Bias-correcting simulated wind power in Austria and in Brazil from the ERA-5 reanalysis data set with the DTU Wind Atlas

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Kurzfassung:

In a future world with high shares of renewable energy globally, reliable time series of potential renewable power generation are of high importance to estimate costs and the needs for integration measures in the electricity grid. Such time series can be synthetically generated from reanalysis data, which are recently gaining popularity in the energy modelling community. ERA5, provided by the ECMWF, is a cutting-edge global reanalysis dataset providing climatic variables at high spatiotemporal resolution. In the present work we assess the capability of ERA5 reanalysis wind speeds in a wind power simulation model in two climatically and topographically different regions and validate the resulting time series with historical wind power generation data. Furthermore, we evaluate the effects of using DTU's Global Wind Atlas (GWA), a high-resolution mean wind speed data source, for bias correction of reanalysis wind speeds applicable globally. Results show that ERA5 provides a high-quality source of wind speed data for wind power simulation, however, using ERA5 for wind power simulation will underestimate historical wind power generation slightly. The GWA, however, does not improve the quality of simulation when used with ERA5 in our case study regions.

Keywords: wind power simulation, bias correction, ERA5 reanalysis, Global Wind Atlas

1 Introduction

Scenarios of future energy systems with high shares of intermittent renewables rely on timeseries data of potential generation to understand the variability of renewable energy production and, in particular, the temporal relationship between different locations and between different renewable energy sources. The data can come from measured generation. Yet, such information is not available for all world regions [1, 2] or in insufficient spatial or temporal resolution. Another means of obtaining renewable energy generation time series is the simulation from meteorological measurements, such as wind speed or solar radiation. However, direct measurements are not always available for all locations, the length of the time series is often limited, the data can be incomplete or subject to measurement errors or bias

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and data moreover is costly in many cases [1, 2]. As an alternative, reanalysis climate data have gained popularity amongst the energy modelling community in recent years. Their main advantages are their high spatial and temporal resolution and their free availability. In many cases, they are available for the whole globe for long time periods and thus provide a useful tool for the simulation of intermittent electricity generation [2, 3, 4]. Commonly used datasets comprise the MERRA and MERRA-2 reanalyses (Modern-Era Retrospective analysis for Research and Applications [5]) from the National Aeronautics and Space Administration (NASA [6]), the Climate Forecast System Reanalysis (CFSR [7]) by the National Centres for Environmental Protection (NCEP [8]) or several datasets provided by the European Centre for Medium-Range Weather Forecasts (ECMWF [9]), such as the ERA-15, ERA-40, ERA-Interim or the most recent ERA5 [10]. The latter is used in the current study, as it is a very recent dataset, with a comparatively high spatial resolution compared to other reanalyses. So far, there is one other analysis assessing the applicability of this dataset, modelling of wind power generation in four countries (Germany, Denmark, France, Sweden) and the Bonneville Power Administration in north-west USA [11]. The results show that wind power generation time series produced from ERA5 data represent historical production better than MERRA-2 wind speed data, but nevertheless the author mentions that especially in complex terrain reanalysis data might not be the optimal data source if used directly, without additional correction measures.

Despite being used for several research purposes, reanalysis data is only available at discrete spatial and temporal intervals and therefore in many cases suffers from significant regional bias, as stated by Cannon et al. [4], Pfenninger and Staffell [1] or Olauson and Bergkvist [12]. We therefore study bias correction of ERA-5 reanalysis wind speed data with another global dataset: : the Global Wind Atlas (GWA [13]) provided by the Technical University of Denmark (DTU) [14]. It comprises mean wind speeds at three heights at a high spatial resolution of 1 km x 1 km, compared to ERA5 data which are at about 30 km resolution. GWA downscales MERRA-2 reanalysis data by using spatially more accurate data on the local topography.

For our analysis, the two regions of Austria and Brazil are selected, on the one hand, to assess the capability of ERA5 reanalysis data to simulate wind power generation in two different parts of the world, and on the other hand, to understand if the same bias correction method can improve timeseries in two climatically and topographically different regions paving the way for a globally applicable bias correction method. The following part of this work describes data and methods used for the simulation and analysis of wind power generation and bias correction in Austria and Brazil. Afterwards results are presented and discussed. In the final section a conclusion is drawn from the presented outcomes.

2 Data and Methods

This section gives an overview of the data and methods used for the model underlying the present study. The work can be subdivided into three main tasks:

1) Simulation of hourly wind power generation from ERA5 wind speeds at current wind power plant locations in Austria and Brazil considering the development of the wind turbine fleet over the past years

2) Bias correction of wind speeds with DTU's Global Wind Atlas to better account for local topography

3) Validation with observed daily nationally aggregated wind power generation data provided by the national transmission grid operator of Brazil and the settlement agency for green electricity of Austria. We use daily data as for Brazil, a sub-daily time-resolution is not available.

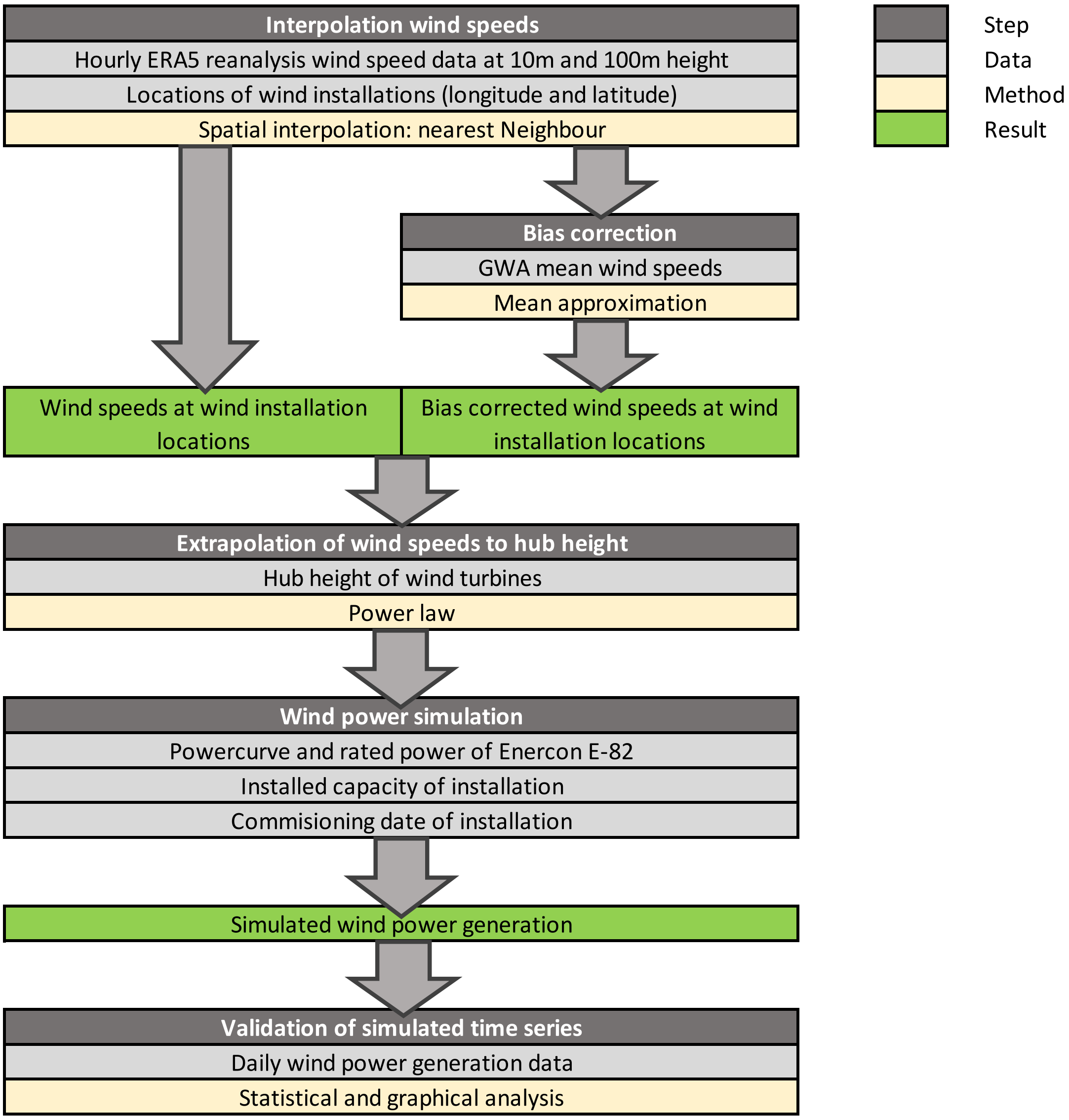

Figure 1: Overview of the approach: steps, methods and data used for simulation, bias correction and validation

Figure 1 shows a detailed outline of the methodological steps and additional information on data and methods applied for this approach. In Table 1 an overview and short description of the datasets used for the present study is given. The model is based on ERA5 [10] wind speed data, a reanalysis dataset recently released by the ECMWF, which features a higher spatial resolution than any of the earlier global reanalyses. Its accuracy has not been validated thoroughly yet, especially regarding wind speeds. The data are available at an hourly temporal resolution and at 0.25° x 0.25° spatial resolution. Wind speeds are provided in two heights (10 m and 100 m above ground) and in two directions (u: eastward wind, v: northward wind) in a time span from currently 1979 until present (data are publicly available three months later). This is shorter than other reanalysis products, however, further years of data are released soon, starting with the year 1950. For the present analysis, data are downloaded for the areas of Brazil and Austria in the spatial extents of WGS84 Bound: -74.1, -33, -36, 5.5 (41 x 19 data points) and WGS84 Bound: 8, 45.5, 18, 50 (153 x 155 data points), respectively. Data can be downloaded with the Climate Data Store Application Program Interface (CDS API [15]) client provided by the ECMWF, which allows easy data access via python scripts.

Table 1: Overview over datasets used for simulation and validation

Data set name	**Description**	**Temporal resolution**	**Spatial resolution**	**Temporal coverage**	**Spatial coverage**	**Source**
ERA5	Reanalysis data, modelled wind speed data	hourly	0.25° x 0.25° (31 km x 31 km)	2000 to 2017	area of Brazil and Austria	ECMWF
Windrad Landkarte	Locations, commissioning dates and capacities	yearly	wind turbines	1994 to 2017	Austria	IG Windkraft
Wind farms	Locations, commissioning dates and capacities	monthly	wind parks	1994 to 2018	Brazil	The Wind Power
Enercon E-82 wind turbine	Power curve					Enercon
Winderzeugung	Wind power generation data	quarter-hourly	nationally aggregated	2003 to 2017	Austria	OeMAG
Histórico da operação	Wind power generation data	daily	nationally aggregated	2006 to 2017	Brazil	ONS

These wind speeds then need to be interpolated to the points of wind power plants or single wind turbines. Previous tests [16] have shown that the Nearest Neighbour method delivers similarly good or even better results compared to other interpolation methods with higher computational effort, which is why we apply this method here. In Brazil locations of wind parks (longitude and latitude) are extracted from The Wind Power [17] database. For Austrian wind parks, coordinates of single wind turbines are available from IG Windkraft (Austrian Wind Energy Association [18, 19]). If wind speeds in u- (ws_u) and v-direction (ws_v) are obtained at the specific locations, the effective wind speed (ws_{eff}) needs to be calculated according to the equation:

$$ws_{eff} = \sqrt{ws_u^{\ 2} + ws_v^{\ 2}}$$

As a means of bias correction, wind speed time series are adjusted to represent mean wind speeds in the GWA [13]. The GWA data are available at a spatial resolution of 1 km x 1 km from the International Renewable Energy Agency (IRENA [20]). The GWA is generated with

DTU's Wind Atlas Analysis and Application Program (WAsP [21]) based on MERRA reanalysis wind speeds [5], which are subject to a downscaling process to achieve data of higher spatial resolution by considering medium and high resolution topography [22]. The MERRA reanalysis timeseries are reduced to multiyear averages in the process. The mean approximation is performed by calculating the mean of the ERA5 wind speeds (ws_{ERA5}) at the location of a particular wind park or wind turbine and dividing the GWA mean wind speed (ws_{GWA}) at the same location by this value. Later this factor is multiplied with the ERA5 wind speeds, resulting in the mean of the wind speed time series being the same as in the GWA:

$$ws_{new} = ws_{ERA5} * \frac{ws_{GWA}}{mean(ws_{ERA5})}$$

The resulting wind speeds can subsequently be used to calculate wind power generation for both selected regions. As a first step, wind speeds are extrapolated to the hub height of wind turbines. In Brazil wind park data do not contain information about the heights of the installed turbines. Therefore, a standard hub height of 108 m of the wind turbine selected for simulation, the Enercon E-82 [23] is assumed. In Austria heights of the wind turbines are available and also used for extrapolation. The Power Law [24] and wind speeds at 10 m and 100 m height above ground are used to derive the wind speeds at the hub height of the respective wind turbines

$$ws_2 = ws_1 \left(\frac{h_2}{h_1}\right)^{\alpha}$$

where first the ground surface friction coefficient α is calculated from the wind speeds at h_1 = 10 m and h_2 = 100 m height and afterwards inserted into the formula, while changing h_2 to the height of the particular wind turbine. The friction coefficient is determined by the structure of the surface, being high in uneven terrain and low in smooth terrain [24].

Finally, wind power can be simulated with the help of the installed capacities, commissioning dates of wind parks and wind turbines and the power curve of the Enercon E-82, which is available in the factsheet [23]. This wind turbine is chosen, as its size is in the medium range of installed wind turbines, considering its capacity of 2 MW. The chosen model has a height of 108 m, which however is only assumed for Brazil as for Austria more precise data are available. As a previous study [25] has shown that the use of more precise data concerning power curves of wind turbines has hardly any impact on the simulation, this simpler approach is considered sufficient here. Commissioning Dates start in 1994 in Austria and in Brazil, but wind power generation is only simulated since 2003 and 2006, respectively, when significant wind power generation started in the selected countries and validation data are available.

Simulated wind power generation time series are aggregated temporally (from hourly to daily values) and spatially (nationally) to fit the validation data. Historic wind power generation in Brazil is provided by the National Electrical System Operator (Operador Nacional do Sistema Elétrico, ONS [26]) on a daily and monthly basis, on national level or disaggregated for subsystems, states or particular wind farms. To limit results and to show comparative values for both of the selected countries, only nationally aggregated wind power generation is evaluated in the present work. In Austria, the Settlement Agency for Green Electricity (OeMAG Abwicklungsstelle für Ökostrom AG [27]) provides nationally aggregated quarter-hourly wind power generation between 2003 and 2017, which is cumulated to daily wind power generation for validation. The statistical parameters root mean square error (RMSE), mean bias error (MBE) and the means of observed and simulated wind power generation are compared to see how large the bias between our and historical time series is to assess the effect of using the GWA on the quality of the simulation. Furthermore, to understand how data are distributed and in which range daily wind power generation lies, also boxplots of daily wind power generation are compared for the simulation with and without wind speed bias correction and the observed wind power generation.

3 Results

Data in general show similar results in Brazil and Austria regarding the fit of the simulation to recorded wind power generation with ERA5 data only, and also when GWA mean wind speeds are used for bias correction. Table 2 presents the statistical parameters and indicates that in Austria, when applying GWA mean approximation, the RMSE as well as the MBE are increased. The positive MBE show that performing wind speed correction leads to a considerable overestimation, compared to a slight underestimation of observed wind power generation if the GWA is not applied.

Table 2: Statistical parameters for comparison of observed (obs, data by OeMAG and ONS) and simulated daily wind power generation with (wpc) and without (wp) GWA mean wind speed correction in Austria (aut) and Brazil (bra)

	wp_aut	wpc_aut	obs_aut	wp_bra	wpc_bra	obs_bra
RMSE [GWh]	1.80	4.43		11.52	9.93	
MBE [GWh]	-0.33	2.85		-1.58	3.69	
Mean [GWh]	6.68	9.86	7.02	24.68	29.95	26.26

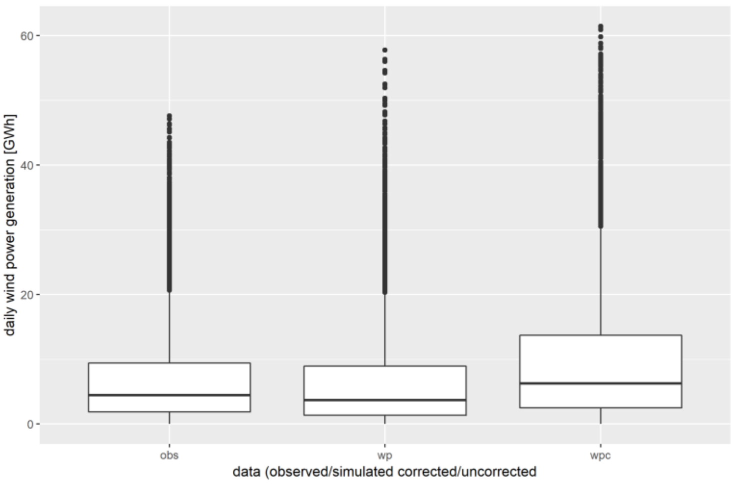

Figure 2: Comparison of observed (obs, data by OeMAG) and simulated daily wind power generation with (wpc) and without (wp) GWA mean wind speed correction in Austria

Figure 2 shows the same characteristics as before wind speed correction the simulated wind power is close, but slightly below observed wind power generation, except for some outliers in the higher range (above 50 GWh per day). Disregarding outliers, simulated daily wind power generation lies below 20 GWh. If bias correction is applied, simulated wind power increases and consequently results in significant overestimation with wind power generation above 5 GWh 50 % of the time.

In Brazil results are mostly similar to those in Austria, in general pointing to slight underestimation of actual wind power generation with ERA5 wind speeds and overestimation of historical production when applying the GWA. The MBE supports this finding as it is negative without and positive with bias correction, as well as the plots in Figure 3. In contrast to these results, the RMSE is slightly reduced by applying GWA wind speed bias correction, thus indicating a better fit when using mean wind speed bias correction. This is noteworthy, especially considering the aspect that in Austria the RMSE was drastically increased to nearly 2.5-fold when applying GWA data and that all other results imply a negative impact on the simulation when using the mean wind speeds from the DTU. If the calculated measures are normalised by the observed mean wind power generation or mean installed capacity, except for the bias after wind speed correction results in Austria are better compared to those in Brazil.

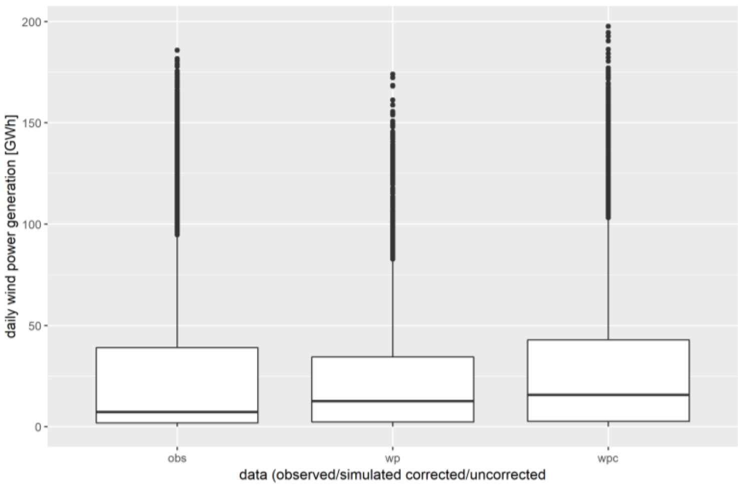

Figure 3: Comparison of observed (obs, data by ONS) and simulated daily wind power generation with (wpc) and without (wp) GWA mean wind speed correction in Brazil

4 Discussion

In the results section two main outcomes were presented: First, ERA5 is a high-quality wind speed data source for modelling wind power generation, and second, applying the GWA for wind speed mean correction reduced the quality of the simulated wind power generation when deriving the fit to historical wind power production. The latter result contradicts our expectations: especially for the case of Austria, we expected that spatially disaggregated data would improve results due to the rather complex terrain. Only for the case of Brazil, a slightly lower RMSE was achieved when applying the GWA.

Our results match those in earlier studies [28, 29, 30, 31] which state that downscaling does not always lead to better results. Olauson [11], for example, found that wind power generation simulated with ERA5 delivers better results compared to the “EMHIRES” dataset [29], which results from downscaling MERRA-2 reanalysis with the GWA. However, he did not attempt to use ERA5 data and apply the GWA to this dataset. Table 3 shows an overview of results from other analyses compared to ours. Observe that our results are in daily resolution, compared to an hourly resolution for all other results. For Austria, the RMSE is higher than González-Aparicio’s [29] one for Belgium, but comparing to results for Austria or Ireland, including Pfenninger and Staffell [1] or Cradden et al. [32], the RMSE is lower. The relative RMSE in Brazil, however, is considerably higher than those of other studies. If GWA correction is applied, our relative RMSE is lower than that presented in [29] for Austria, but countries with a similar installed capacity (Belgium and Ireland) have significantly lower values.

Regarding MBEs, our results from using uncorrected ERA5 data are similar to those calculated by González-Aparicio et al. [29] for Austria, although negative. Also Cradden et al.’s [32] bias for wind power simulation in Ireland is close to ours. In Brazil, however, the bias is larger than in the other studies presented in Table 3. If the GWA is applied for mean wind speed bias correction, we obtain considerably higher relative bias than González-Aparicio et al. [29], in Austria as well as in Brazil.

Considering the results of applying the GWA, different overall outcomes were described by González-Aparicio et al. [29], who claimed that using information from the GWA additionally to reanalysis data improved the fit of their wind power simulation to transmission system operators’ data. However, they used the coarser MERRA data, which, as mentioned before, are less reliable than the ERA5 reanalysis wind speeds with higher spatial resolution. Although others are in favour of using bias correction methods instead of only relying on reanalysis data [25], according to our results, we cannot recommend using the GWA in combination with ERA5 as a source for spatial downscaling, at least based on our selection of case studies. In our particular case, one plausible explanation why applying the GWA on ERA5 data does not lead to better fit of simulated time series to historical values is but does in [29], that the GWA is based on MERRA-2 data and may therefore be more suitable for these.

Comparing the results of Austria and Brazil, we gauged that in general the simulation worked slightly better in Austria than in Brazil, with lower relative RMSEs and MBEs. This may be due to more precise location data for Austria, where the coordinates of each single wind turbine were given, contrary to Brazilian data, which only included the approximate locations of aggregated wind parks.

On the other hand, we could have expected that in Brazil simulated wind power time series might be more accurate, as due to a larger area a higher smoothing effect is possible and the terrain (where wind parks are built, mostly near the coast) is less complex than the mountainous, small area of Austria.

Table 3: Comparison of calculated RMSEs and biases with other analyses. Values based on bias-correction with GWA are in bold, our results are marked in yellow. Values are normalised by installed capacity. For studies featuring many results, only a few countries were selected: Belgium and Ireland have similar installed capacities as in Austria. As there was no other analysis for Brazil, also results from Germany are included as an example of a country with high production capacity. A full collection of results in different countries can be found in the Appendix.

Source	**Dataset**	**Region**	**Temporal resolution**	**Rel. RMSE**	**Rel. Bias**	
This study	ERA5	Austria	daily	4.90%	-0.9%	1
González-Aparicio et al. [27]	MERRA	Austria	hourly	12.9%	0.6%	2
González-Aparicio et al. [27]	ECMWF[1]	Austria	hourly	9.8%	1.0%	2
González-Aparicio et al. [27]	MERRA	Belgium	hourly	4.5%	-1.4%	2
González-Aparicio et al. [27]	ECMWF[1]	Belgium	hourly	3.0%	0.0%	2
González-Aparicio et al. [27]	MERRA	Ireland	hourly	6.5%	0.6%	2
González-Aparicio et al. [27]	ECMWF[1]	Ireland	hourly	11.6%	0.0%	2
Pfenninger and Staffell [1]	MERRA	Ireland	hourly	6.65%		
Cradden et al. [30]	MERRA	Ireland	hourly	10.2%	-0.79%	
This study	ERA5	Brazil	daily	15.5%	-2.1%	1
González-Aparicio et al. [27]	MERRA	Germany	hourly	3.8%	0.7%	2
González-Aparicio et al. [27]	ECMWF[1]	Germany	hourly	4.4%	1.6%	2
Olauson [11]	ERA5	Germany	hourly	2.35%		
Olauson [11]	MERRA-2	Germany	hourly	2.82%		
Pfenninger and Staffell [1]	MERRA	Germany	hourly	3.11%		
This study	**ERA5**	**Austria**	**daily**	**12.10%**	**7.8%**	**1,3**
González-Aparicio et al. [27]	**MERRA**	**Austria**	**hourly**	**14.0%**	**-1.2%**	**2,3**
González-Aparicio et al. [27]	**MERRA**	**Belgium**	**hourly**	**4.2%**	**-0.2%**	**2,3**
González-Aparicio et al. [27]	**MERRA**	**Ireland**	**hourly**	**6.6%**	**0.9%**	**2,3**
This study	**ERA5**	**Brazil**	**daily**	**13.40%**	**5.0%**	**1,3**
González-Aparicio et al. [27]	**MERRA**	**Germany**	**hourly**	**7.3%**	**2.9%**	**2,3**

[1] non-freely available [2] for single years [3] with GWA correction

Although simulated wind power time series in general represent observed wind power generation well, still some bias is perceptible, especially if comparing to results from other analyses. Part of it may be explained by inexact information on the wind speed to power conversion as a generic power curve is applied instead of a particular one for each turbine type, which is also described as likely error source by González-Aparicio et al. [29]. Nevertheless, others state, that the use of more precise wind turbine information in such a model only brings minor improvements in simulation quality [33]. Another factor which may contribute to some bias are uncertainties about the quality and inhomogeneities in validation data [29].

5 Conclusion

By evaluating the simulation quality and potential of spatial wind speed correction with the GWA in two different countries, we attempt to obtain a first insight into global applicability of the proposed method. Our results show, that ERA5 wind speed data produce satisfactory wind power generation in a simple simulation approach for both regions, indicating that ERA5 may perform well globally. Results from bias correction with the GWA, however, exhibit a negative impact of this data source on simulation quality and we therefore do not recommend it as a source for wind speed bias correction when using ERA5 reanalysis as a primary data source. In the future, a more thorough investigation of the applicability of the presented method is recommended, especially regarding validation for other regions of the world, in order to reach a more definite conclusion on how useful GWA data are for wind power modelling.

Acknowledgements

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Appendix

Collection of statistical parameters (rel. RMSEs and rel. MBEs) from other studies for comparison to our results. Some of the results were given as absolute values (in the table in the columns “RMSE” and “MBE” and relative values were calculated from those by normalising by the installed capacity)

Source	**Dataset**	**Region**	**Temporal resolution**	**RMSE**	**Rel. RMSE**	**MBE**	**Rel. Bias**	
Olauson [11]	ERA5	Germany	hourly		2.35%			
Olauson [11]	MERRA-2	Germany	hourly		2.82%			
Olauson [11]	ERA5	Denmark	hourly		5.45%			
Olauson [11]	MERRA-2	Denmark	hourly		5.40%			
Olauson [11]	ERA5	France	hourly		2.97%			
Olauson [11]	MERRA-2	France	hourly		3.49%			
Olauson [11]	ERA5	Sweden	hourly		4.40%			

Source	**Dataset**	**Region**	**Temporal resolution**	**RMSE**	**Rel. RMSE**	**MBE**	**Rel. Bias**	
Olauson [11]	MERRA-2	Sweden	hourly		6.10%			
Olauson [11]	ERA5	BPA	hourly		9.10%			
Olauson [11]	MERRA-2	BPA	hourly		18.40%			
Pfenninger and Staffell [1]	MERRA	Germany	hourly		3.11%			
Pfenninger and Staffell [1]	MERRA	Spain	hourly		6.07%			
Pfenninger and Staffell [1]	MERRA	Britain	hourly		4.68%			
Pfenninger and Staffell [1]	MERRA	France	hourly		4.39%			
Pfenninger and Staffell [1]	MERRA	Italy	hourly		7.44%			
Pfenninger and Staffell [1]	MERRA	Sweden	hourly		5.66%			
Pfenninger and Staffell [1]	MERRA	Denmark	hourly		6.75%			
Pfenninger and Staffell [1]	MERRA	Ireland	hourly		6.65%			
Cradden et al. [32]	MERRA	Ireland	hourly		6.40%		-9.91%	2,4
Cradden et al. [32]	MERRA	Ireland	hourly		16.29%		5.37%	2,5
Cradden et al. [32]	MERRA	Ireland	hourly		10.2%		-0.79%	
González-Aparicio et al. [29]	MERRA	Austria	hourly	11.6	12.9%	11.6	0.6%	2
González-Aparicio et al. [29]	MERRA	Belgium	hourly	-29.8	4.5%	-29.8	-1.4%	2
González-Aparicio et al. [29]	MERRA	Bulgaria	hourly	-108.7	22.2%	-108.7	-15.5%	2
González-Aparicio et al. [29]	MERRA	Cyprus	hourly	-10.7	13.2%	-10.7	-6.9%	2
González-Aparicio et al. [29]	MERRA	Czech Republic	hourly	2.7	11.8%	2.7	1.0%	2
González-Aparicio et al. [29]	MERRA	Germany	hourly	315.8	3.8%	315.8	0.7%	2
González-Aparicio et al. [29]	MERRA	Denmark	hourly	-0.5	4.9%	-0.5	0.0%	2
González-Aparicio et al. [29]	MERRA	Estonia	hourly	1.5	7.8%	1.5	0.5%	2
González-Aparicio et al. [29]	MERRA	Spain	hourly	364.9	9.4%	364.9	1.6%	2
González-Aparicio et al. [29]	MERRA	Finland	hourly	20.4	9.1%	20.4	1.9%	2
González-Aparicio et al. [29]	MERRA	France	hourly	142	5.9%	142	1.4%	2
González-Aparicio et al. [29]	MERRA	Greece	hourly	-31.8	11.4%	-31.8	-1.8%	2
González-Aparicio et al. [29]	MERRA	Croatia	hourly	-24.9	15.7%	-24.9	-6.5%	2
González-Aparicio et al. [29]	MERRA	Hungary	hourly	-19.6	12.2%	-19.6	-6.0%	2
González-Aparicio et al. [29]	MERRA	Ireland	hourly	15.1	6.5%	15.1	0.6%	2
González-Aparicio et al. [29]	MERRA	Lithuania	hourly	-15.7	12.0%	-15.7	-5.4%	2
González-Aparicio et al. [29]	EMHIRES	Austria	hourly	277.7	14.0%	-23.2	-1.2%	2,3
González-Aparicio et al. [29]	EMHIRES	Belgium	hourly	92.0	4.2%	-4	-0.2%	2,3
González-Aparicio et al. [29]	EMHIRES	Bulgaria	hourly	156.1	22.3%	-109.2	-15.6%	2,3
González-Aparicio et al. [29]	EMHIRES	Cyprus	hourly	21.5	13.9%	-12.4	-0.8%	2,3
González-Aparicio et al. [29]	EMHIRES	Czech Republic	hourly	47.7	17.2%	9.4	3.4%	2,3
González-Aparicio et al. [29]	EMHIRES	Germany	hourly	3169.9	7.3%	1264.9	2.9%	2,3
González-Aparicio et al. [29]	EMHIRES	Denmark	hourly	274.6	5.4%	72.5	1.4%	2,3
González-Aparicio et al. [29]	EMHIRES	Estonia	hourly	24.4	8.1%	3.8	1.3%	2,3
González-Aparicio et al. [29]	EMHIRES	Spain	hourly	2244.0	9.8%	393.4	1.7%	2,3
González-Aparicio et al. [29]	EMHIRES	Finland	hourly	64.5	6.0%	6.5	0.6%	2,3
González-Aparicio et al. [29]	EMHIRES	France	hourly	650.5	6.3%	176.8	1.7%	2,3

Source	**Dataset**	**Region**	**Temporal resolution**	**RMSE**	**Rel. RMSE**	**MBE**	**Rel. Bias**	
González-Aparicio et al. [29]	EMHIRES	Greece	hourly	203.4	11.5%	-29.7	-1.7%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Croatia	hourly	55.6	14.5%	-24.9	-6.5%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Hungary	hourly	42.2	12.9%	-19.6	-6.0%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Ireland	hourly	157.7	6.6%	21.1	0.9%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Lithuania	hourly	33.2	11.4%	-15.8	-5.4%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Latvia	hourly	4.7	6.7%	0	0.0%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Netherlands	hourly	446.2	12.3%	-335.3	-9.2%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Poland	hourly	371.9	7.2%	91.9	1.8%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Portugal	hourly	608.9	12.6%	-135.3	-2.8%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Romania	hourly	412.4	14.1%	-185.1	-6.3%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Sweden	hourly	872.1	28.8%	184.2	6.1%	[2,3]
González-Aparicio et al. [29]	EMHIRES	United Kingdom	hourly	630	4.2%	-78.6	-0.5%	[2,3]
González-Aparicio et al. [29]	EMHIRES	Switzerland	hourly	13	21.7%	5.1	8.5%	[2,3]
González-Aparicio et al. [29]	ECMWF[1]	Austria	hourly	194.3	9.8%	19.7	1.0%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Belgium	hourly	65.1	3.0%	0.9	0.0%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Bulgaria	hourly	89.2	12.7%	-24.3	-3.5%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Cyprus	hourly	19.5	12.6%	-5.7	-3.7%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Czech Republic	hourly	48.6	17.5%	5.8	2.1%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Germany	hourly	1898.7	4.4%	711.6	1.6%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Denmark	hourly	213.5	4.2%	-8.8	-0.2%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Estonia	hourly	21	7.0%	3.4	1.1%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Spain	hourly	1651.5	7.2%	154.6	0.7%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Finland	hourly	70.5	6.5%	12.2	1.1%	[2]
González-Aparicio et al. [29]	ECMWF[1]	France	hourly	610.5	5.9%	190.9	1.9%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Greece	hourly	194.9	11.0%	-38.2	-2.2%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Croatia	hourly	69.7	18.2%	-24.9	-6.5%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Hungary	hourly	35.3	10.8%	-19.5	-5.9%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Ireland	hourly	277.2	11.6%	-0.6	0.0%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Lithuania	hourly	30.9	10.7%	-15.9	-5.5%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Latvia	hourly	4.1	5.9%	0	0.0%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Netherlands	hourly	238.3	6.5%	74.3	2.0%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Poland	hourly	243.7	4.7%	52	1.0%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Portugal	hourly	686.4	14.2%	-188.9	-3.9%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Romania	hourly	373.6	12.8%	-186.7	-6.4%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Sweden	hourly	918.2	30.3%	193.7	6.4%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Slovakia	hourly	0.8	26.7%	0.5	16.7%	[2]
González-Aparicio et al. [29]	ECMWF[1]	United Kingdom	hourly	560.6	3.7%	-268.5	-1.8%	[2]
González-Aparicio et al. [29]	ECMWF[1]	Switzerland	hourly	20.4	34.0%	5.1	8.5%	[2]

Source	Dataset	Region	Temporal resolution	RMSE	Rel. RMSE	MBE	Rel. Bias	

[1] non-freely available
[2] for single years
[3] with GWA correction
[4] min result
[5] max result