Assessment of the Performance of Climate Models Downscaling for Solar Radiation in Brazil

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Abstract

Long-term projections of solar resources are key for planning and adapting future energy systems. Global Climate Models (GCMs) simulate future scenarios, and their outputs are often downscaled to represent regional patterns and shorter timescales. This study assesses the performance of statistical and dynamical downscaling of GCMs in representing the climatology of surface solar irradiance across four regions in Brazil. Comparisons were made with ERA5 reanalysis using CMIP5/CMIP6 data from CORDEX and NEX-GDDP. Results show that CMIP6 generally outperforms CMIP5 in areas A1, C1 and D1; and statistically downscaled data yield similar mean values and climatological variability. Dynamical downscaling, however, may surpass statistical methods in specific models and regions — such as HadGEM and MPI in A1 and NorESM in D1 — while statistical refinement improved only NorESM in C1. Therefore, refinements do not necessarily improve the climatological representation of solar irradiance.

Keywords: Solar Radiation, Climate Change, Downscaling, CORDEX, NEX-GDDP

1. Introduction

Changes in the atmospheric pattern caused by climate change are a significant challenge for solar renewable resources (De Lima et al., 2024). Cloudiness, water vapor content, and aerosols are the atmospheric components that most attenuate solar radiation. To better understand these changes, we rely on future climate projections produced by GCMs, which are at the forefront of climate research. These experiments are organized in the Coupled Model Intercomparison Project (CMIP), currently in its sixth edition (CMIP6). GCMs operate with relatively coarse spatial resolutions, generally ranging between 100 and 300 km on the horizontal grid (Pietikäinen et al., 2018). However, it is essential to have more detailed spatial information for solar energy, which is highly sensitive to local atmospheric conditions. A downscaling method is crucial in refining GCM predictions to enhance the spatial resolution and preserve regional-local characteristics. There are two approaches to downscaling: statistical and dynamic.

Statistical downscaling reduces uncertainties in GCM outputs by incorporating ground-based observations through approaches such as Quantile Mapping (QM) and Bias Correction/Spatial Disaggregation (BCSD) (Wood et al., 2004). The NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset applies the BCSD method to refine large-scale CMIP6 climate projections (Thrasher et al., 2012). Dynamic downscaling uses outputs from global climate models (GCMs) as boundary conditions for regional climate models (RCMs), enabling the simulation of climate processes at higher spatial resolutions (Giorgi et al., 2012). RCMs are capable of capturing local-scale variations, particularly those associated with atmospheric gradients and land surface heterogeneities, such as forests, rivers, and lakes, that influence cloud formation and energy exchange via latent heat. The Coordinated Regional Climate Downscaling Experiment (CORDEX) is a global initiative coordinated by the World Climate Research Programme (WCRP) to improve regional climate projections through the application of dynamic downscaling techniques (Gutowski Jr. et al., 2016). The CORDEX framework primarily relies on GCM projections from the CMIP5 archive and includes the RegCM4 model developed by the International Centre for Theoretical Physics (ICTP) and REMO developed by the Climate Service Center Germany (GERICS).

10.18086/swc.2025.04.06 Available at http://proceedings.ises.org

This work addresses a key question regarding the reliability of GCM downscaling approaches. Specifically, which downscaling method — statistical or dynamical — is more suitable for future climate predictions in Brazil, and how do these methods improve the surface solar irradiance data? To answer these questions, we evaluate the performance of both statistical and dynamical downscaling techniques applied to downward surface solar irradiance in four regions of Brazil. The results will support the informed selection of refined climate datasets, enhancing the robustness and reliability of regional climate and energy studies.

2. Data and Methodology

The analysis is based on data from three GCMs: HadGEM, MPI, and NorESM in CMIP5 and CMIP6 archives. We use RCM data for each GCM from the CORDEX dataset (list the models) and the NEX-GDDP dataset (list the models). The ERA5 reanalysis data were used as a reference climatology due to its ability to represent the spatial and seasonal variability of solar irradiance (De Lima et al., 2024).

All datasets were pre-processed using bilinear interpolation onto a 0.25° × 0.25° grid, and a continental land mask was applied to exclude offshore regions. The analysis covers 25 years, from January 1, 1980, to December 31, 2005. Although each subregion contains a different number of grid points, the number of pixels within each subregion is consistent across all models, ensuring uniformity in spatial averaging and comparability of results. The selected subregions Area 1 (lon: -48 to -35; lat: -8 to 0), B1 (lon: -48 to -35; lat: -24 to -8), C1 (lon: -58.5 to -48.5; lat: -24 to -10), and D1 (lon: -58.5 to -48.5; lat: -34 to -24.5) were chosen for their relevance to Brazil's solar energy sector (Fig. 1). The climatology of solar radiation highlights the regions with higher incidence — areas A1 and B1 —, which integrate the "*Brazilian Solar Belt*", as identified in the Brazilian Atlas of Solar Energy (Pereira et al., 2017).

Initially, we evaluate the behavior of the data without any refinement. The objective of this analysis is to measure the quality of original data and, subsequently, the comparison with the quality after the application of refinements. Thus, the quality of the refinements was assessed using climatological fields and the distribution of spatial means for each area, represented by probability density functions (PDFs). Hellinger distance (*H*) was used to quantify the similarity between the probability distributions of the models (PDF_{models}) and the ERA reanalysis (PDF_{ERA5}). This metric measures the degree of overlap between two probability distributions, having the largest intersection for the smallest distance between them. Thus, when $H \rightarrow 0$ (Eq. 1) is an indication that the distributions are practically identical ($PDF_{models} \approx PDF_{ERA5}$), while values close to 1 indicate completely distinct distributions with little or no overlap (González-Castro et al., 2013). Additionally, the methodology involves comparing the mean and standard deviation (STD) of the climatological fields simulated by the GCMs with those from ERA5. This approach aims to assess how different downscaling techniques influence the climatological spatial patterns of solar irradiance projections in a regional context.

$$H(PDF_{models}, PDF_{ERA5}) = \sqrt{1 - \int_{-\infty}^{+\infty} \sqrt{PDF_{models}(x) PDF_{ERA5}(x)} dx} \quad \text{(eq. 1)}$$

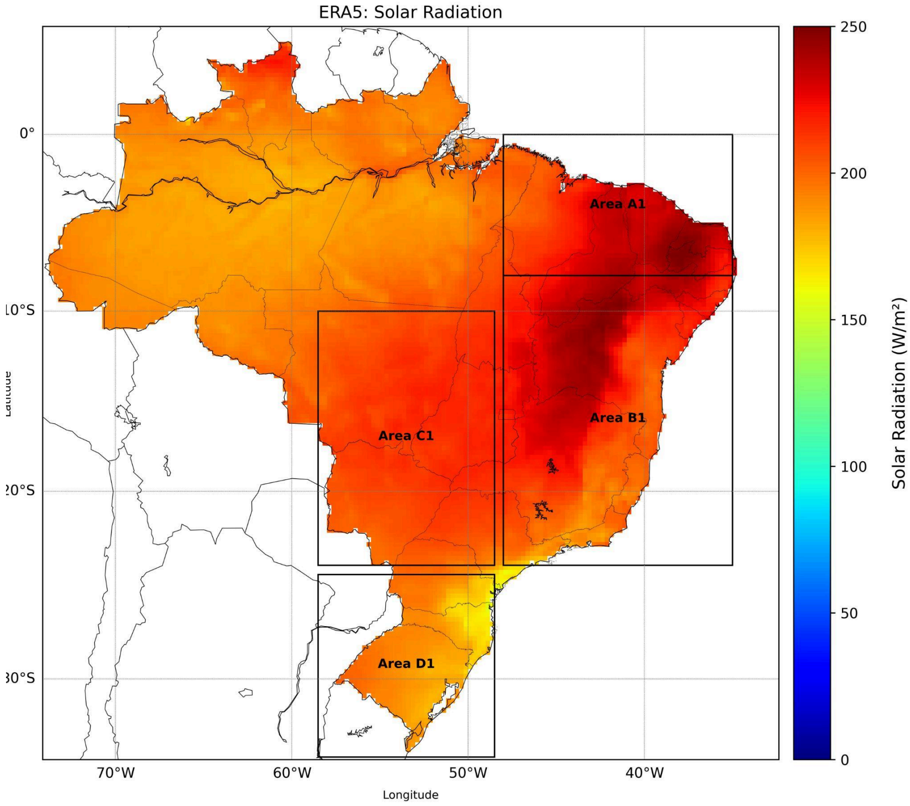

Figure 1: Climatology of solar radiation from the ERA5 reanalysis used in this work and location of the study areas.

3. Results

The climatology of the no-downscaling data indicates improvements between CMIP5 and CMIP6 for most models. HadGEM and NorESM decrease their bias in the current version, while MPI intensifies the areas with negative/positive differences (Fig. 2). HadGEM is closer to that observed in the CMIP6 and NEX-GDDP experiments and the models have greater divergence in the tropical regions (A1, B1 and C1). The dynamic refinement in CORDEX data was performed over the CMIP5 experiment, while the statistical refinement were applied to the outputs of the CMIP6 experiment models. Therefore, it is necessary to evaluate the quality of both versions in order to understand the no-downscaling data quality and the relative improvement between both approaches. In addition, it is not possible to identify a clear pattern between refinement and areas in these figures.

The behaviors of PDFs shown in Figure 3 indicate that areas A1, B1 and C1 have higher frequencies towards average. These behaviors reveal lower variability of the attenuating atmospheric components of solar radiation, in addition to its higher incidence. Area D1 has lower frequencies towards average showing and greater variability. This can be attributed to the higher solar declination due latitude and meteorological systems acting in the region, such as cold fronts and the influence of low-level jets, among others. Regarding the quality of the refinements, it is observed that in some cases PDFs associated with CMIP5 and CORDEX show a shift in relation to the others, as well as a wider distribution, indicating greater data dispersion.

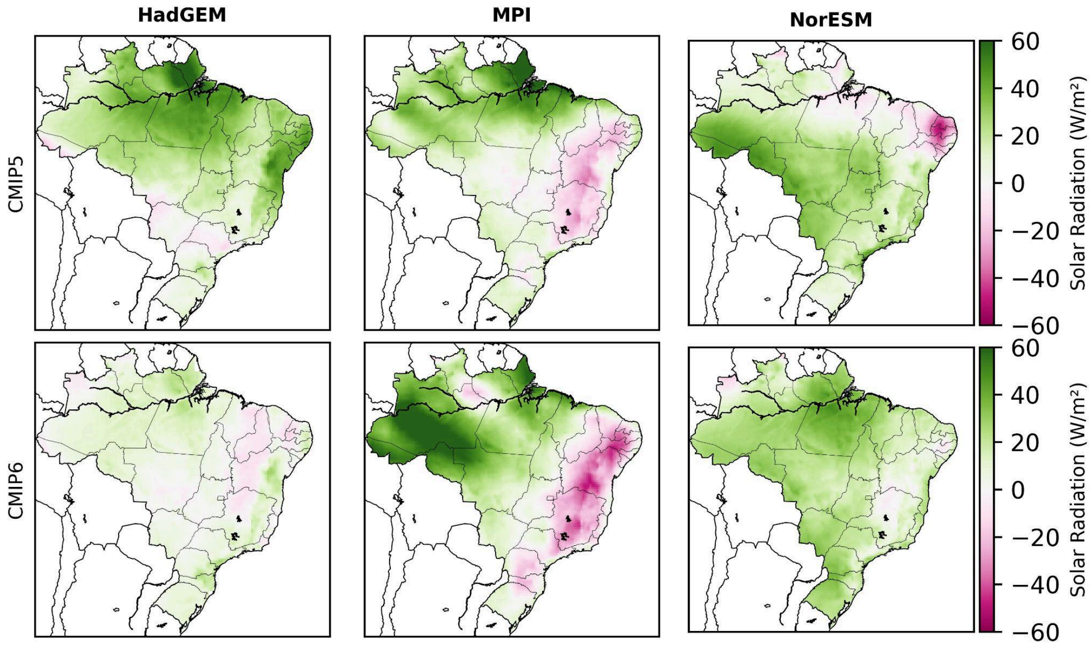

Figure 2: Climatological data of solar radiation for the HadGEM, MPI and NorESM models. The first line of maps, are represented the climatologies of the models of the CMIP5 version, while in the bottom line are the results corresponding to the CMIP6 version.

Table 1: *H* index dedicated to presenting the similarity of the modelled data and the ERA5 reanalysis.

	CMIP5	GERICS-REMO	ICTP-RegCM4	CMIP6	NEX-GDDP
HadGEM	**Area A1: 0,28** Area B1: 0,14 Area C1: 0,26 Area D1: 0,14	Area A1: 0,33 Area B1: 0,18 Area C1: 0,19 Area D1: 0,11	**Area A1: 0,24** Area B1: 0,28 Area C1: 0,25 Area D1: 0,21	Area A1: 0,08 Area B1: 0,18 Area C1: 0,12 Area D1: 0,11	Area A1: 0,24 Area B1: 0,27 Area C1: 0,11 Area D1: 0,21
MPI	**Area A1: 0,26** Area B1: 0,13 Area C1: 0,11 Area D1: 0,08	Area A1: 0,29 Area B1: 0,12 Area C1: 0,21 Area D1: 0,15	**Area A1: 0,23** Area B1: 0,20 Area C1: 0,28 Area D1: 0,26	Area A1: 0,20 Area B1: 0,19 Area C1: 0,12 Area D1: 0,07	Area A1: 0,24 Area B1: 0,27 Area C1: 0,11 Area D1: 0,21
NorESM	Area A1: 0,28 Area B1: 0,14 Area C1: 0,26 **Area D1: 0,14**	Area A1: 0,31 Area B1: 0,23 Area C1: 0,24 **Area D1: 0,08**	Area A1: 0,25 Area B1: 0,34 Area C1: 0,32 Area D1: 0,23	Area A1: 0,24 Area B1: 0,12 Area C1: 0,20 Area D1: 0,14	Area A1: 0,24 Area B1: 0,27 Area C1: 0,11 Area D1: 0,21

The *H* index is presented in Table 1. It is observed that the values of *H* are mainly concentrated between 0.1 and 0.3. The results indicate that, in general, no models outperform others in representing the solar irradiance of the reanalysis. To evaluate the impact of refinements, it is relevant to analyze changes between data with and without downscaling.

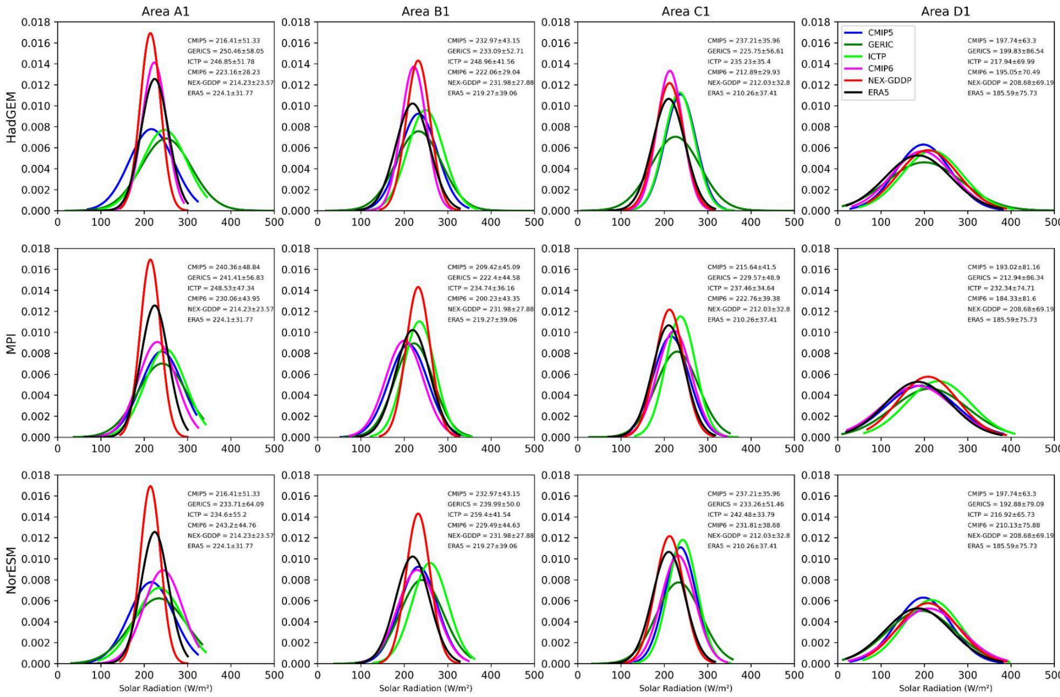

Figure 3: Probability Density Function (PDF) of the spatial means of each study area in the time series. The first line of graphs corresponds to GCM-HadGEM, second line GCM-MPI, and third GCM-NorESM.

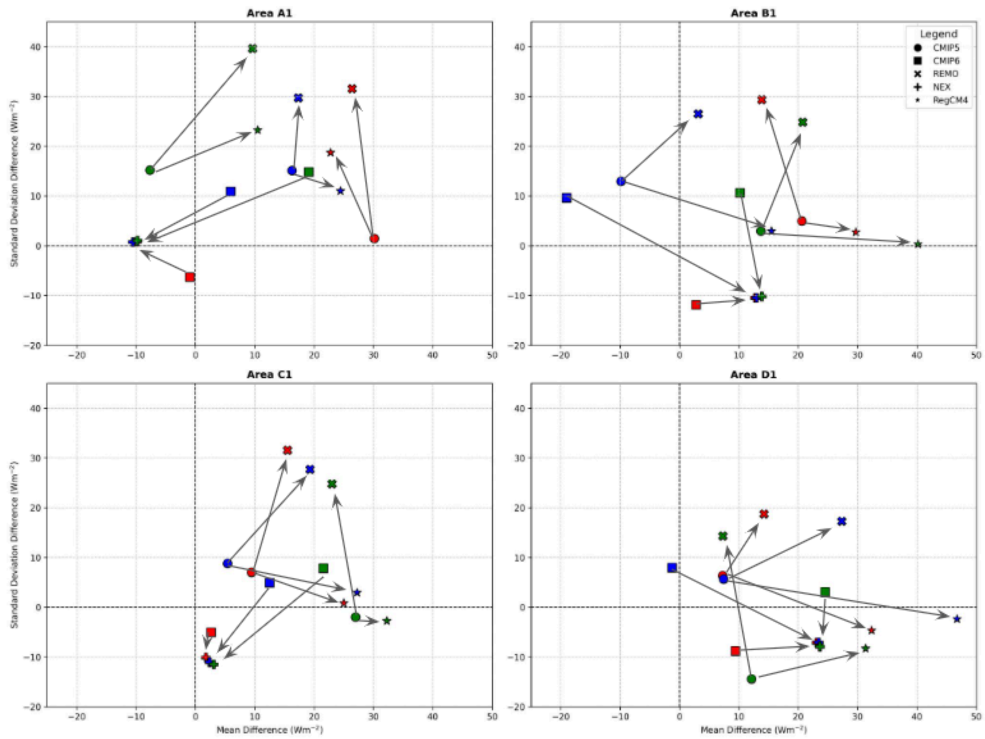

Fig. 4: Differences between the mean surface solar irradiance and its variability provided by GCM and RCM models regarding climatology from the ERA5 reanalysis. The colors represent the GCM models: the HadGEM (red), MPI (blue)and NorESM (green).

Figure 4 shows the differences in the mean surface solar irradiance (x-axis) and its variability represented by the STD (y-axis) achieved by each of the GCM and RCM models concerning the climatological values provided by the ERA5 reanalysis. The arrows point out changes in climatological biases resulting from the application of downscaling methods to GCM from CMIP5/CMIP6 data. The red, blue, and green colors correspond to the HadGEM, MPI, and NorESM models, respectively. For example, in the Area A1 region, it is observed that the dynamic downscaling using REMO regional model applied to the CMIP5-NorESM overestimates variability (STD) by 40 W/m² compared to the ERA5. Table 1 showed that there are few cases in which dynamic downscaling approximates the results of observations: two in area A1 (HadGEM-ICTP and MPI-ICTP) and one in area D1 (NorESM-GERICS). However, statistical downscaling tends to reduce similarity in all cases, that is, this refinement worsens the quality of solar irradiance information on the surface in the cases analyzed in the transition from CMIP6 to NEX-GDDP.

In general, the HadGEM was the GCM that provided the lowest mean and variability differences from the climatology. Also, it is observed that the NEX-GDDP (statistical downscaling approach) data present similar performance for all CMIP6 GCM models; i.e., the mean and the variability of the statistical regional climate predictions converge to the same values, independent of the GCM model used as input. It was expected since statistical downscaling empirically transform variables into an observed target (observation). Differences in mean and STD from NEX-GDDP to ERA5 are simply the differences on the reference observed datasets. More important, the results show that dynamic downscaling did not result consequently in an improvement. In several cases, the RCMs increase the differences in solar irradiance variability or mean climatological conditions. It is shown that REMO regional model tend to increase variability (STD) from global models (frequently worsening the results) while RegCM4 tends to increase mean values. These results suggest that aggregate skill of regional models depends more on the model internal dynamics than on the geographical location or the prescribed global model deviations. Therefore, the use of dynamical downscaling can not guarantee better performance of climate simulations. A previous knowledge of GCM bias and cautious assessment of historical downscaled performance is essential to assure reliable future predictions.

4. Conclusions

The statistical refinement effectively adjusts all model outputs to the same target observed value, which show differences compared to ERA5 reanalysis in terms of climatological mean and variability. Statistically downscaled distributions showed lower variability than ERA5 what may be due to choice of reference observed dataset. Dynamic refinement, in contrast, does not guarantee better performance. Results pointed that regional model internal dynamics is superimposed over former GCM outputs nevertheless of geographical location and bias. This indicates that dynamical downscaling is not an appropriate technique to remove bias from GCM simulations. Importantly, its application requires thorough validation over historical periods to account for inherent biases and uncertainties. Overall, statistical downscaling demonstrated the more stable and predictable performance across regions while dynamical downscaling may provided better performance if GCM dias and RMC internal dynamic is properly assessed for a target region and variable.

5. Acknowledgments

The authors thank FAPESP (São Paulo State Research Foundation) for funding (process: 23/13978-0), the UNIFESP and the INPE for their institutional support and the CORDEX and NEX-GDDP projects for providing data and resources that made this work possible.

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