livelihood.

Energy has become an essential good in modern society, necessary to meet basic human needs (e.g. lighting, refrigeration, communication) and sustain productive processes. In addition, the need for social and economic development, as well as the improvement of human health and well-being makes the demand for energy and services to grow. Therefore, alternative energy sources must be found, that can act as alternatives within the next decade, thus making it possible to save the fossil fuels currently consumed, letting them be used only to meet demands without alternative solutions.

There are several alternative solutions to meet the global demand for energy, namely improving energy efficiency, replacing fossil fuels with renewable energy (RE) or nuclear energy. Among these options, renewable energies stand out, which in addition to have great potential to mitigate the effects of climate change, enable a wide range of benefits if implemented properly, including: the contribution to economic and social development, access to energy, secure energy supply and reduction of negative impacts on the environment and health. Furthermore, some of the renewable energy production technologies can be deployed in a decentralized manner – close to consumers – in order to accelerate the economic and social development of small regions, such as rural communities and small towns.

Solar energy stands out among renewable energies, not only for its high exploitation potential, but also for the wide range of technologies that can contribute to meet the demand for various energy services. Solar energy conversion systems can generate heat, cold, natural light, electricity and fuels. Although the energy generated by solar conversion systems currently represents only a small fraction of the total energy consumed, the market for solar technologies has been growing rapidly.

Financing renewable energy systems with high initial investment, such as solar systems, requires detailed risk analysis (Hirsch, 2017). The studies of such system should consider all effects that could impact the thermal and economic performance of the plant. Therefore, engineers use different software tools that provide a realistic estimate of energy production, which require meteorological data as input. This data can be created from various sources, such as ground measurements, satellite images, and atmospheric models. Due to the interannual variability of the meteorological parameters, it is necessary to use a dataset that represents one typical meteorological year (TMY), which provides at least two advantages: it avoids the possibility of extreme variations contained in a particular year or a long-term period (Wilcox e Marion, 2008) and reduces the volume of meteorological data needed, speeding up the simulation of solar systems (Cebecauer e Suri, 2015).

In the literature, although there are many approaches available for the construction of TMY files, the conventionally approach used to create such dataset is the Sandia method proposed by (Hall *et al*., 1978). These datasets usually contain 8760 hourly records of meteorological parameters that represent climate conditions of a certain region. Originally, this method considered hourly data (air temperature, dew point, wind speed and global horizontal solar irradiance) measured over a long period to generate a single year of data that represents the climate conditions of a given location stably.

The use of clean energy sources in Brazil is increasing, but there is still great potential for the growth of solar energy applications in the country. Thus, as these solar energy conversion systems become more prevalent in the energy matrix, it is necessary to provide means for planners and operators of the energy system to understand how variations in the solar resource will affect the transmission network. In this regard, it is necessary to model the long-term performance and short-term variability of solar technologies and synchronize these models with the load and other variable generation sources such as wind power. In that regard, (Dorneles *et al*., 2019) provided 441 TMY files generated using data from the largest weather station network in Brazil, operated by the National Institute of Meteorology (INMET). The authors used the Sandia Method for TMY generation and a separation model to estimate the diffuse irradiance from global irradiance measurements.

Although (Dorneles *et al*., 2019) generated and provided TMY files across Brazilian territory, no cross-validation was presented, in which the generated TMY files were compared with another database. Therefore, the aim of this work is to compare the irradiance values in the TMY files against the irradiance data provided in the Brazilian Solar Atlas (Pereira *et al*., 2017). Thus, it is possible to provide not only the required dataset (TMY) to assess the performance and financial risk of solar energy systems but provide an estimate of the deviations of the irradiance values related to the reference values provided in the Brazilian Solar Atlas.

2. DATA AND METHODOLOGY

The present paper focuses on the validation of TMY for Brazil, therefore, the concepts relating the weather data, and the treatment employed are going to be explained in detail in the present section. Firstly, the weather data source, and the DNI estimation method are explained, followed by procedure employed to generate the TMY. Lastly the statistical analysis for de cross-validation is explained.

2.1 Weather data

The meteorological data were obtained from the Brazilian National Institute of Meteorology (INMET), which is recognized as the National Weather Service and is linked to the World Meteorology Organization. Since 2005, the INMET has installed and operated about 564 Automatic Weather Stations (AWS) along Brazil (Moura *et al*., 2016). Although the AWS measure global horizontal irradiance and auxiliary meteorological variables (air temperature, relative humidity, wind direction and wind speed, precipitation, and barometric pressure). As presented in (Dorneles *et al*., 2019) the meteorological parameters considered are: mean, maximum and minimum air temperature, maximum and mean wind speed, mean, maximum and minimum relative humidity, total daily global horizontal and direct normal irradiation. The time-series have hourly temporal resolution and about 13 years (2005-2018) of data, however due to the commissioning and/or operational problems, each station has a different period of recorded data. Regarding the specifications of the sensors installed in the AWS network they can be checked in detail in (Dorneles *et al*., 2019).

The Brazilian Solar Atlas (Pereira *et al*., 2017) is a technical bibliography that provides a survey of solar energy availability in the Brazilian territory, using a radiative transfer model fed by climatological data and information extracted from geostationary satellite images, and validated by data collected from surface stations. The Brazilian Solar Atlas uses the Brasil-SR model to estimate the solar radiation, that is based on the IGMK model. In the present work, the annual averages of the daily totals of GHI, DNI and DIF and monthly averages of the daily totals of GHI, DNI and DIF were used to compare the results obtained in the TMY.

2.2 Direct normal irradiance estimate

As neither the diffuse horizontal irradiance (DIF) nor the direct normal irradiance (DNI) were measured in the network, the BRL-Brazil model (Lemos *et al*., 2017) was used to estimate the diffuse horizontal irradiance (DIF), and obtain the DNI. The BRL-Brazil model estimates the diffuse fraction of solar irradiance using a sigmoid function and has been shown to deliver better irradiance estimates in Brazil than other hourly separation models widely mentioned in the literature. This model is an adjustment of the BRL separation model for the Brazilian weather data, that uses measured GHI, DNI and DIF data from INPE (Brazilian Institute for Space Research) weather stations.

2.3 TMY Generation procedure

Since the measured data can exhibit some strange behavior, a quality control (QC) procedure must be employed. For the solar radiation, this procedure is based on the quality checks proposed by Long and Dutton (2010), being this method recommended by the Baseline Surface Radiation Network (BSRN) (Driemel *et al*., 2018). In this process, the GHI must fulfill some conditions that are based on the solar zenith angle and the solar constant adjusted for Earth-Sun distance throughout the year.

For the auxiliary meteorological variables, the criteria proposed by Fiebrich *et al*. (2010) was applied for suspect variables. The measured data must lay inside an expected range, and consecutive values are also compared. After the quality control, the time-series of each station contains some missing data spaces -"gaps”-, that must be filled before creating the TMY. As explained by (Dorneles *et al*., 2019), the gaps were divided in three groups, and filled with different methods. For gaps length between 1 and 3 hours a linear interpolation was used, as proposed by Wilcox and Marion (2008). For gaps between 3 and 24 hours each hourly gap was filled using the mean between the values of the previous and next day for that hour, as suggested by Liston and Elder (2006). The gaps greater than 24 hours were filled using ERA5 reanalysis data from ECMWF (European Centre for Medium-Range Weather Forecasts) (ECMWF, 2017).

The procedure employed to develop the TMY is divided in four consecutive steps, as presented in (Dorneles *et al*., 2019). The first steps consist in the generation of the Cumulative Distribution Functions (CDFs) for each variable used in the TMY, with Short-term CDFs for the individual months, using the generated daily data, and Long-term CDFs using the daily data from all years for the 12 months. In the second step, each short-term CDF is compared against the long-term CDFs using the Finkelstein–Schafer (FS) statistic to find five candidate months for each month of the year. In this sense, an weighted sum indicator is used, with the weights assigned, in agreement to the NSRDB TMY2 and TMY3 (Wilcox e Marion, 2008), using the relative humidity instead of the dew point, and can be checked in (Dorneles *et al*., 2019). The chosen five candidate months are those with the lowest weighted sums, representing the closeness to the long-term.

In the third step the absolute difference between the short-term (ST) mean and long-term (LT) mean, and for the median for temperature and total daily GHI, ranking the candidates in ascending order of their maximum absolute difference. In the fourth and last step the persistence of mean temperature and total daily GHI are evaluated by calculating the frequency and the length of runs above and below a fixed parameter for each candidate month. Based on the persistence evaluation, a process of elimination occurs for each group of five candidates, to exclude months under extreme conditions.

As reported by (Dorneles *et al*., 2019), after the first analysis of the data (564 AWS time-series from the INMET Brazil network), it can be noticed 9% of missing data over the whole database that includes all meteorological variables.

Figure 1a depicts the classification of gap lengths of the missing data found before applying the quality control procedure. Approximately 60% of the missing data (9 % of all data) was found on GHI measurements, while all auxiliary meteorological variables represented the remaining amount (40 %).

Also, there were no gaps greater than 24 hours on GHI measurements since nighttime gaps were replaced by zero. The quality control procedure removed an additional 7 % of data that was classified as erroneous or suspect data.

Figure 1b depicts that after the QC was applied, gaps between 1 and 3 hours represented 88% of the missing data, which were filled using a linear interpolation method. Moreover, 11,4% of the gaps were filled with mean between the previous and next day, since its lengths were between 3 and 24 hours. Consequently, more than 99% of the gaps were filled with statistical methods. On the other hand, larger gaps (greater than one day), which represented approximately 0,5% of set of gaps, were then filled with ERA5 data. Therefore, all gaps were successively filled.

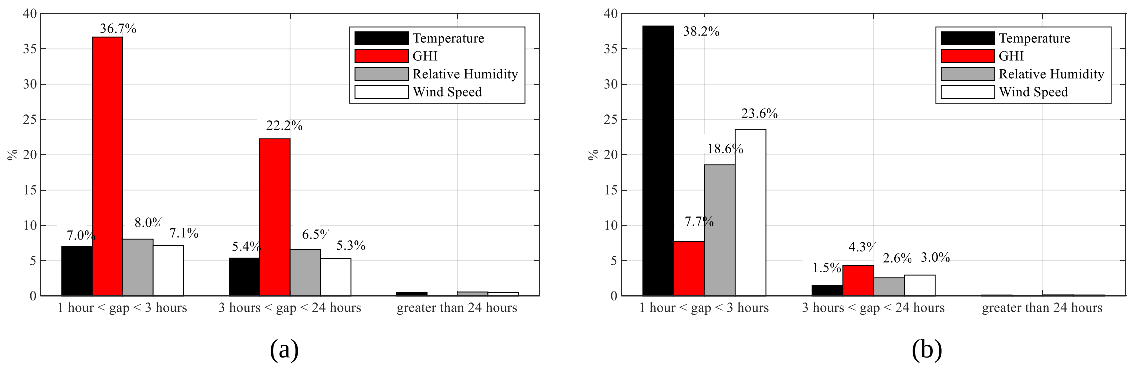
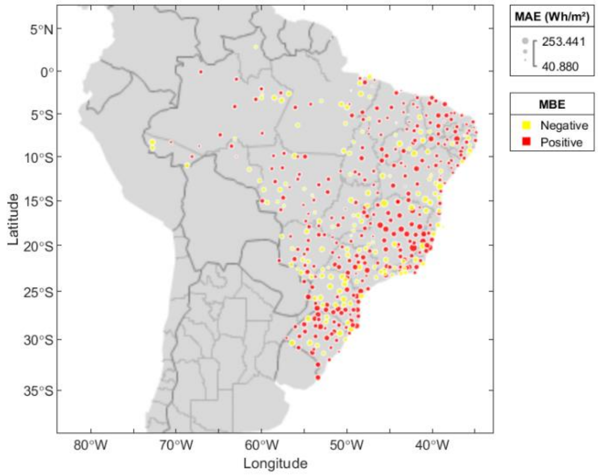


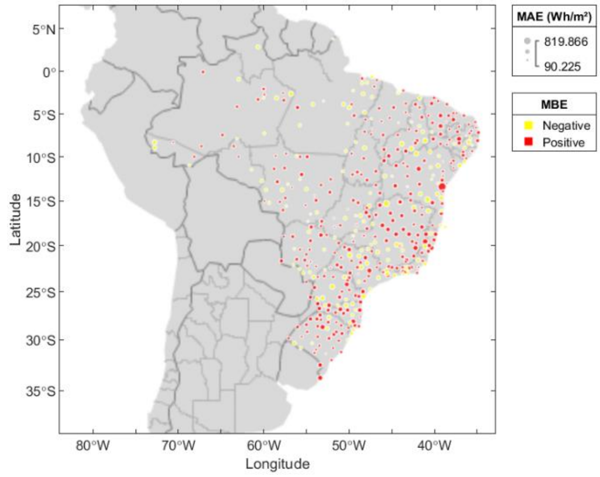
Figure 1 – Length of missing data before (a) and after (b) data quality control for INMET – BRAZIL network.

After que quality control and data filling procedures, (Dorneles *et al*., 2019) applied the Sandia method to generate the TMY for the INMET Brazil network. The first step consists of selecting only stations that have more than five years of data, resulting in 441 of 564 stations that fulfill this requirement and could be used to generate the TMY files. To assess the 441 generated TMY files, the mean bias error (MBE) between the values of the monthly global horizontal and monthly direct normal irradiance obtained from the TMY and the values from long-term data were calculated and depicted in

Figure 2. The individual biases derived for each station indicate that there are more positive (overestimation) values for both solar variables



(a)



(b)

Figure 2 – Mean bias error (MBE) for monthly GHI (a) and DNI (b) from TMY at each INMET Brazil station. The red color indicates positive bias, while yellow color indicates negative bias. The magnitude of the error is represented by the size of the circle.

2.4 Statistical analysis

The Brazilian Solar Atlas provides means of daily irradiation totals, in both yearly and monthly basis. Each of the 441 generated TMY was compared with the Atlas, via the statistical analysis described below.

First, the TMY were used to calculate yearly and monthly means of daily total irradiation. This allow data from the TMYs to be directly compared to Atlas data. A direct comparison between yearly means from the TMY and from the Atlas is presented in the validation section. To compare monthly means, two statistical indicators were calculated for each generated TMY, namely the normalized mean bias error (nMBE) and the normalized root mean square error (nRMSE), defined as follows:

$$\text{nMBE} = \left(\frac{100}{\bar{A}}\right)\frac{\sum_{i=1}^{12}(TMY_i - A_i)}{12} \qquad (1)$$

$$RMSE = \left(\frac{100}{\bar{A}}\right)\sqrt{\frac{\sum_{i=1}^{12}(TMY_i - A_i)^2}{12}} \qquad (2)$$

where TMY_i is the monthly mean of irradiation from a given TMY, at month i; A_i is the monthly mean of irradiation from the Atlas; $\bar{A}$ is the average of all 12 values of A_i.

By calculating the nMBE, it is possible to assess whether the generated TMY tends to overestimate or underestimate irradiation values. On the other hand, the nRMSE helps to assess the magnitude of the deviations between TMY and Atlas.

3. RESULTS OF THE CROSS-VALIDATION

A comparison between yearly means from the TMY and from the Atlas is shown in Figure 3 and Figure 4. Figure 3 presents dispersion plots of the yearly means of irradiation calculated from the TMYs, plotted against the yearly means from the Atlas. The relative deviations between means from the TMY and from the Atlas are further depicted in Figure 4, where histograms and empirical CDF for the relative deviations are plotted.

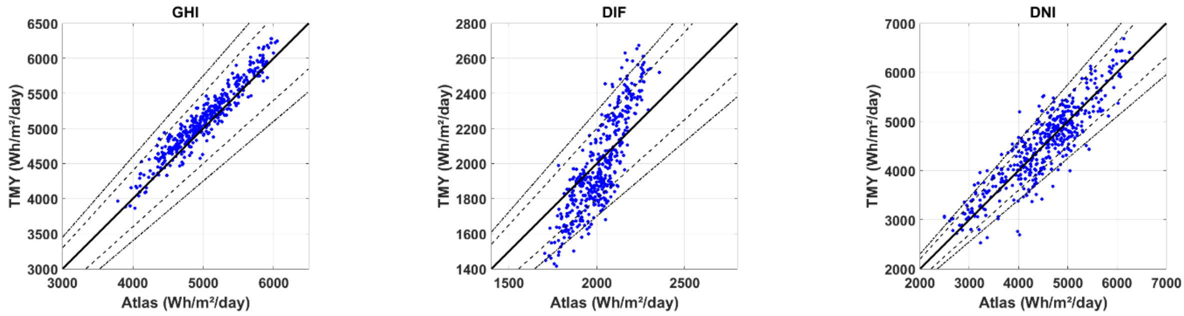


Figure 3 – Dispersion plots comparing yearly means of daily totals for global (GHI), direct normal (DNI) and diffuse (DIF) irradiation, as obtained from the TMY versus from the Solar Atlas. Lines in the plots show the exact match, 10% relative deviation, and 15%.

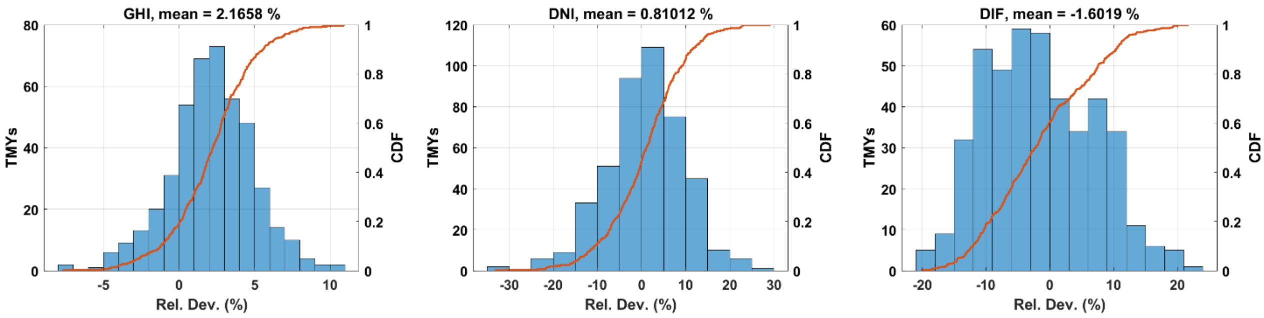


Figure 4 – Histograms and CDF for the relative deviation between yearly means from TMY and Atlas data.

As can be seen from these figures, yearly means of global irradiation (GHI) from the TMY are similar to the means from the Solar Atlas, with relative deviations between TMY yearly GHI and Atlas yearly GHI staying mostly below 10% (in Figure 3, the 10% deviation zone is shown as plotted dashed lines). As depicted in Figure 4, relative deviations in yearly GHI are distributed around a mean of 2%.

For direct normal irradiation (DNI), however, there is a greater dispersion in the data, with most deviations below 15% (the 15% deviation zone is depicted as dot-dashed lines in Figure 3). Nonetheless, there is still a considerable amount of TMY whose yearly means deviate more than 15% from the Atlas means, as clearly depicted in Figure 4, where it can also be seen those deviations in DNI means are distributed around a mean of 1%. Finally, the dispersion plot for diffuse irradiation (DIF) is also shown, indicating a trend in TMY yearly totals. As with the DNI, most deviations between TMY DIF and Atlas DIF are below 15%, with some outliers.

However, care must be taken when evaluating these results. The Atlas GHI data was validated by its authors using measured, long-term GHI data from INMET, the same source of the measurements used for TMY generation in the present work. The authors of the Atlas found that their GHI estimates were in good agreement with INMET measurements, with a maximum of ±6% for the relative deviations between yearly means from the Atlas and from INMET. This allows one to conclude that, since the TMY presented here have been obtained from INMET data, and since there is good agreement between GHI yearly means from the TMY and from the Atlas, then the TMY generation procedure described in the previous sections is suitable for the selection of representative GHI values, for each of the 441 locations analyzed.

As for the DNI and DIF, for which the deviations in yearly means were much larger than for GHI, attention must be paid to the fact that the INMET measurements used for TMY generation contained only GHI observations, and that DNI and DIF were estimated using the BRL model. Besides, since there was no INMET data for DNI, the authors of the Atlas compared their DNI estimates with data from the SONDA stations network, which, despite measuring DNI and DIF, has only a few operating meteorological stations when compared with INMET. This means that there was less data available for calibration and validation of the Atlas DNI than there was for GHI, and deviations between Atlas DNI yearly means and that of SONDA were within the ±10% range.

Thus, since the Atlas DNI has a larger uncertainty than GHI, and since there is also an uncertainty associated to the BRL model used for the generation of DNI and DIF in the TMY, it is expected that larger deviations will be found between Atlas and TMY estimates of DNI and DIF. The larger Atlas DNI and DIF uncertainties compound with the BRL model uncertainty, resulting in the trends and in the larger deviations depicted in Figure 3 and Figure 4, thus the yearly results for DNI and DIF do not indicate any flaw in the TMY generation procedure itself, which was presented in previous sections – rather, these results emphasize the need for further research in separation models and DNI estimation models, in order to reduce uncertainties in estimates of direct and diffuse radiation.

So far only the yearly results have been analyzed, showing that there is good agreement between GHI yearly data from the TMY and from the Atlas, but not so good an agreement between DNI and DIF yearly data. A similar behavior is found in monthly data, as can be seen from Figure 5 and Figure 6.

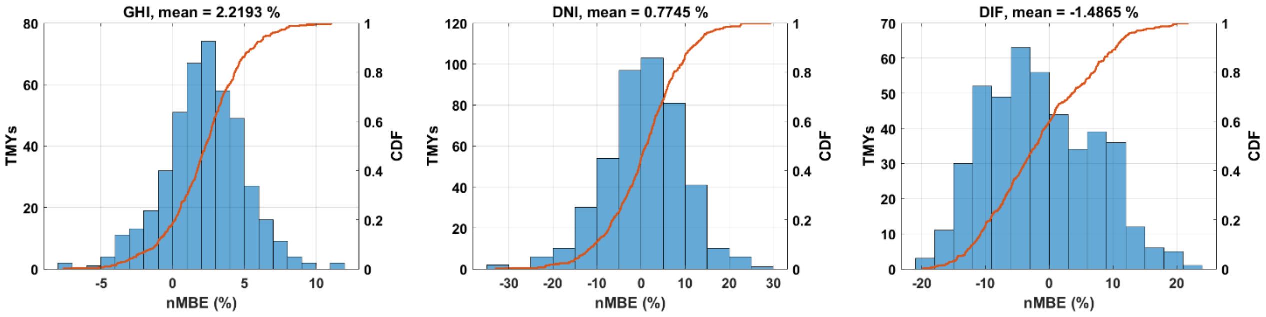


Figure 5 – Histograms and CDFs for the normalized mean bias error (nMBE), for GHI, DNI and DIF.

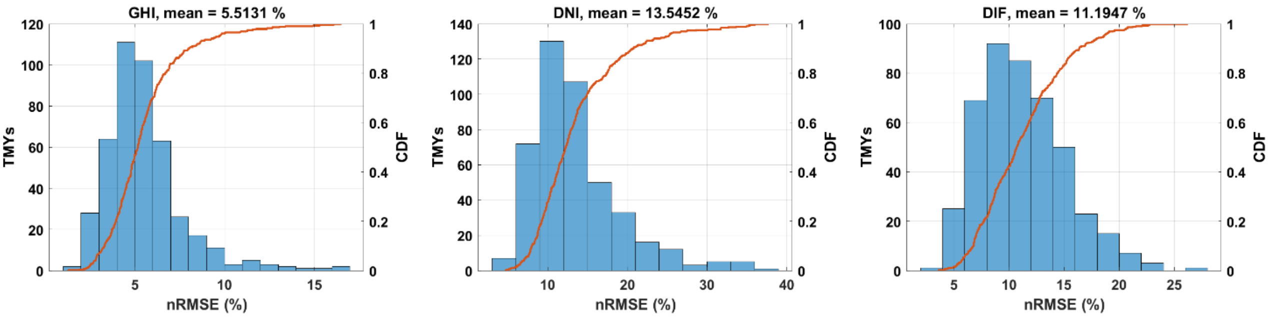


Figure 6 – Histograms and CDFs for the normalized mean bias error (nRMSE), for GHI, DNI and DIF.

The errors associated with TMY monthly means are much larger for DNI and DIF than for GHI, as can be seen from the x-axis scales in Figure 5 and Figure 6. The nMBE histograms in Figure 5 show that there is a slight tendency of the TMYs to overestimate GHI monthly means, by around 2%, while DIF estimates from the TMYs are usually underestimated by around 1.5%, when compared to the Atlas.

Nevertheless, as can be seen from the nRMSE histograms in Figure 6, GHI monthly means from the TMYs deviate, on average, around 5% when compared to the Atlas monthly means, with maximum deviations no larger than 17%. For DNI monthly means, the average deviation is on 13%, with maximum deviations as high as 40%. Finally, in the DIF case, deviations are around 11%, and can be as high as 30%.

To further investigate the deviations in monthly means between the TMYs and Atlas, a geographical distribution of these errors is presented in Figure 7, Figure 8 and Figure 9 where the nMBE and nRMSE calculated for GHI, DNI and DIF are shown in a map of Brazil. Please note that the color and marker scales are different in each figure, to ease visualization. In the maps for nMBE, the marker size denotes the absolute value of nMBE, while the color scale informs whether the nMBE is positive or negative. In the nRMSE maps, on the other hand, both the marker size and the color scale indicate the absolute value of nRMSE.

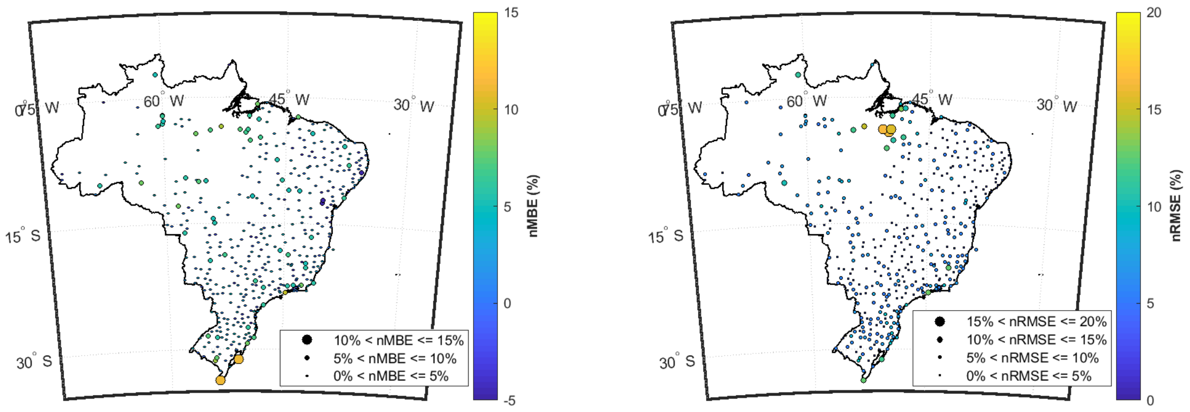


Figure 7– Spatial distribution of the nMBE (left) and nRMSE (right) for the GHI monthly means.

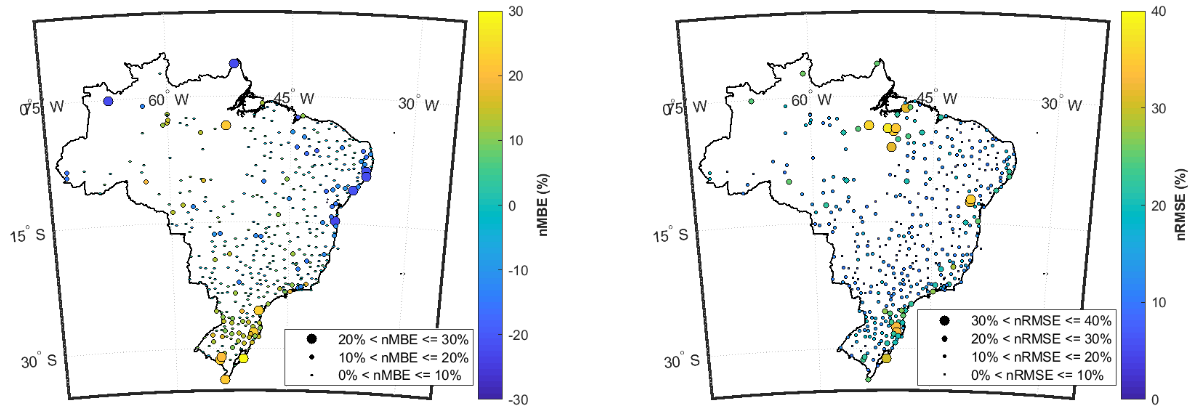


Figure 8 – Spatial distribution of the nMBE (left) and nRMSE (right) for the DNI monthly means.

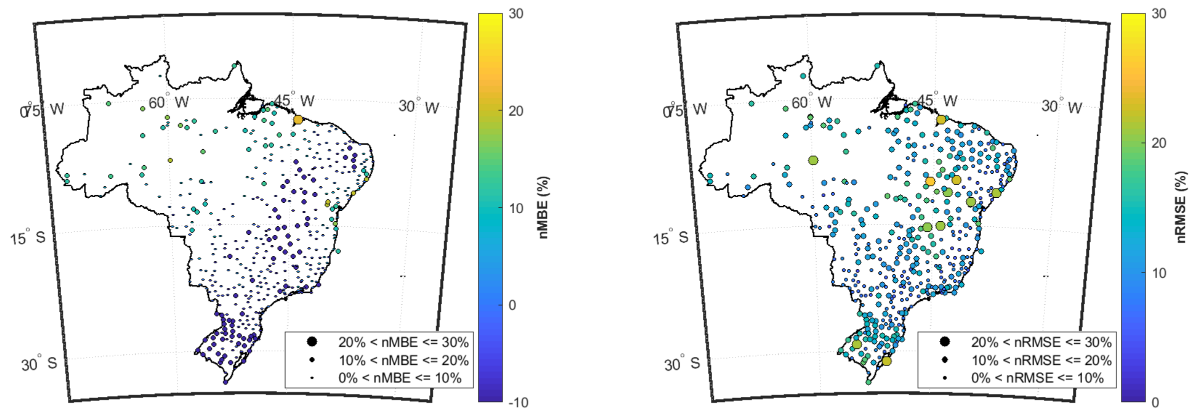


Figure 9 – Spatial distribution of the nMBE (left) and nRMSE (right) for the DIF monthly means.

As previously mentioned, the nMBE and nRMSE in Figure 7, Figure 8 and Figure 9 are considerably smaller for GHI than for DNI and DIF. A few locations stand out in the GHI nMBE map (in the northern part of the country, near the Amazon River delta) and in the nRMSE map (in the southernmost part of Brazil). These sparse locations, however, are not enough to indicate a geographical trend in GHI deviations between TMY and Atlas. As for the DNI maps, larger deviations are seen in the southern part of the country, the northeastern coast and near the Amazon River delta. In the DIF case, larger nMBE are seen in central and southern Brazil, while large nRMSE are verified all over the country.

From these maps it is difficult to see any overall, country-wide trend in nMBE and nRMSE that affects estimates of GHI, DNI and DIF at the same time. However, attention must be paid to the southern part of the country and the Amazon delta region, where larger deviations were consistently identified. This is an opportunity for further studies on the performance of the BRL and Brasil-SR models in these regions.

4. CONCLUSIONS

The considerable growth in the use of clean energy sources in Brazil indicates the great potential for solar energy applications in the country. In this context, to provide weather files to use in computer simulation for design and research on buildings and energy systems, we have presented the generation of the typical meteorological years using data from the largest weather station network in Brazil, operated by INMET.

To develop the TMY, the Sandia Method was used, which is widely adopted to establish typical weather files. In a comparison between the monthly GHI from the generated TMYs and from INMET long-term measurements, little deviations were detected, with the TMYs presenting around 110 Wh/m² mean absolute error when compared to INMET long-term data. This indicates the validity of the TMY generation method.

The validity of the procedure was further demonstrated by comparing yearly and monthly means of daily GHI totals, both from the TMY and from the Brazilian Solar Atlas. Once again, little difference was found, with TMY yearly means of GHI differing an average 2% in relation to the Atlas, with maximum deviations no larger than 10%. As for the monthly means of GHI, the normalized mean bias error between the TMY and the Atlas was also found to be around 2%, with very few TMY having a nMBE between 5 to 10%. Thus, the validity of a TMY generation procedure for GHI has been demonstrated by cross-validation against two different solar datasets.

Meanwhile, regarding the DNI and DIF values from the TMY, the deviations between the TMY and the Solar Atlas were significantly larger than the deviations found for GHI. However, as more thoroughly discussed in the Results section, this is an expected result, since both the BRL-Brazil separation model used for TMY generation, and the Brazil-SR satellite model used for the Solar Atlas, have an inherent uncertainty in DNI and DIF estimation. Thus, by comparing DNI and DIF from both these sources, the uncertainties in those models add up, generating larger deviations between both datasets. Nonetheless, mean bias differences between DNI and DIF from the TMY and from the Atlas were found to be not larger than 20%.

Finally, a geographical analysis of the deviations between TMY and Atlas was carried out, showing no overall, countrywide trend in the differences between both these datasets. However, some regions of the country have shown some unusual deviations between TMY and Atlas, such as southern Brazil, the Amazon River delta and the northeastern coast. This is an opportunity for further studies on the accuracy of the BRL-Brazil and Brazil-SR models in those areas of the country.

After these validation studies, Brazil now has a database with TMY for 441 cities, generated from measured GHI data, and including estimated DNI and DIF, all of which can be used to support solar studies on a continental scale.

5. ACKNOWLEDGMENTS

The authors would like the Brazilian National Institute of Meteorology (INMET) for providing the ground measurements. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

6. REFERENCES

Cebecauer, T., Suri, M., 2015. Typical Meteorological Year data : SolarGIS approach 69, 1958–1969.

Dorneles, R., Bravo, G., Starke, A., Lemos, L., Colle, S., 2019. Generation of 441 Typical Meteorological Year from Inmet Stations - Brazil. In: Proceedings of the ISES Solar World Congress 2019. International Solar Energy Society, Freiburg, Germany, p. 1–12.

Driemel, A., Augustine, J., Behrens, K., Colle, S., Cox, C., Cuevas-agulló, E., Denn, F.M., Duprat, T., Fukuda, M., Grobe, H., 2018. Baseline Surface Radiation Network (BSRN): structure and data description (1992 – 2017). Earth Sysytem Sci. Data 10, 1491–1501.

ECMWF, 2017. Copernicus Climate Change Service: ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. [WWW Document].

Fiebrich, C.A., Morgan, Y.R., Mccombs, A.G., Hall, P.K., Mcpherson, R.A., 2010. Quality assurance procedures for mesoscale meteorological data. J. Atmos. Ocean. Technol. 27, 1565–1582.

Hall, I.J., Prairie, R.R., Anderson, H.E., Boes, E.C., 1978. Generation of a Typical Meteorological Year for 26 SOLMET stations, SAND-78-1096C; Albuquerque, New Mexico, USA.

Hirsch, T., 2017. SolarPACES guideline for bankable STE yield assessment. IEA-SolarPACES 190.

Lemos, L.F.L., Starke, A.R., Boland, J., Cardemil, J.M., Machado, R.D., Colle, S., 2017. Assessment of solar radiation components in Brazil using the BRL model. Renew. Energy 108.

Liston, G.E., Elder, K., 2006. A Meteorological Distribution System for High-Resolution Terrestrial Modeling (MicroMet). J. Hydrometeorol. 7, 217–234.

Long, C.N., Dutton, E.G., 2010. BSRN Global Network recommended QC tests, V2.0. Bremerhaven, PANGAEA.

Moura, A.D., Tadeu, L., Fortes, G., 2016. The Brazilian National Institute of Meteorology (INMET) and its contributions to agrometeorology. Agrometeoros 24, 15–27.

Pereira, E.B., Martins, F.R., Abreu, S.L., Rüther, R., 2017. Brazilian Atlas for Solar Energy.

Wilcox, S., Marion, W., 2008. Users Manual for TMY3 Data Sets, National Renewable Energy Laboratory.