Title: Assessing simulation and bias correction methods for wind power generation in Brazil – can global datasets compete with local measurements?

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Assessing simulation and bias correction methods for wind power generation in Brazil – can global datasets compete with local measurements?

Abstract

For the integration of higher shares of volatile renewables, it is important to analyse long- and short-term variations. We propose and evaluate different methods for wind power simulation on four spatial resolution levels in Brazil using NASA’s MERRA-2 reanalysis data set. In particular we assess spatial interpolation methods and spatial as well as spatiotemporal wind speed bias correction using wind speed measurement data and mean wind speeds. The resulting time series are validated with daily wind power generation. The main purpose of our analysis is to understand whether global information on wind speeds can compete with locally measured wind speed data as a source of bias correction, and which combinations of methods work best. Results show that more sophisticated methods, for both spatial interpolation and wind speed correction, are not always necessary to obtain good simulation results. Global Wind Atlas data can compete with measured wind speeds as a source for bias correction, a result which, due to the global availability and high spatial resolution, paves the way for bias-corrected global wind power simulation. Only on the level of wind parks, bias correction did not improve results. To achieve better results here, higher spatial resolution reanalysis data would be needed.

Keywords: wind power simulation, bias correction, Brazil, Global Wind Atlas, MERRA-2 reanalysis

1 Introduction

In recent years a significant growth in demand for electricity has been observed in Brazil [1, 2]. This expansion is driven by similar developments as observed in other rapidly growing regions of the world: Most importantly, economic as well as population growth, but also urbanisation, higher living standards, and the increase of access to electricity are responsible for demand growth. Historically, Brazil has high renewable electricity generation due to the large hydropower share [1], but in more recent years also wind power is gaining importance, especially in the North-East and South [1, 2].

To get a first idea of the wind power potential at specific locations, data sets on average wind speeds, such as the Global Wind Atlas (GWA) [3], can be consulted. However, when planning the integration of new wind power plants in combination with other sources of electricity to provide a stable supply, it is necessary to understand seasonal, annual as well as very short and long-term variabilities. This is necessary to adequately estimate the needs for flexibility [4, 5], as incorporating higher shares of wind power into the electricity generation matrix comes with its drawbacks: due to higher variability and intermittency compared to other sources of electricity, the availability of wind power and the effects on the electrical grid as well as on the electricity market are of concern for grid operators, stakeholders and investors [6, 7, 4].

Time series of wind power generation are limited to the time frame of actual production, which usually is about one to two decades, in the case of Brazil since 2006. However, it might be interesting to examine longer periods of wind power generation as well as locations where wind power is not yet developed, which is why simulation of synthetic wind power time series is very useful. Measured wind speed data can be used as input for such simulations, however they are only available for selected locations. Other sources of data may be more convenient for modelling renewable energy, such as globally available reanalysis data. Reanalysis data provide numerous benefits such as easy, open, and often free access, which makes them an attractive data source for scientific research. Furthermore, they are available without spatial or temporal gaps, qualifying them for a continuous model [8]. One of the main drawbacks of such data sources, however, are their bias, which can be significant and thus make production estimates unreliable.

Past studies have on the one hand focused on assessments of reanalysis wind speeds, and on the other hand attempted modelling wind power and testing different bias correction methods, either for single countries or for larger regions as Europe. Sharp et al. [9], for example, assess the quality and accuracy of CFSR [10] reanalysis with 264 onshore and twelve offshore wind stations in the UK. They find that in areas of irregular topography
there is some bias, but also reveal differences between reanalysis and measured wind speeds dependent on land use and mean wind speeds. The same reanalysis dataset is used by Rose and Apt [11] for simulation of wind power generation in the US to estimate the variability of wind power as well as the smoothing effect of spatial aggregation. They apply bias correction to correct for the deviation of simulated wind power generation from observed generation data. González-Aparicio et al. [4] used MERRA [12] and non-publicly available ECMWF [13] data to simulate wind power generation in Europe and created a new dataset by spatial downscaling to estimate the effect of the higher spatial resolution on the quality of their simulation.

In a further analysis [14], Monforti and González-Aparicio assessed the importance of considering uncertainties in modelling wind power generation by testing their model with different parameters in Europe. Cannon et al. [15] simulated wind power generation in Great Britain with MERRA reanalysis data to quantify the frequency of extreme wind power generation events. In a study by Bett and Thornton [16], another reanalysis dataset, the ERA-Interim [17], is used to simulate not only wind power but also PV generation in Britain. They examine different scenarios to find the optimal combination of wind and PV in order to reduce variability in power generation. Staffell and Pfenninger [18] rely on MERRA and MERRA-2 data for the simulation of wind power generation with the help of the Virtual Wind Farm model. Their analysis has shown that in some countries the modelled wind power generation over-, whereas in others underestimates the actual wind power output. As a consequence, they determine national correction factors for the 23 European countries they study.

The aforementioned GWA is not useful when hourly or daily time series of wind power generation are needed. But they can be combined with wind speed time series as a mean of bias correction to simulate wind power generation from reanalysis data with coarse spatial resolution. This approach was applied by Gonzalez-Aparicio et al. [4] who compared the performance of MERRA and ECMWF reanalysis and their EMHIRES dataset downscaled with GWA data for the simulation of European wind power generation. Two other studies similarly apply the GWA for spatial downscaling of MERRA-2 wind speeds in order to simulate global onshore [19] and offshore [20] wind power potential, while also considering the factors of land-use, topography and technology.

Previous examples show that reanalysis data provide vital sources for different types of analyses and simulations and are gaining popularity in research. However, none of the studies made a systematic effort to understand the impact of different methods on the quality of simulations and none of them assessed how different data sources used for bias-correction affect the outcome. Additionally, most published work was made for Europe. In this work, methods for generating wind power generation from MERRA-2 reanalysis data are therefore systematically assessed and two sources of bias correction are tested, in particular to understand if global bias correction datasets work well in comparison to local meteorological information. We also test the quality of simulations on different spatial levels, from wind park to country-wide, an analysis we have not seen in any of the published studies. We simulate wind power generation in Brazil, as it has a growing wind power fleet [2], but assessments of simulation approaches are scarce there.

2 Method

The graph in Figure 1 gives an overview of the data and methods used for simulating and bias-correcting wind power generation as well as the data used for validation and subsequent analysis. The method can be described in three steps:

1. Wind power generation is simulated while testing four simple interpolation methods with little computational effort for reanalysis wind speeds: Nearest Neighbour, Bilinear and Bicubic Interpolation and Inverse Distance Weighting. Resulting time series are compared to observed wind power generation by statistical evaluation and the best method is selected.

2. Two different sources of wind speeds are used for bias correcting the mean wind speeds: wind speed measurement data from the national institute of meteorology of Brazil (INMET) and mean wind speeds from DTU’s Global Wind Atlas (GWA). The results of the correction with both sources are validated against wind power generation data and the better one is determined.

3. The final step consists in adding the temporal component to the spatial bias correction with hourly INMET data, where it is tested whether hourly and monthly or only monthly wind speed correction improve the fit of wind power generation to observed data.
In this study, several sources of data are used for the purpose of generating a model, which simulates wind power generation output from reanalysis wind speed data in Brazil. The used datasets are listed in Table 1, together with their temporal availability (at the moment of download). In Table 2 additional information on installed capacity per investigated region and the beginning of time series are specified.

![Diagram](image)

**Figure 1:** Overview of the approach: used data and methods for the wind power simulation model and bias correction

**Table 1:** Summary of data used for modelling of wind power and for analysis

| Data set name         | Description                                                                 | Temporal resolution | Coverage      | Source            |
|-----------------------|-----------------------------------------------------------------------------|---------------------|---------------|-------------------|
| MERRA-2               | Reanalysis data, modelled wind speed data                                    | Hourly             | 1980-Aug 2017 | NASA              |
| BDMEP                 | Wind speed measurement data                                                  | Hourly             | 1999-2016     | INMET             |
| Global Wind Atlas     | Mean wind speeds                                                             | Mean               | 2015          | DTU, IRENA        |
| Wind farms            | Wind park data, geographical locations and installed capacities with commissioning dates (complemented with data from different sources) | Monthly            | 1998-2017     | The Wind Power   |
| Enercon E-82 wind turbine | Power curve                                                                 |                    |               | Enercon          |
| Histórico da operação | Historical wind power generation data                                       | daily              | 2006-Oct 2017 | ONS               |
Table 2: Mean and maximum installed capacities and start dates of simulation and validation time series of investigated regions

| Region               | Startdate Simulation | Startdate Validation | Installed capacity [MW] Mean | Installed capacity [MW] Max |
|----------------------|----------------------|----------------------|-----------------------------|-----------------------------|
| Brazil               | 2006-01              | 2006-03              | 3043                        | 11749                       |
| Northeast Brazil     | 2006-01              | 2006-03              | 2367                        | 9511                        |
| South Brazil         | 2006-01              | 2006-05              | 639                         | 2076                        |
| States               |                      |                      |                             |                             |
| Bahia                | 2012-07              | 2012-06              | 867                         | 1149                        |
| Ceará                | 2006-01              | 2009-07              | 1393                        | 2307                        |
| Pernambuco           | 2008-07              | 2015-01              | 388                         | 444                         |
| Piauí                | 2008-12              | 2015-06              | 535                         | 646                         |
| Rio Grande do Norte  | 2006-01              | 2006-03              | 1393                        | 2307                        |
| Rio Grande do Sul    | 2006-12              | 2006-05              | 1301                        | 1961                        |
| Santa Catarina       | 2006-01              | 2014-01              | 255                         | 288                         |
| Single windparks     |                      |                      |                             |                             |
| Macaubas             | 2012-07              | 2012-06              | 78                          | 78                          |
| Praia Formosa        | 2009-06              | 2009-07              | 78                          | 78                          |
| Sao Clemente         | 2016-04              | 2016-04              | 87                          | 87                          |
| Araripe              | 2016-11              | 2016-12              | 78                          | 78                          |
| Alegria II           | 2011-12              | 2012-01              | 78                          | 78                          |
| Elebras Cidreira 1   | 2011-07              | 2011-05              | 78                          | 78                          |
| Bom Jardim           | 2011-10              | 2014-01              | 78                          | 78                          |

2.1 Simulation of wind power generation

For simulating wind power generation, locations, capacities as well as commissioning dates of present wind parks are required. This information is retrieved from The Wind Power website\(^1\) and comprises the name of the wind farm, the country and county (state) it is located in, the municipality at which it is located, the commissioning date, the number and type of installed wind turbines, the installed capacity, and the geographical coordinates. A few wind parks are lacking information (installed capacities, geographical location, commissioning date, state) which is complemented from other sources, such as the National Agency of Electrical Energy of Brazil (ANEEL) [21] which provides wind parks with the municipality they are located in. Figure 2 depicts location, commissioning year, and capacity of Brazilian wind parks and shows the main wind power generation regions: the North-East and South of Brazil. Wind power generation is calculated starting in 2006, as prior to that no noteworthy capacities were installed (eight wind parks have commissioning dates before 2006 with a capacity of 28.1 MW in total) and there are no data for comparison available for the period before 2006. Furthermore, the graph shows that the majority of wind power plants were installed in the past eight years.

The MERRA-2 (Modern-Era Retrospective analysis for Research and Applications, Version 2) data which are used as a source of wind speed data are a reanalysis dataset provided for free by the National Aeronautics and Space Administration (NASA) [12]. Wind speed data in u- and v- direction at three different heights as well as the according disposition height are available in temporal resolution of one hour and spatial resolution of about 50 km between data points (0.625° longitude and 0.5° latitude). Data are available since 1980 and updated monthly. Download is performed with an R-package which can be found at [22], where also other tools for dealing with MERRA data are available.

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\(^1\) [https://www.thewindpower.net/](https://www.thewindpower.net/)
For determining wind speeds at specific locations from reanalysis data, four different methods are tested: the Nearest Neighbour Method, the Bilinear Interpolation, the Bicubic Interpolation, and Inverse Distance Weighting (see Table 3). The Nearest Neighbour method is the simplest of these methods and consists in using data from the grid point which has the smallest geographical distance to the desired point of interpolation [23]. It is not only fast, but also suitable if many data points are available [24]. Bilinear interpolation uses four surrounding points and is a simple, yet accurate method, which can be applied if data are available in a grid [25]. Inverse Distance Weighting is a method where it is assumed that data from surrounding points around the point of interest influence data on this point inversely to their distance. It is fast and can be used for interpolation of irregularly distributed data [23]. For keeping this method simple and fast and also because grid points are not very close with a distance of about 50 km, only four neighbouring points are considered for interpolation. Inverse Distance Weighting is a commonly used method in meteorology [24], which in several cases has been proved to be the best method for interpolation among others [26] [27], such as Kriging. As in some cases Bicubic Interpolation delivered negative wind speeds it is discarded for further use.

| Method                          | Abbr. | Description |
|---------------------------------|-------|-------------|
| Nearest Neighbour Method        | NN    | Wind speeds of the closest MERRA-2 grid point are used |
| Bilinear Interpolation          | BLI   | The four surrounding points in a square around the point of interest are first linearly interpolated in one direction (resulting in two points), which are afterwards also interpolated in the other direction |
| Bicubic Interpolation (not applied) | BCI   | 16 closest points in square around point of interest are inserted in a cubic equation and with the resulting coefficients calculated by solving the equation system, the wind speed at the point of interest is determined |
| Inverse Distance Weighting      | IDW   | Wind speeds are calculated on the point of interest from the four closest grid points, where each of these points is weighted inversely to its distance from the point of interest |

Effective wind speeds are calculated by the Euclidean norm from wind speeds in u- and v-direction. For inter- and extrapolation of wind speeds to certain heights (of reference wind speeds as well as of wind turbines) the wind profile power law is applied, where the wind speed in a certain height depends on the ratio of the heights and an exponent (alpha friction coefficient), which is higher the lower the surface roughness. The alpha friction
coefficient is determined from the wind speeds in two different heights (10 m above disposition height and 50 m above ground).

For simulation of wind power from wind speeds the power curve of the Enercon E-82 with a rotor diameter of 82 m, a hub height of 108 m and a nominal power of 2 MW is applied by linearly interpolating between given values. Additionally, the capacity is scaled to installed power at the wind parks. Although the number and type of installed wind turbines were included in the wind park data, this information was not used for the simulation of wind power generation, as it was partially incomplete (lacking either number or model type of the installed wind turbines or both). Another disadvantage of using data of the specific wind turbines is that information on the power curves of the about 50 different models would have to be identified. Due to these reasons it was deemed more useful applying a standard wind turbine in the medium range of actually installed wind turbines, as a sensitivity analysis in a different analysis [14] also showed, that the results with exact turbine information or a standard turbine are only marginally different. Enercon E-53’s power curve is available in the fact sheet of the wind turbine [28].

2.2 Bias correction

As mentioned before, reanalysis data can have significant bias. In particular wind speeds in MERRA-2 are subject to bias due to the rather coarse spatial resolution of the underlying model, which is why the present study aims at reducing this bias with various correction methods. For this purpose, reference wind speed data from two different sources are compared: Wind speed measurement data provided by the National Meteorological Institute of Brazil (Instituto Nacional de Meteorología, INMET) as well as mean wind speeds in the Global Wind Atlas (GWA) [3] from DTU’s Department of Wind Energy (Danmarks Tekniske Universitet) available on the IRENA (International Renewable Energy Agency) website. INMET data are available since 1999 in hourly resolution at 10 m height above ground for 481 wind speed measurement stations, of which 478 are on Brazilian mainland (see Figure 3). The GWA mean wind speeds are provided in a raster with 1 km x 1 km resolution in three heights (50 m, 100 m and 200 m above surface). The high resolution of the GWA is harnessed to increase the spatial detail of the coarser reanalysis dataset without applying methods of high computational effort.

For applying bias correction, the reference wind speed \( w_{\text{MERRA}}^{\text{new, wsma}} \) point closest to the wind park is identified and its data is used for mean approximation or temporal wind speed correction. Mean approximation is performed by multiplying with the proportion of mean observed (\( w_{\text{GWA}}^{\text{new}} \) or \( \text{mean}_{h',d',m',y'}(w_{h',d',m',y'}^{\text{INMET}}) \)) and mean reanalysis \( \text{mean}_{h',d',m',y'}(w_{h',d',m',y'}^{\text{MERRA}}) \) wind speeds (Eq. 1, \( w_{\text{GWA}}^{\text{new}} \) is replaced by \( \text{mean}_{h',d',m',y'}(w_{h',d',m',y'}^{\text{INMET}}) \) if INMET wind speeds are used for correction); temporal wind speed correction by aggregating wind speeds in specific months (Eq. 2, \( \sum_{h',d',m',y'} w_{h',d',m',y'}^{\text{MERRA}} \) and \( \sum_{h',d',m',y'} w_{h',d',m',y'}^{\text{INMET}} \) or hours and months (Eq. 3, \( \sum_{h',d',m',y'} w_{h',d',m',y'}^{\text{MERRA}} \)) and multiplying reanalysis wind speeds with the according proportions. Temporal wind speed correction is only possible with INMET data, as GWA data does not contain temporally resolved information.

\[
\begin{align*}
W_{\text{new, wsma}}^{\text{new, wsma}} &= W_{\text{MERRA}}^{\text{new, wsma}} \times \frac{W_{\text{GWA}}^{\text{wsma}}}{\text{mean}_{h',d',m',y'}(w_{h',d',m',y'}^{\text{MERRA}})} \\
W_{\text{new, cm}}^{\text{new, cm}} &= W_{\text{MERRA}}^{\text{new, cm}} \times \frac{\sum_{h',d',m',y'} w_{h',d',m',y'}^{\text{INMET}}}{\sum_{h',d',m',y'} w_{h',d',m',y'}^{\text{MERRA}}} 
\end{align*}
\]

\[\text{http://www.inmet.gov.br/} \]
\[\text{http://www.dtu.dk/} \]
\[\text{http://www.irena.org/} \]
\[ w_{\text{new, chm}}^{h,d,m,y} = w_{\text{MERRA}}^{h,d,m,y} \frac{\sum_{d',j'} w_{\text{INMET}}^{h,d',m,y'}}{\sum_{d',j'} w_{\text{MERRA}}^{h,d',m,y'}} \] (3)

While the GWA is a globally, spatially continuously available dataset that does not need any further treatment, the INMET dataset is based on stationary data, which are not available on a regular grid and where data quality issues remain. We therefore had to clean the dataset and implement rules on which stations to use for bias-correction.

First, data cleaning is performed on measured wind speeds: an analysis of the time series revealed some long sequences of the same wind speed in measured data, especially unusually long sequences of 0 m/s wind speeds. This was considered to be an error in the data. These erroneous sequences were removed using a threshold of five days, meaning any row of same values with a length of at least 120 hours, is discarded. Also missing values (NAs) are removed from measured data before comparison of the time series.

As wind speed measurement data from INMET are only available at specific locations, wind speed correction is not possible for wind parks where the distance to the closest INMET data point is too high. We have introduced a constraint of 80 km maximum distance to the closest INMET wind speed measurement station. This coincides with the diagonal distance between two MERRA-2 grid points. Figure 3 shows which wind parks are not bias corrected with INMET data due to this restriction.

A second restriction was implemented for the hourly and monthly wind speed bias correction regarding the correlation between wind speed time series after wind speed bias correction. In some cases wind speed time series and reanalysis data showed very low correlations. As measurements can be erroneous or local conditions may differ significantly compared to those on the closest reanalysis data point, we introduce a threshold in which case mean approximation is applied instead of temporal bias correction. A minimum of 50 % correlation after correction is required for application of hourly and monthly or monthly wind speed correction.

A third restriction is applied on whether to use the data of a specific wind measurement station depending on data quality and availability. For this purpose, three limits were set: In the years since 1999 at least four complete datasets must be available for each month, i.e. in at least four years there must be data for 30 days of January, March, April etc. (with the exemption of February). If these conditions are satisfied for a particular station, only

![Figure 3: Location of INMET wind speed measurement stations and wind parks (depiction with data from [29], [30] and [31])](image)
data of months which provide at least ten days (240 hours) of data are used. Months with less than ten days of available data are excluded from the analysis. When these restrictions are implemented, only 365 of the 478 wind speed measurement stations are qualified for hourly and monthly or monthly wind speed correction or mean approximation with INMET data – not considering distance or correlation limits.

Figure 3 shows the locations of INMET wind speed measurement stations (red and yellow) and wind parks (blue and black) using wind speed bias correction with Nearest Neighbour interpolation. Wind speed measurement stations available for wind speed correction (i.e. with proper data quality, availability and sufficient correlation between observed and reanalysis wind speeds) are presented in red, those actually utilised for correction are highlighted with Xs. Wind speed measurement stations discarded for their low correlation are represented by smaller light red points and those with insufficient data by yellow points. Wind parks subject to wind speed correction are marked with blue squares, those that remain uncorrected with black squares. As simulated wind power generation on the spatial level of wind parks was not wind speed corrected in most cases, i.e. only for some of the selected wind parks reference stations where available at low distances and high correlations, the distance and correlation limits were disregarded.

During a preliminary analysis some significant differences between simulated and observed wind power generation were found. Discrepancies in installed capacities used for simulation and reported by the ONS are examined as one possible reason. From Brazil’s national system operator monthly time series of installed wind power capacities are available for the whole country or per subsystem. On these levels, mean capacities from ONS and The Wind Power are compared, and capacity bias correction factors $c_{f_{cap}}$ (Eq. 4) for Brazil, the North-East and the South are determined for the whole period. These are all below 1 (Brazil 0.93, North-East 0.92, South 0.99), meaning that the capacities given by The Wind Power are decreased to the level of ONS capacities.

$$c_{f_{cap}} = \frac{\text{mean}(\text{cap}_{ONS})}{\text{mean}(\text{cap}_{TWP})}$$  \hspace{1cm} (4)

2.3 Validation and selection of methods

Wind power generation data for validation of simulated wind power time series is available on the homepage of the electrical grid operator (Operador Nacional do Sistema Elétrico, ONS) of Brazil [32]. These data can be downloaded in different spatial and temporal resolutions: for the whole of Brazil, for four Brazilian subsystems, for every state or even for single wind power parks time series of daily, weekly, monthly or yearly wind power generation are available for download. For this study, daily data are applied on all spatial disaggregation levels. Wind power generation currently occurs in the subsystems South, North-East and North. However, the latter is not considered in the analysis, as wind power generation is comparatively low there. Of the eight available states (Bahia, Ceará, Maranhão, Pernambuco, Piauí, Rio Grande do Norte, Rio Grande do Sul, and Santa Catarina) only seven are used for comparison with simulated wind power generation, as in Maranhão wind power generation started only recently (May 2017) and thus the time span is rather short. On the level of wind parks, in each state preferably the wind park with the largest installed capacity is selected for comparison of wind power generation time series, provided data of observed and simulated wind power generation are available. In some cases, names of wind parks in the wind parks dataset and in the ONS database do not always match or are not available from ONS. The wind parks selected for the analysis are listed in Table 4.

The wind power generation time series from these wind parks as well as for the larger areas are assessed with simple error measures: in the first step of method selection, i.e. the choice of interpolation methods, correlations are most relevant and chosen as criterion for selection. In the second step, i.e. the selection of a data source for wind speed mean approximation, the focus is on reducing the average bias between the simulation and observed wind power generation, which is represented by the root mean square error (RMSE) and the mean bias error (MBE) for different levels of spatial disaggregation. For the third step, i.e. the temporal bias correction, also the correlation is of interest, as it is tested whether it can be increased by applying temporal bias correction. In the Appendix some additional measures will be provided.
Table 4: Locations selected for the analysis of simulation results on the level of wind parks

| Windpark     | State       | Comment                                                                 |
|--------------|-------------|-------------------------------------------------------------------------|
| Macaúbas     | Bahia       | Third largest, the two largest are new and time spans for comparison are short |
| Praia Formosa| Ceará       | Largest                                                                  |
| São Clemente | Pernambuco  | Consists of 8 parts, only matching wind park in Pernambuco, only short time series of 1.2 years available |
| Araripe III  | Piauí       | Only matching wind park, less than one year data available               |
| Alegria II   | Piauí do Norte | Second largest wind park, after São Miguel do Gostoso, which has no available data |
| Elebras Cidreira 1 | Rio Grande do Sul | Second largest, for largest wind park (Hermenegildo) no historical generation available |
| Bom Jardim   | Santa Catarina | Only matching wind park                                                  |

3 Results

In this section the main outcomes of the analysis of the simulation of wind power generation in Brazil with different interpolation and bias correction methods will be presented. The results of the three steps (i) simulation with interpolated reanalysis data, (ii) bias correction of the mean wind speed, and (iii) temporal wind speed corrections are analysed and a method selection is performed to limit the amount of results to relevant ones. Results are displayed as graphs for easier comparison. A collection of statistical parameters can be found in the Appendix (Table A 1, Table A 2, Table A 3).

The correlations of simulated and observed daily wind power generation shown in Figure 4 are usually high, at least at spatially aggregated levels (Brazil and subsystems), where they are above 94 %. Using Bilinear Interpolation or Inverse Distance Weighting instead of the Nearest Neighbour method does not have any significant impact. For lower spatial aggregation levels, i.e. states and particular wind parks, correlations are different from the higher aggregated levels, but no differences in the quality of interpolation methods can be observed. Correlations are in a similar range as for Brazil and its subsystems in most cases except in Pernambuco and Santa Catarina, where they are significantly lower - but this applies to all examined interpolation methods. For particular wind parks, correlations are in general lower, ranging between 0.5 and 0.9, indicating a better quality of simulation at the higher level of spatial aggregation. Overall, no preferable method can be selected from evaluation of correlations, as the differences are only minor.

Figure 4: Correlations of observed and simulated daily wind power generation time series with three interpolation methods (Nearest Neighbour: NN, Bilinear Interpolation: BLI, Inverse Distance Weighting: IDW) for Brazil, the North-East and South subsystems, seven states and seven selected wind parks
If relative RMSEs (Figure 5) are compared for the tested interpolation methods, no significant differences can be observed either. For certain regions (North-East, Rio Grande do Norte, Rio Grande do Sul, Alegria II, Elebras Cidreira 1) RMSEs are slightly higher when using the Nearest Neighbour method, but for others (Ceará, Pernambuco, São Clemente) RMSEs are lowest when applying this simple method.

Other statistical parameters and plots used for comparison are shown in the Appendix (Table A 1, Figure A 1). However, neither MBEs nor comparison of means indicate a favourable method. Our results show that the Nearest Neighbour method yields comparably good results in terms of correlations and RMSEs of simulated and observed wind power generation time series in particular for aggregated regions, and thus is chosen as the favourable method, as it is very simple and has low computational needs. For simulating single wind parks, it may be beneficial to test other methods too, as in some cases the results of the Nearest Neighbour method could be improved.

In order to reduce the previously discussed bias between observed and simulated wind power generation time series, bias correction is applied. The first step consists in selecting a favourable data source for mean wind speed correction: The two examined in this study are the mean wind speeds from DTU’s Global Wind Atlas (GWA) and measured wind speeds from the national meteorological institute of Brazil (INMET). Three measures for bias, the RMSE, the MBE and the deviation in means, are examined. Only the relative RMSEs and MBEs (which apart from the bias also indicates whether observed wind power generation is over- or underestimated), normalised by the mean installed capacity in the period of validation for easier comparison between different regions, are shown here, the other parameters can be found in the Appendix (Table A 2, Figure A 2, Figure A 3, Figure A 4). An investigation of this error measure on the level of Brazil or the subsystems (Figure 6) shows a clear tendency: The highest RMSEs occur if no mean approximation is applied, which can be reduced by applying wind speed bias correction with measured wind speeds (INMET) and even more when applying the GWA mean wind speeds. If looking at spatially disaggregate analysis, results are different: On the level of states, correction with the GWA still results in the lowest RMSEs, whereas when analysing time series of particular wind parks, this effect is not as clearly visible. What is striking, however, is that on the level of states and wind parks mean approximation with INMET has a negative effect, as it drastically increases RMSEs for some of the locations (Pernambuco, Piauí, Santa Catarina and the wind parks evaluated in these states). Overall, GWA bias correction seems to deliver the best results as it reduces RMSEs compared to no bias correction and also if mean approximation with measured INMET wind speeds is applied. For other statistical parameters, results are similar.
Figure 6: Comparison of relative root mean square errors (RMSEs) of simulated daily wind power generation with different sources for wind speed mean approximation: INMET wind speed measurements (INMET), Global Wind Atlas mean wind speeds (GWA) and no correction (Nearest Neighbour, NN). Note that for Bom Jardim the value is missing for correction with INMET because it is far higher than the other values shown and therefore out of range of the graph. The two wind parks marked as squares are not corrected because they are too far away from the closest INMET wind speed measurement station.

Figure 7 shows the relative mean bias errors (MBEs) between observed and simulated daily wind power generation using different bias correction methods. When comparing methods with the MBE indicator, it is more recommendable to apply mean approximation with INMET data in Brazil and the North-East subsystem, as the values are closer to 0 than with GWA or without correction. For areas of lower spatial aggregation, however, INMET correction mostly leads to a higher error for overall results. Only for specific locations (Rio Grande do Norte, Rio Grande do Sul, Ceará, Alegria II) it may bring benefits, whereas in other locations, especially Bom Jardim, the error is increased.
In fact, it cannot be determined definitely which data source is better for wind speed mean approximation, especially as different statistical parameters do not result in the same conclusions. Results with GWA are not always the best, but rarely the worst. Wind speed mean approximation with measured wind speeds sometimes delivers good results, compared to mean approximation with GWA wind speeds or without wind speed mean correction, for example in Brazil, its North-East, in Rio Grande do Norte or at the wind park in Alegria II. In other cases, however, it leads to considerable reduction of wind speeds, resulting in underestimation of wind power generation, such as in Ceara, Pernambuco, Piaui or the windparks of Araripe or Sao Clemente. When using GWA wind speeds for correction, however, resulting simulated wind power generation usually is in a similar range as the observed and no extreme outliers are observed. Therefore, GWA is the more stable source for bias-correction and is used for further analysis.

In the next step, GWA mean approximation is combined with a more precise method of wind speed correction with the help of measured wind speeds. Hourly and monthly as well as only monthly wind speed correction are tested, to see if spatiotemporal correction can improve results compared to only spatial bias correction. Figure 8 shows the relative RMSEs between simulated and observed wind power generation time series. In general, simple wind speed correction with GWA or with monthly bias correction results in simulated wind power generation having the best fit to observed values. This applies especially to larger areas, such as the whole country, the subsystems, or the states. For single wind parks, spatiotemporal wind speed correction usually increases the errors between simulated and observed wind power generation. However, wind speed correction with measured wind speeds sometimes shows a positive impact on correlations for single wind parks (Table A 3). Only at the wind park Alegria II, the RMSE is decreased by both types of spatiotemporal correction.

Figure 8: Comparison of relative root mean square errors (RMSEs) of simulated daily wind power generation with different methods for wind speed bias correction: mean approximation with Global Wind Atlas data (wma), mean approximation with Global Wind Atlas data combined with monthly wind speed correction with INMET wind speed data (wsc_m) and mean approximation with Global Wind Atlas data combined with hourly and monthly wind speed correction with INMET wind speed data (wsc_hm). Note that for Araripe the values are missing for monthly as well as hourly and monthly correction with INMET because they are far higher than the other values shown and therefore out of the range of the graph. The locations marked as squares are not corrected because they are too far away from the closest INMET wind speed measurement station or correlation after correction is below 50%. Only on the level of wind parks temporal wind speed correction is performed despite not satisfying the limits, as with the limits correction only applies to Alegria II and Elebras Cidreira 1 for hourly and monthly correction.

When assessing the bias by MBEs (Figure 9), results are mostly similar to those from RMSEs. In most of the areas, correction with INMET wind speed measurements does not reduce the error (also see Table A 3, Figure A 5, Figure A 6 and Figure A 7). An exception are the North-East as well as all of Brazil, which have MBEs close to 0 when applying hourly and monthly wind speed bias correction. This shows, that it may not be useful to apply this
kind of bias correction to specific locations or small regions in order to reduce the error between simulated wind power generation and observed data, but can help to reduce the bias on a larger scale.

![Figure 9: Comparison of relative mean bias errors (MBEs) of simulated daily wind power generation with different methods for wind speed bias correction: mean approximation with Global Wind Atlas data (wma), mean approximation with Global Wind Atlas data combined with monthly wind speed correction with INMET wind speed data (wsc_m) and mean approximation with Global Wind Atlas data combined with hourly and monthly wind speed correction with INMET wind speed data (wsc_hm). The locations marked as squares are not corrected because they are too far away from the closest INMET wind speed measurement station or correlation after correction is below 50%. Only on the level of wind parks temporal wind speed correction is performed despite not satisfying the limits, as with the limits correction only applies to Alegria II and Elebras Cidreira 1 for hourly and monthly correction.]

4 Discussion

In the first part of the analysis three spatial interpolation methods for gridded wind speeds are tested for the simulation of wind power. Our results show, that more advanced methods (BLI and IDW) do not contribute to higher correlations compared to the Nearest Neighbour method. Especially if spatially aggregated areas are examined, there is no improvement in correlations. For single wind parks, there may be some benefits in using BLI and IDW.

Considering correlations, our results are similar to those reported in other studies (see Appendix Table A 4), such as by Cannon et al. [15], Cradden et al. [33], or Pfenninger and Staffell [18]. Only González-Aparicio et al. [4], who study simulation of wind power generation in European countries using three different wind speed data sets also report some lower correlations than ours. Evaluating relative biases and RMSEs (see Appendix Table A 4) only González-Aparicio et al. [4] obtain some similar values to ours, or few even higher (Sweden and Switzerland), whereas in other cases RMSEs [18, 33] and biases [33] are lower than in our study.

Part of this can be explained by a more inhomogeneous topography in Brazil compared to countries like Ireland or Germany which are analysed in the other studies, especially due to the large spatial extent. It has to be noted, however, that these examples consider monthly [18, 33] and hourly [4, 15, 18] time series, while we considered daily wind power generation, which can have an impact on results. On the other hand, it should be considered that the area of Brazil is larger than European countries which is likely to have a higher smoothing effect. This shows in the correlations which are high and thus indicate a good simulation quality by MERRA reanalysis data, confirming the Cannon et al. results [15] for a different world region.

González-Aparicio et al. [4] also found that the data for comparison of power time series from the transmission system operators show some inhomogeneities, which may be a possible explanation for some of the error in the present study. Furthermore, they state that another possible source of error in MERRA data, or wind power generation calculated from those data, is that the coarse spatial resolution results in an underestimation in variability of wind speeds, especially in areas of complex terrain.
The fact that reanalysis data often neglect local conditions and therefore may lead to some bias is stated by others too, such as Cannon et al. [15], Pfenninger and Staffell [18] or Olauson and Bergkvist [34]. Previous research has shown that such bias can be reduced by spatially aggregating power output of several wind farms, as then the simulation takes advantage of smoothing effects [5, 35]. The second part of the present work focused on reducing the bias between simulated and observed wind power generation by applying wind speed correction, comparing two different sources for reference wind speeds. Results from this section did not indicate a clear tendency whether correction with measured wind speeds or with mean wind speeds delivers a smaller error between simulated and historical wind power generation. However, it showed that bias correction in many cases has a positive effect on the simulation, especially in areas of higher spatial aggregation (Brazil and subsystems). There, lowest RMSEs are obtained when wind speeds are corrected with the GWA, but MBEs being closer to 0 when approximating to INMET data. On the levels of states or particular wind parks, correction with GWA mean wind speeds mostly led to a better fit of the simulation to observed wind power. A probable conclusion that can be drawn from this result is that spatially detailed information – i.e. in our case GWA data – is especially important if wind power generation for small areas is modelled because there the relative error is high, however, less important when larger areas are considered. We would also expect a positive impact of adding this information on the level of wind parks. However, the data quality (especially of observed wind power generation data) may not be sufficient to see the benefits of this. Nevertheless, as recommended also by Monforti and Gonzalez-Aparicio [14], correction of reanalysis data should be applied, at least at larger spatial levels, but in the best case at wind farm level. Otherwise, according to Rose and Apt [11] who examined the variability of wind energy in the U.S. Great Plains by simulation from reanalysis data, it is likely that reanalysis data might underestimate wind speeds and thus wind power generation for particular locations. This cannot be supported by our results, as on the level of wind parks, wind power simulated directly from reanalysis data usually is in a similar range as the historical data, or slightly above. Only when measured wind speeds are used in bias correction, the simulations underestimate observations. Another study [4] which takes a similar approach simulating wind power generation from MERRA data with bias correction with GWA wind speeds, generating a new dataset called EMHIRES, finds that adding spatially detailed information improves the representation of historical data of wind power generation. Bosch et al. [19] [20] use a similar approach with GWA data for simulating wind power generation from MERRA-2 wind speeds. They however do only calculate wind power potentials for several countries while assuming that GWA provides more accurate data, thus allowing no basis for comparison to our results.

In the last step of our analysis, bias correction was refined. Measured wind speed data were used to not only correct the overall mean but also seasonal and diurnal means of wind speeds, by applying monthly as well as hourly and monthly wind speed correction factors. However, for the majority of regions and wind parks assessed, the fit of the simulated time series to historical wind power generation data did not improve. Only single wind parks gained higher correlations with hourly and monthly wind speed correction. According to our analysis, the average bias cannot be further reduced by temporal bias correction with INMET data, only the ranges of the simulation are sometimes closer to observed wind power when applying hourly and monthly correction. Overall, we determined that for spatially aggregated areas spatiotemporal bias correction is not necessary, although it can reduce bias slightly. For particular locations it can be useful – but only if data in good quality are available. Other studies provided no means of comparison as temporal bias correction, if performed, relied on wind power instead of wind speed data, such as the investigation of Olauson and Bergkvist [34], or directly used measured wind speed data for simulating wind power generation and compared the results to TSO and simulations from reanalysis [36].

5 Conclusion
In this paper we assess the results of a simulation of wind power generation in Brazil and compare different approaches for interpolation and bias correction on different spatial levels. The aim is to select the best of the examined methods for generation of wind power time series. In particular, we explore the capabilities of the Global Wind Atlas for wind speed bias correction in comparison with locally measured data, to assess their potential of global bias correction. Results show that (i) interpolation methods of higher computational effort...
are usually not necessary as they do not improve results, with the exception of simulating single wind parks, (ii) bias-correction with GWA delivers results comparable to locally measured data and in general improves results compared to simulations without any correction on all spatial levels with the exception of single wind parks, and (iii) spatiotemporal bias-correction is only advised if high quality measured data is available.

In the future, results found in this study can be applied to simulate wind power generation time series, which can consequently be used to assess potentials of renewable energy. The outcome that GWA data can contribute to smaller bias in estimation of wind power generation, is especially important as this method can be applied globally, paving the way for studies considering the entire world or at least different spatially distant regions such as Europe and the Americas.

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References

[1] J. Schmidt, R. Cancella and A. O. Pereira Junior, “An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil,” Renewable Energy, pp. 137-147, January 2016.

[2] J. Schmidt, R. Cancella and A. O. Pereira Junior, “The effect of windpower on long-term variability of combined hydropower resources: The case of Brazil,” Renewable and Sustainable Energy Reviews, pp. 131-141, March 2016.

[3] [dataset] International Renewable Energy Agency, “Map: DTU Global Wind Atlas 1 km resolution,” Danmarks Tekniske Universitet, 7 February 2018. [Online]. Available: https://irena.masdar.ac.ae/gallery/#!/map/103. [Accessed 30 July 2018].

[4] I. González-Aparicio, F. Monforti, P. Volker, A. Zucker, F. Careri, T. Huld and J. Badger, “Simulating European wind power generation applying statistical downscaling to reanalysis data,” Applied Energy, pp. 155 - 168, 9 May 2017.

[5] R. Goić, J. Krstulović and D. Jakus, “Simulation of aggregate wind farm short-term production variations,” Renewable Energy, pp. 2602-2609, 1 May 2010.

[6] M. Barasa and A. Aganda, “Wind power variability of selected sites in Kenya and the impact to system operating reserve,” Renewable Energy, pp. 464-471, 2015.

[7] I. González-Aparicio and A. Zucker, “Impact of wind power uncertainty forecasting on the market integration of wind energy in Spain,” Applied Energy, pp. 334-349, 16 September 2015.

[8] L. Bengtsson, S. Hagemann and K. I. Hodges, “Can climate trends be calculated from reanalysis data?,” Journal of Geophysical Research, 16 June 2004.

[9] E. Sharp, P. Dodds, M. Barrett and C. Spatharou, “Evaluating the accuracy of CFSR reanalysis hourly wind speed forecasts for the UK, using in situ measurements and geographical information,” Renewable Energy, pp. 527-538, 09 Jan 2015.

[10] [dataset] S. Saha, S. Moorthi, H. L. Pan, X. Wu, J. Wang, S. Nadiga, P. Tripp, R. Kistler, J. Woollen, D. Behringer, H. Liu, D. Stokes, R. Grumbine, G. Gayno, J. Wang, Y. Hou, H. Chiang, H. H. Juang, J. Sela, M. Iredell, R. Treadon and e. al., “NCEP Climate Forecast System Reanalysis (CFSR) Selected Hourly Time-Series Products, January 1979 to December 2010,” Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory, 2010. [Online]. Available: https://doi.org/10.5065/D6513W89. [Accessed 04 12 2018].

[11] S. Rose and J. Apt, “What can reanalysis data tell us about wind power?,” Renewable Energy, pp. 963-969, 05 Jun 2015.

[12] [dataset] Global Modeling and Assimilation Office, “Modern-Era Retrospective analysis for Research and Applications, Version 2,” National Aeronautics and Space Administration, 12 December 2017. [Online]. Available: https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/. [Accessed 30 July 2018].

[13] European Centre for Medium-Range Weather Forecasts, “ECMWF,” ECMWF, 11 10 2018. [Online]. Available: https://www.ecmwf.int/. [Accessed 04 12 2018].

[14] F. Monforti and I. González-Aparicio, “Comparing the impact of uncertainties on technical and meteorological parameters in wind power time series modelling in the European Union,” Applied Energy, pp. 439-450, 04 Sept 2017.

[15] D. J. Cannon, D. J. Baryshaw, J. Methven, P. J. Coker and D. Lenaghan, “Using reanalysis data to quantify extreme wind power generation statistics: A 33 year case study in Great Britain,” Renewable Energy, pp. 767-778, March 2015.

[16] P. E. Bett and H. E. Thornton, “The climatological relationships between wind and solar energy supply in Britain,” Renewable Energy, pp. 96-110, 2016.

[17] [dataset] D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A. C. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani and e. al., “The ERA-Interim reanalysis: configuration and performance of the data assimilation system,” Quarterly Journal of the Royal Meteorological Society, no. 137, pp. 553-597, 28 Apr 2011.

[18] S. Pfenninger and I. Staffell, “Using bias-corrected reanalysis to simulate current and future wind power output,” Energy, pp. 1224-1239, November 2016.

[19] J. Bosch, I. Staffell and A. D. Hawkes, “Temporally-explicit and spatially-resolved global onshore wind energy potentials,” Energy, pp. 2017-2017, 09 May 2017.

[20] J. Bosch, I. Staffell and A. D. Hawkes, “Temporally explicit and spatially resolved global offshore wind energy potentials,” Energy, pp. 766-781, 23 Aug 2018.

[21] ANEEL, “ANEEL Agência Nacional de Energia Elétrica,” ANEEL, 2019. [Online]. Available: http://www.aneel.gov.br/. [Accessed 04 Mar 2019].

[22] Github Repository, “MERRABin,” [Online]. Available: https://github.com/joph/RE_EXTREME/tree/master/scripts.

[23] J. Li and A. D. Heap, “A Review of Spatial Interpolation Methods for Environmental Scientists,” Geoscience Australia, Canberra, 2008.

[24] R. Sluiter, “Interpolation methods for climate data,” KNMI, De Bilt, 2009.

[25] E. Svensson, Performance of Long Term Wind Estimation Method at Wind Power Development, Göteborg: Chalmers University of Technology, 2012.
[26] M. Keskin, A. Ozgur Dogru, F. Bektaş Balci, C. Goksel, N. Ulugtekin and S. Sozen, “Comparing Spatial Interpolation Methods for Mapping Meteorological Data in Turkey,” Energy Systems and Management, pp. 33-42, 26 March 2015.

[27] M. Bilala, G. Arayab and Y. Birkelund, “Preliminary assessment of remote wind sites,” in The 7th International Conference on Applied Energy – ICAE2015, Abu Dhabi, 2015.

[28] ENERCON, ENERCON Produktübersicht, Aurich, Germany: ENERCON GmbH, 2015.

[29] [dataset] G. Cruz, F. Estrela, B. Junior and M. Lima, “Shapefiles do Brasil para download,” CodeGeo, 16 April 2013. [Online]. Available: http://www.codegeo.com.br/2013/04/shapefiles-do-brasil-para-download.html. [Accessed 05 January 2018].

[30] Brasil Governo Federal, “INMET Instituto Nacional de Meteorologia,” [Online]. Available: http://www.inmet.gov.br/portal/. [Accessed 11 February 2018].

[31] [dataset] P. Michaël, “The Wind Power. Wind Energy Market Intelligence,” The Wind Power, [Online]. Available: https://www.thewindpower.net/. [Accessed 11 February 2018].

[32] [dataset] ONS, “GERAÇÃO DE ENERGIA,” ONS, 2018. [Online]. Available: http://www.ons.org.br/Paginas/resultados-da-operacao/historico-da-operacao/geracao_energia.aspx. [Accessed 05 January 2018].

[33] L. C. Cradden, F. McDermott, L. Zubiate and C. Sweeney, “A 34-year simulation of wind generation potential for Ireland and the impact of large-scale atmospheric pressure patterns,” Renewable Energy, pp. 165-176, 28 Dec 2017.

[34] J. Olauson and M. Bergkvist, “Modelling the Swedish wind power production using MERRA reanalysis data,” Renewable Energy, pp. 717-725, April 2015.

[35] F. J. Santos-Alamillos, D. Pozo-Vázquez, J. A. Ruiz-Arias, V. Lara-Fanego and J. Tovar-Pescador, “A methodology for evaluating the spatial variability of wind energy resources: Application to assess the potential contribution of wind energy to baseload power,” Renewable Energy, pp. 147-156, 2014.

[36] M. Kubik, D. Brayshaw, P. Coker and J. Barlow, “Exploring the role of reanalysis data in simulating regional wind generation variability over Norther Ireland,” Renewable Energy, pp. 558-561, 21 Mar 2013.
Appendix
A.1 Additional results

This part contains supplementary results of the statistical analysis of the simulated time series. On the one hand, tables (Table A 1, Table A 2, Table A 3) with the statistical parameters correlations, root mean square errors, mean bias errors (MBEs) and means of observed and simulated daily wind power generation are provided on different spatial levels (Brazil, subsystems, states, individual wind parks). On the other hand, boxplots (Figure A 1 – Figure A 7) of daily wind power generation are provided, for an easy comparison of the ranges of simulated and observed daily wind power generation. The results of the statistical analysis will not be discussed in detail, as this has been done in the main section.

Table A 1: Correlations of observed and simulated daily wind power generation time series with three interpolation methods (Nearest Neighbour: NN, Bilinear Interpolation: BLI, Inverse Distance Weighting: IDW) for Brazil, its North-East and South, seven states and seven selected wind parks

| Correlation | RMSE [GWh] | MBE [GWh] | Mean [GWh] |
|-------------|------------|-----------|------------|
|             | NN     | BLI    | IDW     | NN     | BLI    | IDW     | NN     | BLI    | IDW     | NN     | BLI    | IDW     |
| Brazil      | 0.982  | 0.981  | 0.980  | 15.798 | 15.329 | 15.624 | 11.386 | 10.918 | 11.122 | 34.493 | 34.026 | 34.229 |
| North-East  | 0.979  | 0.978  | 0.977  | 13.347 | 12.986 | 13.035 | 9.718  | 9.323  | 9.313  | 28.410 | 28.015 | 28.005 |
| South       | 0.951  | 0.949  | 0.946  | 3.250  | 3.167  | 3.445  | 1.541  | 1.461  | 1.693  | 5.969  | 5.889  | 6.122  |
| Bahia       | 0.959  | 0.956  | 0.954  | 2.537  | 2.541  | 2.588  | 0.801  | 0.420  | 0.296  | 9.982  | 9.6   | 9.476  |
| Ceará       | 0.934  | 0.935  | 0.933  | 5.583  | 5.708  | 5.742  | 4.573  | 4.574  | 4.599  | 10.887 | 10.887 | 10.912 |
| Pernambuco  | 0.853  | 0.848  | 0.845  | 1.479  | 1.511  | 1.531  | -0.354 | -0.404 | -0.426 | 4.100  | 4.05  | 4.028  |
| Piauí       | 0.928  | 0.923  | 0.925  | 2.462  | 2.426  | 2.352  | 1.166  | 1.049  | 0.952  | 8.585  | 8.467  | 8.371  |
| Rio Grande do Norte | 0.966 | 0.965 | 0.965 | 6.381 | 6.204 | 6.298 | 4.526 | 4.375 | 4.425 | 12.132 | 11.982 | 12.032 |
| Rio Grande do Sul | 0.951 | 0.952 | 0.950 | 2.802 | 2.538 | 2.604 | 1.107 | 0.84 | 0.842 | 5.457 | 5.19 | 5.192 |
| Santa Catarina | 0.692 | 0.733 | 0.738 | 0.881 | 1.185 | 1.549 | 0.552 | 0.870 | 1.283 | 1.424 | 1.742 | 2.155 |
| Macaúbas    | 0.602  | 0.594  | 0.610  | 0.180  | 0.181  | 0.174  | -0.117 | -0.116 | -0.108 | 0.228  | 0.228  | 0.237  |
| Praia Formosa | 0.728 | 0.749 | 0.753 | 0.476 | 0.512 | 0.581 | 0.331 | 0.382 | 0.456 | 1.070  | 1.121  | 1.196  |
| São Clemente | 0.544  | 0.536  | 0.533  | 0.884  | 0.913  | 0.936  | -0.375 | -0.444 | -0.449 | 2.123  | 2.054  | 2.049  |
| Araripe     | 0.879  | 0.873  | 0.871  | 1.414  | 1.343  | 1.312  | 0.807  | 0.509  | 0.496  | 3.775  | 3.567  | 3.464  |
| Alegria II  | 0.538  | 0.537  | 0.535  | 0.812  | 0.788  | 0.806  | 0.696  | 0.674  | 0.690  | 1.362  | 1.34  | 1.355  |
| Elebras Cidreira 1 | 0.828 | 0.828 | 0.818 | 0.262 | 0.250 | 0.258 | 0.032 | 0.012 | 0.011 | 0.616  | 0.596  | 0.595  |
| Bom Jardim  | 0.480  | 0.573  | 0.583  | 0.194  | 0.179  | 0.177  | -0.023 | -0.008 | -0.001 | 0.201  | 0.216  | 0.223  |

Figure A 1 shows a comparison of differences between simulated and observed daily wind power generation for seven wind power plants in Brazil (a comparison on the level of states, subsystems or the whole country are not shown, as differences between the three interpolation methods are negligible for these realms). In general, the graphs indicate that the simulations fit observed wind power generation well, only slightly over- (Praia Formosa, Alegria II) or underestimating (São Clemente) observed generation. The most notable differences between the interpolation methods are observed in Araripe, although they are not substantive. Similar to larger areas, the simulations for particular wind parks are close to observed wind power generation and although some bias between simulations and observed wind power generation is notable, it is mostly small.

Figure A 1: Comparison of differences between observed and simulated daily wind power generation with three interpolation methods (Nearest Neighbour: NN, Bilinear Interpolation: BLI, Inverse Distance Weighting: IDW) for seven wind power plants in Brazil
Table A 2: Comparison of root mean square errors (RMSEs), mean bias errors (MBEs) and means of simulated daily wind power generation with different sources for wind speed mean approximation: INMET wind speed measurements (INMET), Global Wind Atlas mean wind speeds (GWA) and no correction (Nearest Neighbour, NN)

| Source            | RMSE [GWh] | MBE [GWh] | Mean [GWh] |
|-------------------|------------|-----------|------------|
|                  | NN         | INMET     | GWA        | NN         | INMET     | GWA        | NN         | INMET     | GWA        |
| Brazil            | 15.798     | 10.627    | 9.799      | 11.386     | -1.620     | 6.144      | 34.493     | 21.488    | 29.252     | 23.107     |
| North-East        | 13.347     | 11.033    | 8.650      | 9.718      | -2.770     | 5.280      | 28.410     | 15.923    | 23.972     | 18.692     |
| South             | 3.250      | 2.673     | 2.413      | 1.541      | 1.222      | 0.765      | 5.969      | 5.651     | 5.194      | 4.429      |
| Bahia             | 2.537      | 3.421     | 2.700      | 0.801      | -1.437     | -0.408     | 9.982      | 7.744     | 8.772      | 9.180      |
| Ceará             | 5.583      | 3.687     | 4.683      | 4.573      | -2.401     | 3.825      | 10.887     | 3.913     | 10.139     | 6.314      |
| Pernambuco        | 1.479      | 4.298     | 2.397      | -0.354     | -3.603     | -1.822     | 4.100      | 0.850     | 2.632      | 4.454      |
| Piauí             | 2.462      | 6.208     | 2.269      | 1.156      | -4.938     | -0.343     | 8.585      | 2.480     | 7.076      | 7.419      |
| Rio Grande do Norte | 6.381 | 4.030     | 4.256      | 4.526      | 0.747      | 2.076      | 12.132     | 8.354     | 9.683      | 7.606      |
| Rio Grande do Sul | 2.802      | 1.907     | 2.007      | 1.107      | -0.180     | 0.237      | 5.457      | 4.169     | 4.587      | 4.350      |
| Santa Catarina    | 0.881      | 2.236     | 0.919      | 0.552      | 2.181      | 0.596      | 1.424      | 3.053     | 1.468      | 0.872      |
| Macaubas          | 0.180      | 0.180     | 0.167      | -0.117     | -0.117     | -0.095     | 0.228      | 0.228     | 0.250      | 0.344      |
| Praia Formosa     | 0.476      | 0.476     | 0.502      | 0.331      | 0.331      | 0.365      | 1.070      | 1.070     | 1.104      | 0.739      |
| São Clemente      | 0.884      | 2.375     | 1.354      | -0.375     | -2.214     | -1.111     | 2.123      | 0.284     | 1.387      | 2.498      |
| Araripe           | 1.414      | 2.795     | 1.175      | 0.807      | -2.067     | -0.041     | 3.775      | 0.901     | 2.927      | 2.968      |
| Alegria II        | 0.812      | 0.336     | 0.878      | 0.696      | -0.090     | 0.772      | 1.362      | 0.576     | 1.437      | 0.666      |
| Elebras Cidreira I | 0.262 | 0.303     | 0.305      | 0.032      | -0.171     | 0.136      | 0.616      | 0.413     | 0.720      | 0.584      |
| Bom Jardim        | 0.194      | 0.521     | 0.196      | -0.023     | 0.476      | -0.040     | 0.201      | 0.701     | 0.184      | 0.224      |

The graphs in Figure A 2 show slightly different results than from the statistical analysis: Except for Macaubas and Praia Formosa where all simulations are in about the same range, the smallest differences between simulated and observed wind power generation are either the ones without wind speed mean approximation or when GWA data are applied. Only in Alegria II the simulation with INMET mean wind speed approximation fits the range of observed daily wind power generation better than the other methods.

Figure A 2: Comparison of differences between observed and simulated daily wind power generation with different wind speed mean approximation methods (no correction/Nearest Neighbour: NN, correction with measured wind speeds: INMET, Global Wind Atlas: GWA) for Brazil (a), its North-East and South (b)
Comparison of simulation results by boxplots reveals different findings than those of the statistical analysis. In Figure A 5, for example, the graphs of daily wind power generation in Brazil, as well as in the North-East and the South, indicate that wind power is simulated best if hourly and monthly wind speed correction is applied, whereas monthly wind speed correction or mean approximation lead to overestimation of observed wind power generation. This contrasts the findings presented previously in Figure 8 and Table A 3, where lowest RMSEs were obtained with mean approximation.

In contrast to results from Brazil and the subsystems, on the level of single states (Figure A 6), the simulations with hourly and monthly wind speed correction usually are not as close to observed wind power generation as with other bias correction methods. It also stands out, that monthly wind speed correction never seems to be applied. In fact, in most wind parks the correlations between corrected reanalysis and measured wind speeds of the closest wind speed measurement station are too low and correction is not performed. Consequently, the results of mean approximation and monthly wind speed correction are very similar. These results are only partly supported by those from the statistical analysis, where the hourly and monthly, but also the monthly wind speed correction do not deliver closer fit to observed wind power generation for most of the cases. However, the
statistical analysis does not concur with the results of mean approximation and monthly wind speed correction being very close.

As for the selected wind parks wind speed correction was hardly applied, the limits of 50% minimum correlation and 80 km maximum distance were discarded, to show the effect of different wind speed correction methods on wind power simulation for particular wind parks. The graphs in Figure A 7 illustrate how wind speed bias correction affects wind power generation at particular locations. However, except for the wind park Alegria II, the effects are not beneficial, which fits the results from the statistical analysis. At Araripe, a wind park in the state of Piaui, wind speed correction with measured wind speeds even results in significant overestimations of wind power generation. These results support the importance of choosing limitations for wind speed correction (distance to closest wind speed measurement station and correlation of wind speeds). With these limits, wind speed correction is applied on two wind parks (Elebras Cidreira 1 and Alegria II) with hourly and monthly wind speed correction.

Table A 3: Comparison of correlations, root mean square errors (RMSEs), mean bias errors (MBEs) and means of simulated daily wind power generation with different methods for wind speed bias correction: mean approximation with Global Wind Atlas data (GWA), mean approximation with Global Wind Atlas data combined with monthly wind speed correction with INMET wind speed data (GWA<sub>hm</sub>) and mean approximation with Global Wind Atlas data combined with hourly and monthly wind speed correction with INMET wind speed data (GWA<sub>hr</sub>)

| Region            | Correlation | RMSE [GWh] | MBE [GWh] | Mean [GWh] |
|-------------------|-------------|------------|-----------|------------|
|                   | GWA<sub>hm</sub> | GWA<sub>hr</sub> | GWA<sub>hm</sub> | GWA<sub>hr</sub> | GWA<sub>hm</sub> | GWA<sub>hr</sub> | GWA<sub>hm</sub> | GWA<sub>hr</sub> | obs |
| Brazil            | 0.964       | 0.964      | 0.976     | 14.405     | 10.703     | 9.799     | -3.770     | 1.125     | 6.144 |
| North-East        | 0.976       | 0.960      | 0.972     | 12.802     | 14.240     | 8.650     | -3.418     | -4.879    | 5.280 |
| South             | 0.880       | 0.851      | 0.948     | 3.057      | 9.210      | 2.413     | -0.447     | 6.405     | 0.765 |
| Bahia             | 0.948       | 0.912      | 0.958     | 3.502      | 6.900      | 2.700     | 2.042      | -4.456    | -0.408 |
| Ceará             | 0.867       | 0.593      | 0.935     | 3.423      | 4.189      | 4.683     | 1.166      | 0.367     | 3.825 |
| Pernambuco        | 0.712       | 0.527      | 0.834     | 3.993      | 3.553      | 2.397     | -3.317     | -2.679    | -1.822 |
| Piaui             | 0.900       | 0.903      | 0.909     | 3.590      | 3.467      | 2.269     | -2.429     | -2.311    | -0.343 |
| Rio Grande do Norte | 0.968     | 0.968      | 0.953     | 9.425      | 6.073      | 4.256     | -4.669     | -2.784    | -2.076 |
| Rio Grande do Sul | 0.910       | 0.854      | 0.951     | 3.922      | 6.701      | 2.007     | -2.149     | 4.284     | 0.237 |
| Santa Catarina    | 0.524       | 0.575      | 0.704     | 2.558      | 4.023      | 0.919     | 2.491      | 3.946     | 0.596 |
| Macaubas          | 0.612       | 0.591      | 0.608     | 0.304      | 0.362      | 0.167     | -0.271     | 0.333     | -0.095 |
| Praia Formosa     | 0.738       | 0.671      | 0.729     | 0.539      | 0.609      | 0.502     | -0.431     | -0.500    | 0.365 |
| São Clemente      | 0.498       | 0.565      | 0.542     | 1.689      | 2.063      | 1.354     | -1.487     | -1.905    | -1.111 |
| Araripe           | -0.605      | 0.214      | 0.886     | 5.376      | 5.650      | 1.175     | -4.474     | 5.109     | -0.041 |
| Alegria II        | 0.551       | 0.544      | 0.538     | 0.394      | 0.608      | 0.878     | -0.257     | -0.516    | 0.772 |
| Elebras Cidreira 1| 0.671       | 0.703      | 0.829     | 0.429      | 0.535      | 0.305     | -0.298     | -0.434    | 0.136 |
| Bom Jardim        | 0.369       | 0.435      | 0.477     | 0.237      | 0.263      | 0.196     | 0.123      | 0.156     | -0.040 |

Figure A 5: Comparison of differences between observed and simulated daily wind power generation with different wind speed bias correction methods (mean approximation with Global Wind Atlas wind speeds: GWA, mean approximation combined with monthly wind speed correction with INMET wind speeds: GWA<sub>hm</sub>) for Brazil (a), its North-East and South (b)
Figure A 6: Comparison of differences between observed and simulated daily wind power generation with different wind speed bias correction methods (mean approximation with Global Wind Atlas wind speeds: GWA, mean approximation combined with monthly wind speed correction with INMET wind speeds: GWA$_m$, mean approximation combined with hourly and monthly wind speed correction with INMET wind speeds: GWA$_{hm}$) for Brazilian states.

Figure A 7: Comparison of differences between observed and simulated daily wind power generation with different wind speed bias correction methods (mean approximation with Global Wind Atlas wind speeds: GWA, mean approximation combined with monthly wind speed correction with INMET wind speeds: GWA$_m$, mean approximation combined with hourly and monthly wind speed correction with INMET wind speeds: GWA$_{hm}$) for seven Brazilian wind power plants.
A.2 Results from other studies
Table A 4 shows results from other studies to compare our values to. A description can be found in the Discussion.

**Table A 4: Collection of statistical parameters (correlations, rel. RMSEs and rel. MBEs) from other studies for comparison to our results. The results of González-Aparicio et al. [4] were given as absolute values, relative values were calculated from those by normalising by the installed capacity**

| Source | Dataset | Region | Temporal resolution | Correlation | Rel. RMSE | Rel. Bias | Notes |
|--------|---------|--------|---------------------|-------------|-----------|----------|-------|
| Cannon et al. [15] | MERRA | Great Britain | monthly | 0.96 | | | |
| Cradden et al. [33] | MERRA | Ireland | monthly | 0.97 | 10.17% | -0.79% | |
| Pfenninger and Staffell [18] | MERRA | Germany | hourly | 0.981 | 3.11% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Spain | hourly | 0.917 | 6.07% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Britain | hourly | 0.967 | 4.68% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | France | hourly | 0.956 | 4.39% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Italy | hourly | 0.872 | 7.44% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Sweden | hourly | 0.952 | 5.66% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Denmark | hourly | 0.955 | 6.75% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Ireland | hourly | 0.951 | 6.65% | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | EU (13 European countries) | monthly | 0.951 | | | Mean correlation for 13 countries, correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Germany | monthly | 0.991 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Ireland | monthly | 0.986 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | France | monthly | 0.983 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Denmark | monthly | 0.977 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Spain | monthly | 0.975 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Great Britain | monthly | 0.969 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Norway | monthly | 0.967 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Sweden | monthly | 0.957 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Finland | monthly | 0.952 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Romania | monthly | 0.933 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Portugal | monthly | 0.922 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Italy | monthly | 0.920 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA | Greece | monthly | 0.873 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | EU (13 European countries) | monthly | 0.955 | | | Mean correlation for 13 countries, correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Germany | monthly | 0.989 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Ireland | monthly | 0.985 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | France | monthly | 0.982 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Denmark | monthly | 0.973 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Spain | monthly | 0.976 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Great Britain | monthly | 0.969 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Norway | monthly | 0.968 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Sweden | monthly | 0.947 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Finland | monthly | 0.955 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Romania | monthly | 0.935 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Portugal | monthly | 0.875 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Italy | monthly | 0.925 | | | Correlation calculated from R² |
| Pfenninger and Staffell [18] | MERRA-2 | Greece | monthly | 0.885 | | | Correlation calculated from R² |
| Source                        | Dataset | Region   | Temporal resolution | Correlation | Rel. RMSE | Rel. Bias | Notes          |
|------------------------------|---------|----------|---------------------|-------------|-----------|-----------|----------------|
| González-Aparicio et al. [7] | MERRA   | Austria  | hourly              | 0.904       | 12.9%     | 0.6%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Belgium  | hourly              | 0.937       | 4.5%      | -1.4%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Bulgaria | hourly              | 0.759       | 22.2%     | -15.5%    | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Cyprus   | hourly              | 0.436       | 13.2%     | -6.9%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Czech Republic | hourly          | 0.92        | 11.8%     | 1.0%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Germany  | hourly              | 0.971       | 3.8%      | 0.7%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Denmark  | hourly              | 0.952       | 4.9%      | 0.0%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Estonia  | hourly              | 0.913       | 7.8%      | 0.5%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Spain    | hourly              | 0.916       | 9.4%      | 1.6%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Finland  | hourly              | 0.929       | 9.1%      | 1.9%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | France   | hourly              | 0.952       | 5.9%      | 1.4%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Greece   | hourly              | 0.816       | 11.4%     | -1.8%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Croatia  | hourly              | 0.788       | 15.7%     | -6.5%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Hungary  | hourly              | 0.897       | 12.2%     | -6.0%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Ireland  | hourly              | 0.964       | 6.5%      | 0.6%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Lithuania| hourly              | 0.923       | 12.0%     | -5.4%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Latvia   | hourly              | 0.905       | 7.0%      | 0.0%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Netherlands| hourly          | 0.949       | 12.9%     | -11.3%    | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Poland   | hourly              | 0.967       | 5.0%      | 0.1%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Portugal | hourly              | 0.824       | 13.0%     | -4.9%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Romania  | hourly              | 0.838       | 14.1%     | -6.3%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Sweden   | hourly              | 0.866       | 30.7%     | 5.4%      | only 2015      |
| González-Aparicio et al. [7] | MERRA   | United Kingdom| hourly          | 0.863       | 4.4%      | -0.9%     | only 2015      |
| González-Aparicio et al. [7] | MERRA   | Switzerland| hourly           | 0.581       | 20.5%     | 8.5%      | only 2015      |
| González-Aparicio et al. [7] | EMHIRES | Austria  | hourly              | 0.869       | 14.0%     | -1.2%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Belgium  | hourly              | 0.947       | 4.2%      | -0.2%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Bulgaria | hourly              | 0.733       | 22.3%     | -15.6%    | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Cyprus   | hourly              | 0.427       | 13.9%     | -0.8%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Czech Republic | hourly      | 0.904       | 17.2%     | 3.4%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Germany  | hourly              | 0.972       | 7.3%      | 2.9%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Denmark  | hourly              | 0.957       | 5.4%      | 1.4%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Estonia  | hourly              | 0.920       | 8.1%      | 1.3%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Spain    | hourly              | 0.913       | 9.8%      | 1.7%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Finland  | hourly              | 0.944       | 6.0%      | 0.6%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | France   | hourly              | 0.959       | 6.3%      | 1.7%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Greece   | hourly              | 0.813       | 11.5%     | -1.7%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Croatia  | hourly              | 0.814       | 14.5%     | -6.5%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Hungary  | hourly              | 0.876       | 12.9%     | -6.0%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Ireland  | hourly              | 0.965       | 6.6%      | 0.9%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Lithuania| hourly              | 0.926       | 11.4%     | -5.4%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Latvia   | hourly              | 0.921       | 6.7%      | 0.0%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Netherlands| hourly          | 0.960       | 12.3%     | -9.2%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Poland   | hourly              | 0.965       | 7.2%      | 1.8%      | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Portugal | hourly              | 0.846       | 12.6%     | -2.8%     | with GWA bias correction |
| González-Aparicio et al. [7] | EMHIRES | Romania  | hourly              | 0.836       | 14.1%     | -6.3%     | with GWA bias correction |
| Source                      | Dataset     | Region                | Temporal resolution | Correlation | Rel. RMSE | Rel. Bias | Notes                                      |
|-----------------------------|-------------|-----------------------|---------------------|-------------|-----------|-----------|--------------------------------------------|
| González-Aparicio et al. [7]| EMHIRES     | Switzerland           | hourly              | 0.545       | 21.7%    | 8.5%     | with GWA bias correction                  |
| González-Aparicio et al. [7]| EMHIRES     | United Kingdom        | hourly              | 0.855       | 4.2%     | -0.5%    | with GWA bias correction                  |
| González-Aparicio et al. [7]| ECMWF       | Austria               | hourly              | 0.904       | 9.8%     | 1.0%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Belgium               | hourly              | 0.937       | 3.0%     | 0.0%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Bulgaria              | hourly              | 0.759       | 12.7%    | -3.5%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Cyprus                | hourly              | 0.436       | 12.6%    | -3.7%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Czech Republic        | hourly              | 0.920       | 17.5%    | 2.1%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Germany               | hourly              | 0.971       | 4.4%     | 1.6%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Denmark               | hourly              | 0.952       | 4.2%     | -0.2%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Estonia               | hourly              | 0.913       | 7.0%     | 1.1%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Spain                 | hourly              | 0.916       | 7.2%     | 0.7%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Finland               | hourly              | 0.929       | 6.5%     | 1.1%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | France                | hourly              | 0.952       | 5.9%     | 1.9%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Greece                | hourly              | 0.816       | 11.0%    | -2.2%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Croatia               | hourly              | 0.788       | 18.2%    | -6.5%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Hungary               | hourly              | 0.897       | 10.8%    | -5.9%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Ireland               | hourly              | 0.964       | 11.6%    | 0.0%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Lithuania             | hourly              | 0.923       | 10.7%    | -5.5%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Latvia                | hourly              | 0.905       | 5.9%     | 0.0%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Netherlands           | hourly              | 0.949       | 6.5%     | 2.0%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Poland                | hourly              | 0.967       | 4.7%     | 1.0%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Portugal              | hourly              | 0.824       | 14.2%    | -3.9%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Romania               | hourly              | 0.838       | 12.8%    | -6.4%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Sweden                | hourly              | 0.866       | 30.3%    | 6.4%     | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | Slovenia              | hourly              | 0.863       | 3.7%     | -1.8%    | non-freey available dataset               |
| González-Aparicio et al. [7]| ECMWF       | United Kingdom        | hourly              | 0.581       | 34.0%    | 8.5%     | non-freey available dataset               |