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Towards global validation of wind power simulations: A multi-country assessment of wind power simulation from MERRA-2 and ERA-5 reanalyses bias-corrected with the global wind atlas

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ABSTRACT

Reanalysis data are widely used for simulating renewable energy and in particular wind power generation. While MERRA-2 has been a de-facto standard in many studies for a long time, the newer ERA5-reanalysis recently gained importance. Here, both datasets were used to simulate wind power generation and evaluate their quality in terms of correlations and error measures compared to historical data of wind power generation. Due to their coarse resolution, reanalyses are known to fail to represent local climatic conditions adequately. Hence, mean bias correction was applied with two versions of the Global Wind Atlas (GWA) to the reanalysis data and the quality of the resulting simulations was assessed. Potential users of these datasets can also benefit from our analysis of the impact of spatial and temporal aggregation on indicators of simulation quality. We also assessed regions which differ significantly in terms of the prevailing climate, some of which are underrepresented in similar studies: the US, Brazil, South-Africa, and New Zealand. Our principal findings are threefold. (i) ERA5 outperforms MERRA-2 in terms of the assessed error measures. (ii) Bias-correction with GWA2 does not improve simulation quality substantially, while bias-correction with GWA3 is detrimental. (iii) Temporal aggregation increases correlations and reduces errors, while spatial aggregation does so consistently only when comparing very fine and very coarse granularities.

1. Introduction

Reanalysis climate data sets are frequently used to generate time series of power generation from wind turbines to assess the viability of future electricity systems with high shares of renewables. Two of the most prominent global reanalyses are National Aeronautics and Space Administration's (NASA) MERRA and MERRA-2 and the more recent ERA5 provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). Both, the older MERRA datasets and the more recent ERA5 reanalysis have been used widely for estimating wind power potentials [1–7], or studying the European power system [8,9]. Modelled data do not, however, perfectly replicate wind power production conditions and therefore might introduce variable errors, depending on where they are used globally - and for which purpose. Therefore, reanalysis data should not be relied upon without proper validation. Previous attempts of validating reanalyses for wind power generation include several studies, such as validating MERRA and MERRA-2 in 23 European countries [10], MERRA in Sweden [11] or ERA5 for two wind farms in Ethiopia [12]. More recent contributions also compare the performance of MERRA-2 and ERA5 reanalyses for wind power generation purposes, for example in France [13] or four European countries and a region in the US [14]. Both find that ERA5 performs better than MERRA-2. However, except for the two wind farms in Ethiopia and the region in the US, these publications assessed only regions in Europe. We therefore identify a first research gap in a lack of validation of MERRA-2 and ERA5 reanalyses for the purpose of wind power simulation for a wider variety of world regions with different climatic conditions, in particular outside of Europe. While global reanalysis data sets offer the advantage of conducting multi-country or global analyses without the need for country or region-specific climate data

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sources, their use for wind power simulation would benefit from a more granular spatial resolution [10], as offered by regional reanalyses such as COSMO-REA [15] which in more detail represents the local climatic conditions. Nevertheless, global reanalysis data is used directly in many cases [4,16–22], despite that it is well known that reanalysis data is being subject to bias [9,18,23]. Hence, differences of up to 20% between perturbed and control model-derived, optimally installed wind power capacities can be observed [24]. To enhance simulation quality, efforts should be made to correct this bias [17,24]. This is frequently done using observed wind power generation [9–11,14,25]. Yet, this approach is not globally applicable, for two major reasons: first, observations of wind power generation are unavailable for many world regions and second, data quality and the level of temporal and spatial aggregation vary between countries. Therefore, other forms of bias correction are required when conducting global analysis [10].

A high resolution (250 m) dataset which allows global bias correction by increasing the spatial resolution of global reanalyses of wind speeds is the Global Wind Atlas (GWA) [26]. Recently, the Global Wind Atlas Version 3.0 has been released. For the previous version of the GWA, i.e. GWA 2.0, there is only one assessment for wind power generation in Europe [27]. At the time of writing, the only publication that may have applied the latest GWA version 3.0 [12], does not explicitly state so. Furthermore, the authors do not compare it to a previous version to assess possible improvements. As [12] show that the GWA does not necessarily decrease bias of wind power generation in two wind parks in Ethiopia, we identify as second research gap the lack of validating wind power simulation based on different versions of the GWA against observed wind power generation in climatically diverse regions of the world. Finally, we identify as third research gap a consistent assessment of impact of spatial and temporal aggregation on simulation quality. This has not been studied in any of the previous works, despite being considered highly relevant information for users in power- and energy system models [28]: it will help to determine if a high temporal and in particular spatial resolution can improve those models, or if the introduced error from the climate based simulations is too significant.

In order to close the three research gaps identified above, the following research questions are answered: (1) Does the newer reanalysis ERA5 with higher spatial resolution perform better than the older MERRA-2 when validated against historical wind power generation data? (2) Does bias-correction with the spatially highly resolved GWA increase simulation quality? (3) Does the GWA 3.0 perform better than the previous GWA 2.1.? (4) Does temporal aggregation reduce error? (5) Does aggregating single wind parks to larger systems decrease the error due to spatial complementarity and error compensation effects, as indicated by Goić et al. [29] and Santos-Alamillos et al. [30]? This is the first time wind power simulation based on ERA5 is compared to MERRA-2 for the selected regions outside of Europe, and, to the best of our knowledge, the first large-scale assessment of GWA3 for this purpose. Furthermore, for the first time a systematic comparison of simulation quality on different spatial and temporal levels is conducted. Results of this analysis support future simulation efforts in firstly selecting appropriate datasets for wind power simulation, and secondly in estimating the possible error originating from the application of those datasets in different regions of the world.

In the following sections, first the applied data sets and methods are described. Consecutively, results are presented and finally discussed and concluded. In the supplementary material, additional information on methodology, as well as additional results are supplied.

2. Data & methods

Several data sets were used for simulation, bias correction and validation: wind speeds were taken from the MERRA-2 and ERA5 reanalysis data sets. The GWA was used for mean bias correction. Information on wind park locations and the used turbine technology was collected from different country-specific data sources. Similarly, country-specific wind power generation data was gathered to perform the final step of validation. An overview of the used data sets and steps in the analysis is shown in Fig. 1.

2.1. Reanalysis data

From MERRA-2 [31], the time-averaged, single-level, assimilation, single-level diagnostics (tavg1_2d_slv_Nx) dataset was used, while hourly data on single levels from 1950 to present were used from ERA5 [32]. MERRA-2 reanalysis data are provided by the NASA via the Goddard Earth Sciences Data and Information Services Center and supersede the earlier version of MERRA, while ERA5 is the follow-up product of ERA-Interim provided by the European Centre for Medium-Range Weather Forecast (ECMWF).

MERRA-2 is available for 41 years (1980 - present), while ERA5 has recently been extended to reach back to 1950. While both exhibit a temporal resolution of 1 h, the spatial resolution is higher in the more recent ERA5 data set (~31 km) than in MERRA-2 (~50 km).The reanalysis data were obtained for time periods corresponding to the temporal availability of validation data. Spatial boundaries were defined by the size of the respective country. The obtained parameters are eastward (u) and northward (v) wind speeds at two different heights for each reanalysis data set (ERA5: 10 m and 100 m above surface, MERRA-2: 10 m above displacement height and 50 m above surface), as well as the displacement height for MERRA-2.

2.2. Global Wind Atlas

The Global Wind Atlas [26] provided by the Technical University of Denmark (DTU) was used to spatially downscale the reanalysis data to a resolution of 250 m, to take into account local variations of mean wind speeds. The current version, GWA 3.0, was derived from the ERA5 reanalysis and provides mean wind speeds and mean power densities at five different heights (10, 50, 100, 150 and 200 m), as well as mean capacity factors for three different turbine classes according to the International Electrotechnical Commission (IEC) for the period 2008–2017. Furthermore, there are layers describing the terrain surface and a validation layer showing which countries and wind measurement stations were used to validate the GWA.

The previous version, GWA 2.1, which was also used in this analysis, provides wind speeds at only three heights (50, 100 and 200 m) at the same spatial resolution and was derived from ERA-Interim, the precursor of ERA5 [33] for the period 1987–2016.

For mean bias correction, the wind speed layers at 50 m and 100 m height were obtained for each country. They correspond to the upper layer of reanalysis wind speeds in MERRA-2 and ERA5, respectively. Since the GWA2 is no longer available at the official GWA homepage, data were extracted from the stored global data set [34] for each country separately.

2.3. Wind park information

For the simulation of wind power generation, turbine specific information on location, installed capacity, hub height and rotor diameter were used. The spatial distribution of wind power plants is shown in Fig. 2. Only onshore wind power is considered. In

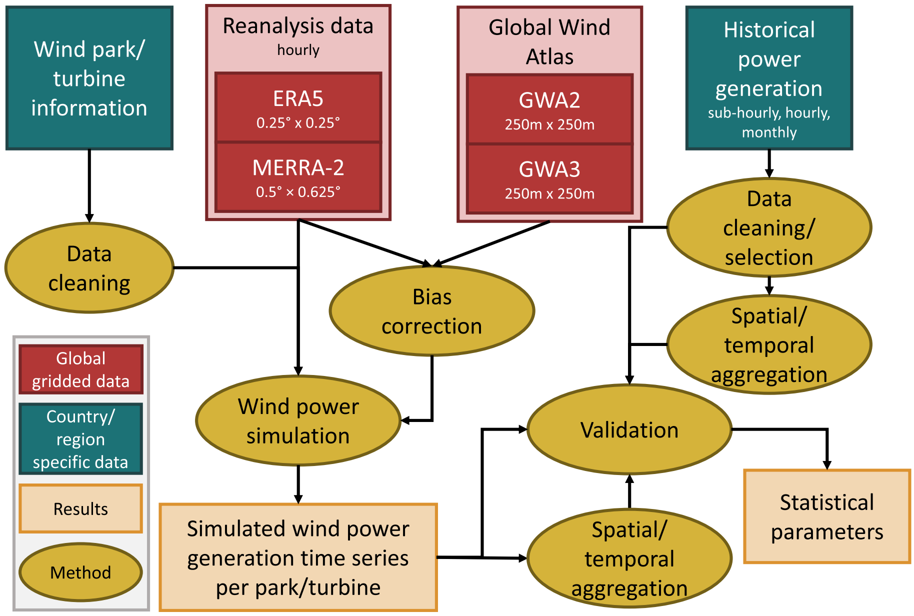

Fig. 1. Overview of data sets and methods applied in the analysis. For data sets temporal and spatial resolution are indicated below.

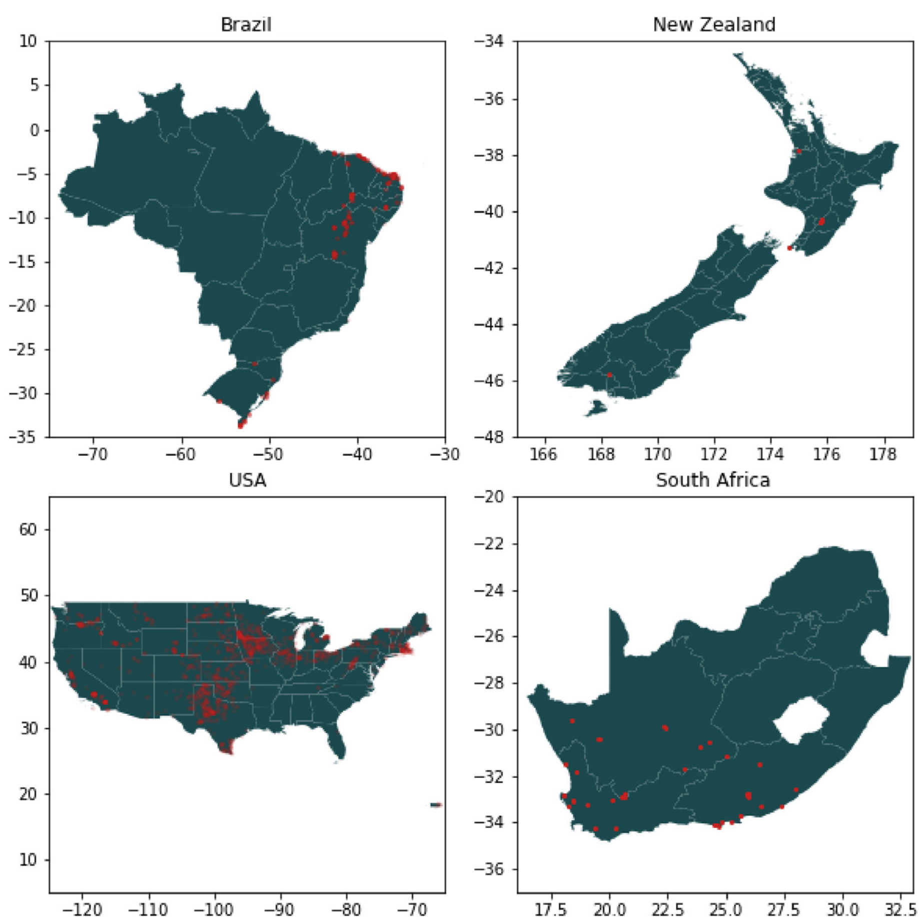

Fig. 2. Locations of wind parks in Brazil, New Zealand, USA (without Alaska and Hawaii) and South Africa.

countries where turbine specific location information was not available, wind park specific data were used. This information was retrieved from freely available country-level data sets (see Table 1).

For Brazil, two data sets, the Geographic Information System of the Electrical Sector (SIGEL) [37] and the Generation Database (BIG) [36], from the National Electrical Energy Agency (ANEEL) [35] were combined using the wind park codes. The use of both datasets was necessary, as SIGEL data contains only the location, installed

Table 1
Wind turbine and wind park data sets used in the simulation.

Country	Brazil	New Zealand	South Africa	USA
Source	ANEEL (BIG, SIGEL) [35–37]	NZWEA [38]	REDIS [39] and various	USWTDB [40]
Location information on level of	Turbines	Wind parks	Wind parks	Turbines
Turbines	7438	405	1466	63 002
Parks	603	10	39	1565
Total capacity [GW]	15.11	5.64	3.55	108.30
Avg. park capacity [MW]	25	56	90	69
Avg. turbine capacity [kW]	2031	1395	2525	1719
Avg. rotor diameter [m]	98	61	105	84
Avg. hub height [m]	87	53	95	75
Share wind power in electricity generation (year) [41]	8.9% (2019)	5.0% (2019)	2.5% (2018)	6.9% (2019)

capacity, hub height and rotor diameter, while the state and the commissioning dates were added from the BIG database. Two wind turbines in the BIG dataset had a hub height and rotor diameter of 0 m. This is obviously an error. Therefore these values were replaced with values from turbines with similar capacity.

The information on ten wind parks with available production data was collected from the New Zealand Wind Energy Association [38]. Similarly, the information on 39 wind parks in South Africa was gathered from the Renewable Energy Data and Information Service (REDIS) [39], while rotor diameters, hub heights and capacities were complemented with information from The Wind Power [42]. Since several data points were obviously erroneous or missing, the database was completed with an online search (see Table A.2). The resulting South African wind park data set is available upon request.

The information on the over 60 000 wind turbines in the USA was obtained from the US Wind Turbine Data Base (USWTDB Version 3.2) [40] which includes most of the necessary data. Missing information (Lacking data of commissioning date: 1540 turbines, turbine capacity: 5530 turbines, hub height: 7790 turbines, and rotor diameter: 6728 turbines) was replaced by the yearly mean (installed capacities, hub heights) or the overall mean (commissioning year) and rotor diameters were completed by fitting a linear model to the hub heights. In some cases, the specific power calculated from rotor diameter and capacity was too low (below 100 W/m^2) resulting in unrealistic power curves. They were thus replaced by the mean specific power of turbines with the same capacity. This applied to 49 wind turbines, of which 48 had incomplete turbine specifications.

2.4. Wind power generation data for validation

The simulated wind power generation time series were validated against observed generation at different spatial and temporal resolutions, gathered from country specific data sources. While there is data available on all time scales (hourly, daily and monthly) for each of the four studied countries or regions in those countries, historical wind power generation records on the level of wind parks are available only for Brazil and New Zealand. In South Africa, the country's observed wind power generation is only available for three of nine provinces (Eastern, Northern and Southern Cape), while for the USA the smallest available level of spatial disaggregation is the state level.Temporal availability of the generation time series varies depending on the data source and commissioning dates of wind parks. Brazil's National Electrical System Operator (ONS) [43] provides data on three temporal (hourly, daily, monthly), as well as four spatial levels (wind park, state, subsystem, country). Out of the 174 wind parks in Brazil for which hourly data were available in the ONS dataset, 70 could be matched by their name to simulated wind parks based on ANEEL data, and 42 showed sufficient data quality (also see Table A.1). They were consequently used for further analysis. Due to data quality issues and the requirement of consistency, only hourly data on the wind park level were used and aggregated spatially and temporally (also see Section A.2). In New Zealand, wind park-specific generation data is also available, however only for ten wind parks. Information on historical wind power generation is provided by the Electricity Market Information (EMI) [44] in half-hour intervals and was aggregated to hourly production values for validation against hourly simulated values.

In South Africa, generation data is provided by REDIS [45] as capacity factors. For observed power generation in the USA, several data sources were used. The U.S. Energy Information Administration (EIA) [46] provides monthly generation data for the USA, its 51 states and 10 sub-regions (New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific Continental and Pacific Non-Continental). For New England (Connecticut, New Hampshire, Maine, Massachusetts, Rhode Island and Vermont), monthly data were retrieved from ISO New England (Independent System Operator New England) [47], as data from EIA had to be discarded due to poor quality (nearly constant/fluctuating generation instead of seasonal pattern and some very low production months, see Figure A.14). The Electric Reliability Council of Texas (ERCOT) [48] provides hourly generation data for Texas. The 5-min wind power generation data in the Bonneville Power Administration (BPA) [49], which is responsible for 49 wind parks in the regions of Oregon and Washington, were aggregated to hourly output.

Table 2 summarises the data sources used for validation. The data partly contained measurement errors and therefore had to be cleaned. Details can be found in Supplementary Material A.2.

2.5. Wind power simulation

Wind power is simulated based on reanalysis data and mean wind speeds in the GWA. In a preparatory step, effective wind speeds were calculated from eastward (u) and northward (v) wind speed components in reanalysis data according to the Pythagorean theorem for the two heights available. From the effective wind speed, the Hellmann exponent α, describing the structure of the surface, was calculated. Using the location information of wind turbines or wind parks, reanalysis and GWA wind speeds were interpolated to the nearest neighbour and extrapolated to the hub height using Hellmann's power law.

When bias correction was applied, mean wind speeds were retrieved from the GWA at the location closest to the wind park or turbine and divided by the average of the reanalysis wind speed time series at the specific locations at the same height, i.e. 50 m for MERRA-2 and 100 m for ERA5, as these are the heights closer to hub height. This quotient was used as a bias correction factor to shift reanalysis wind speeds interpolated to hub height up or down according to the GWA.

Table 2
Data sets applied for validation.

Country	Regions	Temporal resolution	Source
Brazil	42 wind parks, 4 states, country	hourly, daily, monthly	ONS [43]
New Zealand	10 wind parks, country	hourly, daily, monthly	EMI [44]
South Africa	3 capes, country	hourly, daily, monthly	REDIS [45]
USA	25 states, 8 regions, country	monthly	EIA [46]
	Texas	hourly, daily, monthly	ERCOT [48]
	New England	monthly	ISO New England [47]
	BPA	hourly, daily, monthly	BPA [49]

To convert wind speeds to wind power, the power curve model introduced by Ryberg et al. [50] was used. The model estimates power curves empirically from the specific power, i.e. the installed capacity per rotor swept area, of wind turbines. It, therefore, does take into account differences in the power output according to specific power, but additional technology or turbine specific effects are not considered. We followed this approach, as otherwise we would have had to manually research power curves for 283 different turbine models, and as additionally turbine models were not known in 865 cases. Wind power generation was simulated for the whole country-specific time period, but power generation was set to 0 for periods before the commissioning date of the respective wind park. If only the month of commissioning was known, the middle of the month was assumed as commissioning date. For the USA, only the commissioning year was known. To avoid large increments of wind power generation on any particular date, the capacity installed within a year was linearly interpolated from the 1st of January to the end of the year.

2.6. Validation

In total, 218 different data sets of observed generation were suitable for validation across all temporal and spatial scales. Ten data sets were on a country scale, 58 on a state or regional scale, and 150 on wind park scale. Out of all 218 suitable data sets, 62 were resolved hourly, 62 daily, and 94 monthly. Due to data quality issues, not all available time series could be used (see Section A.2). In order for results to be comparable between different levels of spatial and temporal aggregation, as well as countries, generation time series were normalized to capacity factors.

Validation of the simulated time series was performed using three statistical parameters to assess quality. Pearson correlation, RMSE (root mean square error) and MBE (mean bias error) were used, as suggested by Borsche et al. [51].

The RMSE is an indicator that increases if (a) there is a significant difference in the level of simulated and observed time series, and (b) if there is a temporal mismatch between the two. As capacity factors were used which are comparable in scale between regions, the RMSE did not have to be normalized. To assess the different components of mismatch, i.e. temporal mismatch and mismatch in the level of production, the Pearson correlation was calculated which indicates if the temporal profile of simulated and observed generation are similar. To assess differences in levels including over-, or underestimation, the MBE was determined.

Losses due to wakes, downtimes due to maintenance, stops due to birds or bats, or curtailment were not considered, as no reliable data could be found. Consequently, a slight overestimation of generation is expected. Therefore, slightly overestimating models tend to represent the actual level of generation best.

Results for different regions and temporal aggregation levels were compared in notched boxplots. The notches indicate if the medians differ significantly at the 95% level. The notches are determined according to $M \pm 1.57 \cdot IQR \cdot \sqrt{n}$, with M being the median, IQR the interquartile range and n the number of samples. If the notches of two boxes do not overlap, the difference between their medians indicates that they are statistically significant at the 0.05 level [52].

As it cannot be assumed that our sample of wind parks and regions represents a random sample of global wind power generation locations and as there is a bias in the number of time series available for different regions, different results for different countries are reported whenever they deviate from the generally observed pattern. Respective figures are put into the supplementary material.

In order to estimate the effect of system size on simulation quality, a system size parameter was introduced. It measures the number of reanalysis grid cells occupied by wind turbines or parks (see Figure A.1), e.g. per wind park or region (see Fig. 3). Wind parks can have a size larger than 1 if they cover more than one grid cell, but this was mostly not the case. On the country level, the set of all wind parks always covered more than one grid cell.

3. Results

In this section, we first present how the choice of reanalysis dataset affects simulation quality. Subsequently, it is investigated whether the use of the GWA for mean bias correction can improve the simulation's goodness of fit. Finally, the effect of spatial and temporal aggregation of wind power generation on simulation quality is assessed.

3.1. Impact of choice of reanalysis dataset on simulation quality

Here, the difference in simulation quality as implied by using different reanalysis data sets, i.e. MERRA-2 and the more recent ERA5 is assessed. Fig. 4 presents a comparison of statistical parameters between simulations based on ERA5 and MERRA-2 reanalyses for all analysed regions combined, i.e. wind parks, states, regions, and countries, as well as per country. On average, ERA5 correlations (median: 0.82) are higher than the ones achieved with MERRA-2 (median: 0.77) and MERRA-2 has a larger spread of correlations, one of them even being negative. The difference in the median of correlations is however not significant in general, except for South Africa. Overall, there is a significant (notches do not overlap) difference in RMSEs (median ERA5: 0.15, MERRA-2: 0.19), which however only applies to country specific results in the USA and Brazil. In New Zealand and South Africa, however, no significant difference in the median of RMSEs is found. Regarding the MBEs, there is a significant difference between the median MBE of ERA5 (−0.05) and MERRA-2 (0.09), with a slight underestimation by ERA5 on average, and a substantial overestimation by MERRA-2. Underestimation by ERA5 can reach almost 40% for some locations, while MERRA2 overestimates generation by up to 40%. This significant difference translates to all countries. In the USA and Brazil the MBEs are closer to 0 with ERA5, however MERRA-2 performs better in New Zealand. In South Africa the MBEs indicate a similar

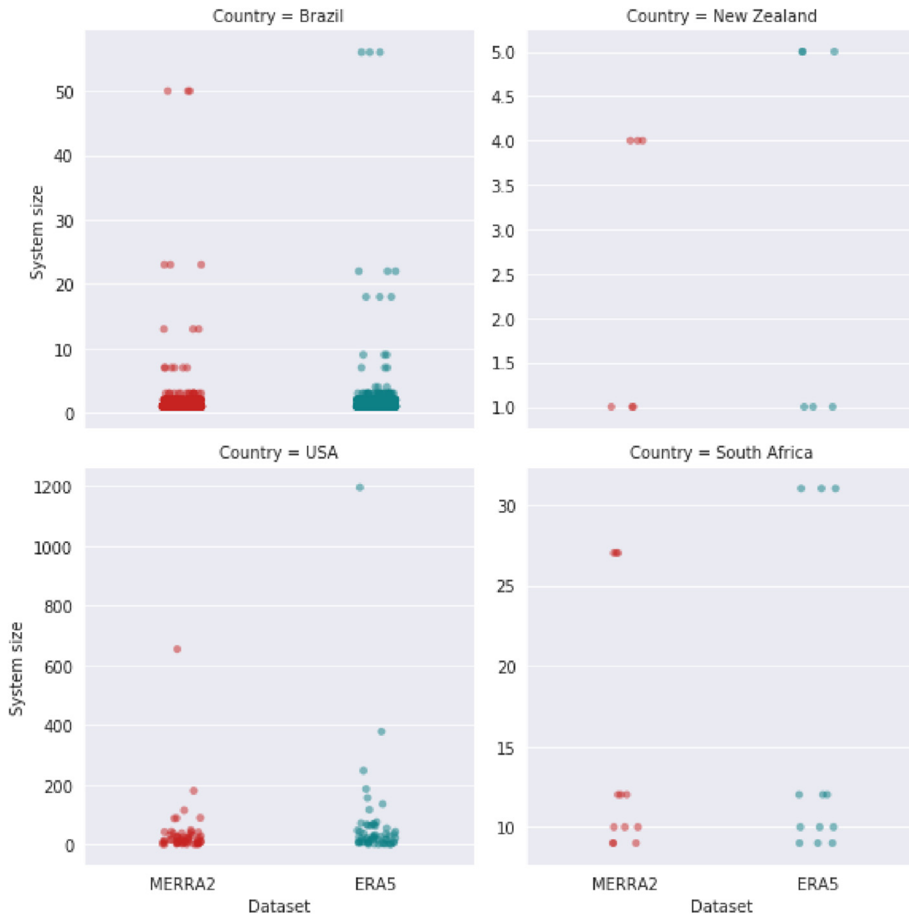

Fig. 3. System sizes per country and data set measured by the number of reanalysis grid cells occupied by wind parks or turbines at different spatial aggregation of parks.

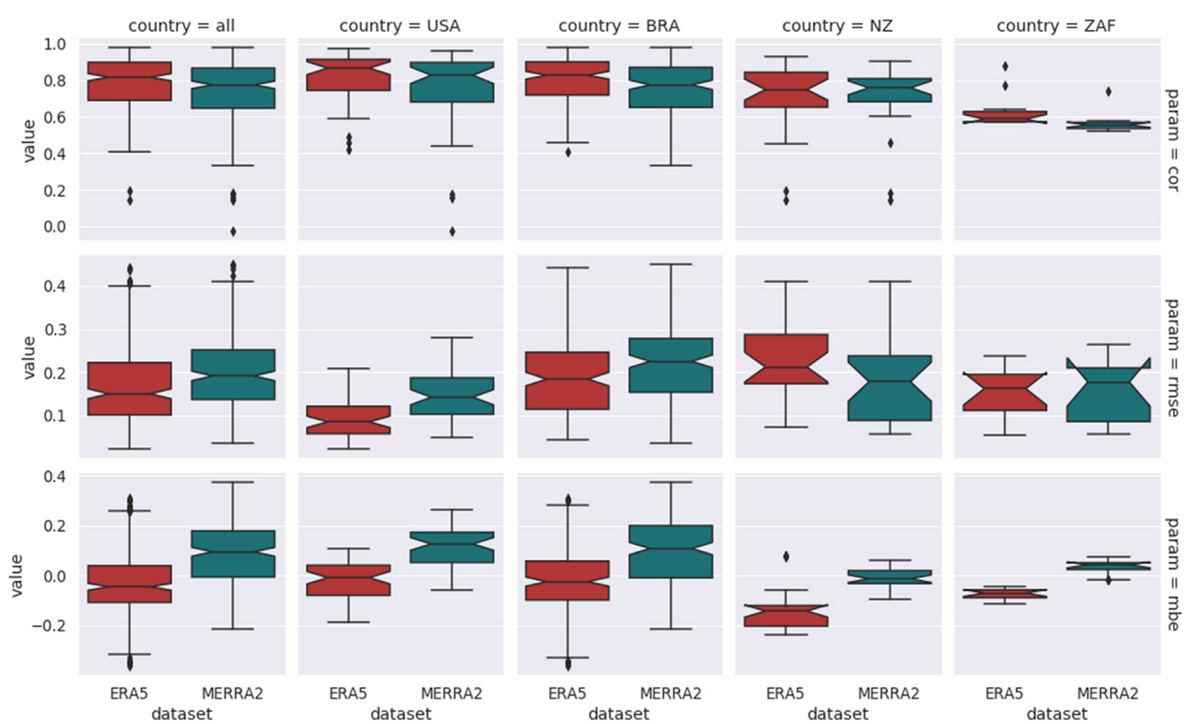

Fig. 4. Comparison of statistical parameters for simulations with ERA5 and MERRA-2 reanalyses for all analysed regions. Non-overlapping notches indicate a difference in the medians statistically significant at the 95% level.

error for both data sets, but ERA5 underestimates while MERRA-2 overestimates. Both data sets do underestimate wind power generation in New Zealand on average, which is the only country where this occurs and the only where all indicators are better for MERRA-2.Overall, it can be concluded that ERA5 performs better than MERRA-2 in terms of higher correlations but lower errors, with the exception of New Zealand. However, only the MBE consistently shows a significant improvement when comparing MERRA-2 with ERA5.

Summing up, wind power simulation based on ERA5 data results in times series of better or equal quality compared to simulations using MERRA-2 data. On average, quality indicators are reasonable, but extreme outliers are observed for both data sets. As they mostly occur for both reanalysis data sets, this may also be a problem of lacking data quality in observed wind power generation.

3.2. Bias correction with GWA

To adjust the mean bias of the wind speeds taken from reanalysis data, the Global Wind Atlas is used. In this section the focus is on ERA5 (Fig. 5), due to its better performance shown in the previous section.

Due to the higher spatial resolution compared to the reanalysis data sets, an improvement in particular in RMSE and MBE can be expected. In most cases, the change in correlation is small and not significant. The effect of bias-correction on correlations depends on the non-linear relationship between wind speeds and wind power, as shifting wind speeds by a constant factor does not imply a proportional shift in wind power output. Hence, bias correction may impact correlations, too. However, in our case the effect is small, also due to high initial correlations. In New Zealand, correlations are slightly increased with GWA2 and in South Africa using any of the GWAs, however these increases are not significant.The decrease of RMSEs by GWA2 in comparison to simulations without bias correction is insignificant in any of the assessed regions. Especially, for all regions together and in the USA there is hardly any effect of applying GWA2, except from a reduction of the spread of RMSEs from between approximately 0.05 and 0.15 (IQR: 0.05) with GWA2 to 0.04 and 0.21 (IQR: 0.1) without GWA in the USA. The simulation with GWA3, however, implies a significant increase in the median of the distribution of RMSEs compared to GWA2, as well as compared to the simulation without mean bias correction. On a country level, however, significant differences in medians of RMSEs are only found in the USA (GWA3 vs. no GWA and GWA2), and in New Zealand (GWA3 vs. GWA2). Hence, the overall results are mainly driven by the US and New Zealand.

If measured by MBEs, a similar conclusion can be drawn: On average, GWA2 reduces the median of the error and shifts it closer to 0. Even though this is not significant for the overall regions, a significant shift towards 0 is seen in New Zealand and South Africa. In Brazil and the USA, however, the best fit according to MBEs is observed without bias correction. The GWA3, in contrast, in all regions leads to a large increase in the MBE. Therefore on average GWA2 is to be preferred over GWA3 in the USA, New Zealand and South Africa, while for Brazil GWA2 is less recommended.However, as no downtime, wake effect or other losses are taken into account in the wind power simulation model, an overestimation as with GWA seems more appropriate. In the USA and New Zealand this is the case with GWA2, while in Brazil and South Africa only with GWA3. GWA3, however, increases the error significantly in South Africa, simulations underestimate observed power generation by circa 10% capacity factor, which is decreased to less than 5% by GWA2, while GWA3 increases the error to nearly 10% capacity factor. In Brazil, MBEs of up to over 40% are observed with GWA3 which by far exceeds what would be expected by typical losses. Therefore, the use of GWA3 is not recommended.

Also spatial patterns in the mean bias correction factors of the GWA (see Supplementary Material Section A.6) and seasonality of the time series (see Supplementary Material Section A.8) were

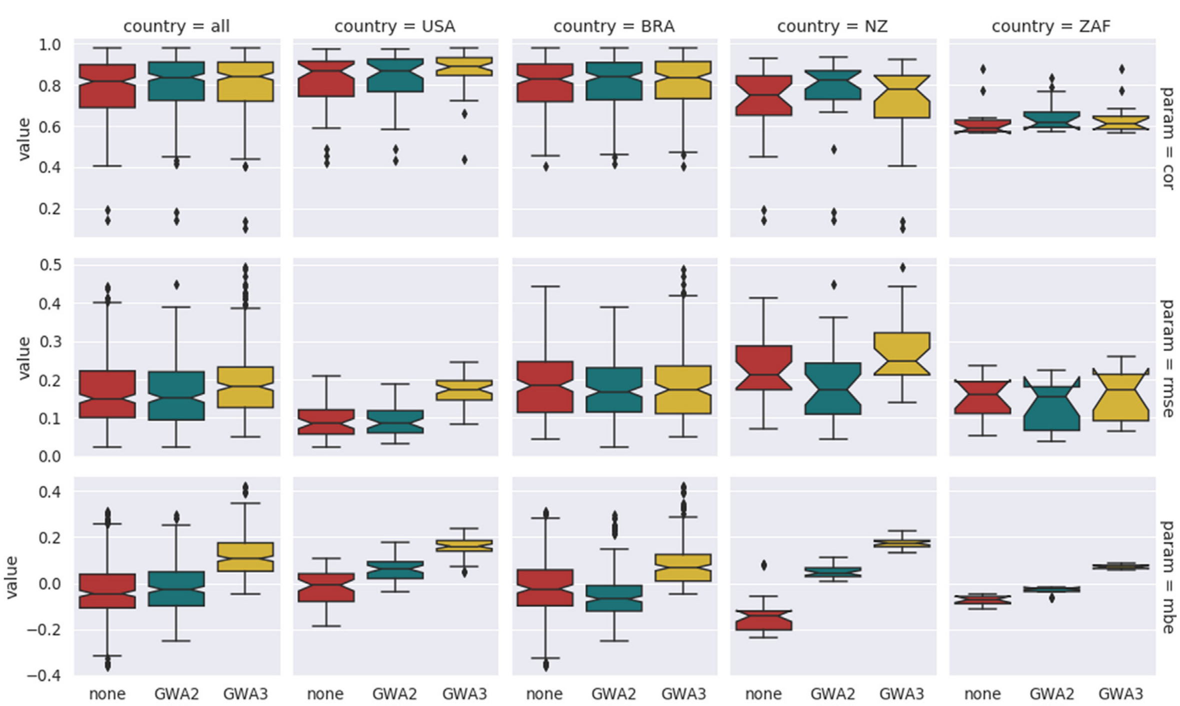

Fig. 5. Comparison of statistical parameters for simulations with ERA5 and different versions of the GWA for all analysed regions. Simulations with bias correction with GWA2 and GWA3 are compared to the simulation without bias correction (none). Non-overlapping notches indicate difference in medians statistically significant at the 95% significance level.

analysed.

To sum up, in most of the investigated regions, the GWA2 may be used to increase correlations (New Zealand, South Africa), decrease the RMSE (all countries) and shift the MBE closer to 0 or to a small positive value (all except Brazil). From our results, GWA3 is not recommended for bias correction as it increases the errors (RMSEs as well as MBEs for three out of four countries, see Fig. 5). A similar analysis was conducted by applying the GWA to MERRA-2 based wind power simulation. The results can be found in Section A.5. For MERRA-2, using the GWA for bias-correction has ambiguous impacts on results. Therefore, applying GWA to MERRA-2 reanalysis wind speeds for bias correction cannot be recommended.

3.3. Impact of spatial and temporal aggregation

In this section, the impact of spatial and temporal aggregation on the quality of wind power simulations is assessed. Country specific results are presented in the Supplementary Material in Section A.7. First, spatial aggregation is considered. The impact of aggregation on the correlation cannot be analytically derived: while an aggregation of two time-series of capacity factors will lower the variance of the combined time-series compared to the maximum of the variance of the original time-series, the change in co-variance of the combined time-series compared to the single locations cannot be analytically derived, as it depends on the co-variances of wind patterns at the two locations.Therefore, here it is assessed empirically, how aggregation impacts time-series quality. For this analysis, the wind power simulations with ERA5 data and bias correction with GWA2 are used, as this combination showed decent simulation quality for all regions. Results for Brazil and New Zealand are shown here, as these are the only countries in which wind park level data are available. Fig. 6 shows the resulting simulation quality indicators. Overall, a tendency that the simulation quality, as measured by increasing correlations and decreasing RMSEs, increases with system size is observed. In particular, the largest system (Brazil) has a significantly lower median RMSE than the smaller systems, although single low outliers of wind parks and states can reach the simulation quality of the largest systems. For New Zealand and South Africa the effect of aggregation cannot be properly assessed due to the lack of variety in different system sizes (see Supplementary Material Section A.7). For the US, simulation quality increases with aggregation as can be observed in Figure A.9.

When assessing the impact of temporal resolution on simulation quality, for the US some locations had to be excluded, as they do not provide hourly time resolution. Therefore, only the regions of Texas and the Bonneville Power Administration were included. In all other countries, all locations are available at hourly resolution. The median correlation significantly increases when going from hourly to daily as well as from daily to monthly aggregation (Fig. 7). While the increase from daily to monthly correlation is at around 6% points, daily correlations are around 12% points higher than hourly ones. This is observed in all individual countries, though only Brazil shows significant changes in median correlation for both temporal aggregation steps (Figure A.10).

The RMSE can be reduced by temporal aggregation, from hourly to daily by about 12% points, and from daily to monthly by around 10% points on average. In all countries except Brazil, the decrease in RMSE is significant (Figure A.10).

To sum up, simulation quality tends to increase rather strongly when aggregating temporally. Spatial aggregation is somehow ambiguous, but when comparing very low to very high resolutions, the effect can also be detected.

4. Discussion

The better performance of ERA5 may be explained by the use of a higher spatial model resolution in the data assimilation process, and also by using a more recent climate model based on a large amount of observed data [53]. Our results coincide with findings of Olauson [14], who studied the performance of these two reanalysis data sets for wind power simulation in four European countries and a region in the USA, as well as Jourdier [13] who compared MERRA-2, ERA5, two high-resolution models and the New European Wind Atlas for the purpose of wind power simulation in France. Olauson found hourly correlations of over 0.94 for all regions investigated (except the BPA with MERRA-2, where it is at 0.75), which is higher than the correlations identified in our study. For most locations, we find correlations above 0.7, only in South Africa they are around 0.6 (ERA5) or even below (MERRA-2). This coincides with the correlations found by Olauson for individual wind parks in Sweden, which are above 0.5 (MERRA-2) and 0.8 (ERA5). While Olauson finds an increase in correlation by ERA5 compared to MERRA-2 by less than 1% point in three of the examined regions (i.e. Germany, Denmark and France), in our study correlations of ERA5 are up to 10% points higher, with a higher increase in some exceptional cases. This is in the range of the increase in correlation reported by Jourdier [13] in France and sub-regions, with the correlation being 0.15 higher for ERA5 compared to MERRA-2. However, in our analysis in some cases, there is also a lower correlation with ERA5 based simulations compared to MERRA-2, in particular in New Zealand. An interesting result is that in Ref. [14] the highest increase in correlation by nearly 20% points is seen in the BPA in the USA, which is in line with the results of our study.

Only for the USA, we estimated RMSEs comparable to the results in Ref. [14], with values between 2.35% and 9.1% for ERA5, and

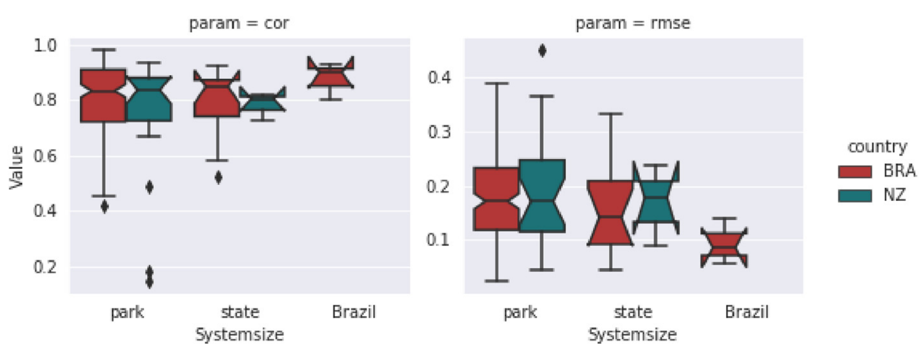

Fig. 6. Impact of spatial resolution (park: wind parks (system size parameter (ssp) < 5), state: states of Brazil (BRA) and country of New Zealand (NZ) (5 ≤ ssp < 25), Brazil: (ssp ≥ 25)) on simulation quality in Brazil and New Zealand. Non-overlapping notches indicate a statistical difference in the median at the 95% significance level.

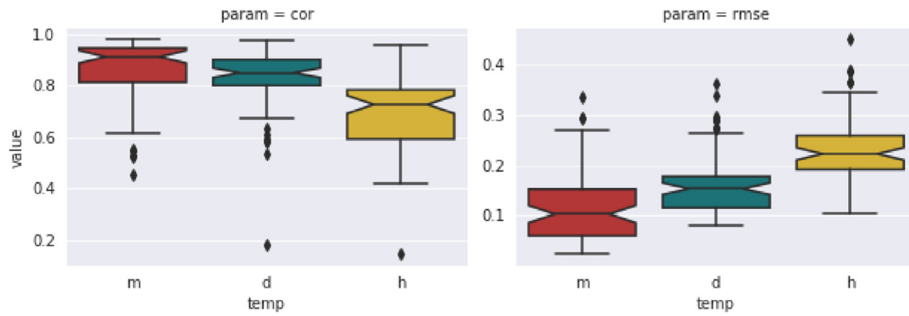

Fig. 7. Impact of temporal resolution on simulation quality. Non-overlapping notches indicate a statistical difference in the median at the 95% significance level.

between 2.82% and 18.4% for MERRA-2. In the other countries (Brazil, New Zealand, South Africa), the RMSE is higher, with about 75% of the locations showing RMSEs above 10%. Reasons for these differences may be explained on the one hand by different quality of validation data, on the other hand by a better fit of the data for the regions of the USA and Europe compared to other world regions (South America, Africa or Oceania).

So far, no other study which clearly used the GWA3 has been conducted, but results from analyses of the previous version showed that applying the GWA for downscaling MERRA reanalysis wind speeds (EMHIRES dataset [54]) has no unambiguously positive effect on the simulation quality when compared to TSO time series. Despite the authors' claim that a simulation based on MERRA data underestimates the variability compared to the GWA-downscaled dataset (EMHIRES), and that downscaling improves results, their statistical results indicate that neither correlations increase (13 of 24 countries investigated have a higher correlation with EMHIRES than with MERRA), nor RMSE (9 countries) or biases (7 countries) decrease consistently [27]. This fits well to the results of our current study, where the results of different countries or regions vary in terms of whether the GWA improves the quality of wind power simulation time series or not. An assessment of wind power generation simulation based on ERA5 and GWA for two Ethiopian wind farms [12] finds that applying the GWA reduces RMSE only for one wind farm significantly by 42%, reducing the RMSE from 11.51% to 6.62%, while for the other wind farm the improvement is insignificant at a 7% reduction of the RMSE only. Another study which uses the GWA and MERRA-2 for wind power simulation in Brazil finds that bias correction, in general, improves results [55]. A possible explanation for the better performance of GWA2 compared to GWA3 are the different time periods for which the GWA has been calculated. For GWA2 the underlying wind speed data span 30 years (1987–2016), while GWA3 is based on wind speeds over ten years (2008–2017) only. This might neglect longer-term variations of wind and thus result in biased mean wind speeds.

We found that temporal aggregation increases simulation quality which is also confirmed by Staffell and Pfenninger who compute higher correlations for eight European countries on a monthly than on an hourly basis [10]. In contrast, for spatial aggregation we could not consistently confirm such an effect. This matches the results of an analysis conducted in Europe, using MERRA and MERRA-2 reanalysis data. Monthly correlations on the country level were lower than correlations on European level only in some of the 13 studied countries (9 for MERRA and 7 for MERRA-2). Also, the median of correlations per country was above the correlations of aggregated data [10]. In contrast, Olauson [14] finds higher correlations, as well as lower RMSEs and errors for wind power generation aggregated to the whole of Sweden, compared to 1051 individual wind turbines when simulating wind power with MERRA-2 and ERA5.

5. Conclusions

In this paper, we assessed how different reanalysis data sets for wind power simulation in different regions of the world, as well as measures for global bias correction of reanalysis wind speeds, affect simulation quality. We additionally looked into the implications of spatial and temporal aggregation on quality measures.

Answering the research questions, it can be concluded (1) that ERA5 on average performs better than MERRA-2 in all regions and for all different indicators, with ERA5 showing approximately 0.05 higher correlations than MERRA-2 and 0.05 lower RMSEs in most regions. Only in New Zealand, MERRA-2 performs better on average than ERA5. (2) No version of the GWA consistently improves simulation quality. (3) GWA2 may be used, although improvements over the use of no bias correction may be minor and in some cases, simulation results may even deteriorate. We discourage the use of GWA3 for bias-correction. (4) Temporal aggregation increases quality indicators due to compensating effects, with an increase of about 0.2 in correlation and about 0.1–0.2 lower RMSEs in most regions when aggregating from hourly to monthly time series. (5) For spatial aggregation, a much more limited effect was found: only when comparing very low and very high spatial aggregations, an increase in quality was observed.

Further work in on this topic, might be the assessment of GWA2 versus GWA3 also in European countries, as well as new versions of the GWA once they are published. Furthermore, the suitability of the applied datasets for offshore wind power simulation might be assessed in future work. Apart from that, the resulting time series and methodology may be applied for other uses.

The results of our analysis [56] can be used as a basis for future wind power simulation efforts and are the foundation for a new global dynamic wind atlas. Access to this global dynamic wind atlas is enabled by making the here developed tool openly available [57]. The tool is able to generate wind power generation time series for all locations worldwide for use in energy system models or for studying the variability of wind power generation. Furthermore, our results allow estimating the magnitude of error that has to be expected when relying on reanalysis data for wind power simulation. These conclusions are important for energy system modellers when designing highly renewable energy systems.

Author contribution

Katharina Gruber: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. Peter Regner: Conceptualization, Methodology, Software, Validation, Resources, Data curation, Writing –

review & editing, Visualization. Sebastian Wehrle: Conceptualization, Resources, Writing – review & editing, Visualization. Marianne Zeyringer: Conceptualization, Resources, Writing – review & editing, Visualization, Supervision. Johannes Schmidt: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.121520.

List of Abbreviations

Abbreviation	*Meaning*
ANEEL	National Electrical Energy Agency of Brazil
BIG	Generation Database of Brazil
BPA	Bonneville Power Administration
BRA	Brazil
DTU	Technical University of Denmark
ECMWF	European Centre for Medium-Range Weather Forecasts
EIA	U.S. Energy Information Administration
EMI	Electricity Market Information New Zealand
ERCOT	Electric Reliability Council of Texas
GWA	Global Wind Atlas
GWA2	Global Wind Atlas Version 2.1
GWA3	Global Wind Atlas Version 3.0
IEC	International Electrotechnical Commission
ISO New England	Independent System Operator New England
MBE	mean bias error
NASA	National Aeronautics and Space Administration
NZ	New Zealand
NZWEA	New Zealand Wind Energy Association
ONS	Brazil's National Electrical System Operator
PV	photovoltaics
REDIS	Renewable Energy Data and Information Service of South Africa
RMSE	root mean square error
SIGEL	Geographic Information System of the Electrical Sector of Brazil
TSO	transmission system operator
US/USA	United States of America
USWTDB	US Wind Turbine Data Base
VRES	variable renewable energy system
ZAF	South Africa

References

[1] Bosch J, Staffell I, Hawkes AD. Temporally-explicit and spatially-resolved global onshore wind energy potentials. Energy Jul. 2017;131:207–17. https://doi.org/10.1016/j.energy.2017.05.052.

[2] Bosch J, Staffell I, Hawkes AD. Temporally explicit and spatially resolved global offshore wind energy potentials. Energy Nov. 2018;163:766–81.

[3] Soares PMM, Lima DCA, Nogueira M. Global offshore wind energy resources using the new ERA-5 reanalysis. Environ Res Lett Oct. 2020;15(10). https://doi.org/10.1088/1748-9326/abb10d.

[4] Shamshirband S, Mosavi A, Nabipour N, Chau K-w. Application of ERA5 and MENA simulations to predict offshore wind energy potential. Feb. 2020. https://doi.org/10.20944/preprints202002.0376.v1.

[5] Ibarra-Berastegi G, Ulazia A, Saénz J, González-Rojí SJ. "Evaluation of Lebanon's offshore-wind-energy potential. J Mar Sci Eng Oct. 2019;7(10):361.

[6] Bloomfield H, Brayshaw D, Charlton-Perez A. ERA5 derived time series of European country-aggregate electricity demand, wind power generation and solar power generation: hourly data from 1979-2019. Oct. 2020.

[7] Sterl S, Liersch S, Koch H, van Lipzig NPM, Thiery W. A new approach for assessing synergies of solar and wind power: implications for West Africa. Environ Res Lett Sep. 2018;13(9). 094 009.

[8] Huber M, Dimkova D, Hamacher T. Integration of wind and solar power in Europe: assessment of flexibility requirements. Energy May 2014;69:236–46.

[9] Olauson J, Bergkvist M. Correlation between wind power generation in the European countries. Energy Nov.2016;114:663–70.

[10] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy Nov. 2016;114:1224–39.

[11] Olauson J, Bergkvist M. Modelling the Swedish wind power production using MERRA reanalysis data. Renew Energy Apr. 2015;76:717–25.

[12] Nefabas KL, Söder L, Mamo M, Olauson J. Modeling of Ethiopian wind power production using ERA5 reanalysis data. Energies Apr. 2021;14:2573. 9.

[13] Jourdier B. Evaluation of ERA5, MERRA-2, COSMO-REA6, NEWA and AROME to simulate wind power production over France. Adv Sci Res Jun. 2020;17:63–77.

[14] Olauson J. ERA5: the new champion of wind power modelling? Renew Energy Oct. 2018;126:322–31.

[15] Hans Ertel Zentrum für Wetterforschung. COSMO regional reanalysis. Hans Ertel Zentrum für Wetterforschung; 2019. https://reanalysis.meteo.uni-bonn.de.

[16] Ren G, Wan J, Liu J, Yu D. Spatial and temporal assessments of complementarity for renewable energy resources in China. Energy Jun. 2019;177:262–75.

[17] Monforti F, Gonzalez-Aparicio I. Comparing the impact of uncertainties on technical and meteorological parameters in wind power time series modelling in the European Union. Appl Energy Nov. 2017;206:439–50.

[18] Cannon D, Brayshaw D, Methven J, Coker P, Lenaghan D. Using reanalysis data to quantify extreme wind power generation statistics: a 33 year case study in Great Britain. Renew Energy 2015;75:767–78.

[19] Cradden LC, McDermott F, Zubiate L, Sweeney C, O'Malley M. A 34-year simulation of wind generation potential for Ire-land and the impact of large-scale atmospheric pressure patterns. Renew Energy Jun. 2017;106:165–76.

[20] Kubik M, Brayshaw D, Coker P, Barlow J. Exploring the role of reanalysis data in simulating regional wind generation variability over Northern Ireland. Renew Energy Sep.2013;57:558–61.

[21] Ramirez-Camargo L, Nitsch F, Gruber K, Valdes J, Wuth J, Dorner W. Potential analysis of hybrid renewable energy systems for self-sufficient residential use in Germany and the Czech republic. Energies 2019;12(21):4185.

[22] Ramirez-Camargo L, Gruber K, Nitsch F. Assessing variables of regional reanalysis data sets relevant for modelling small-scale renewable energy systems. Renew Energy Apr. 2019;133:1468–78.

[23] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy Nov. 2016;114:1251–65.

[24] Henckes P, Frank C, Küchler N, Peter J, Wagner J. Uncertainty estimation of investment planning models under high shares of renewables using reanalysis data. Energy Oct.2020;208:118. 207.

[25] Ramirez-Camargo L, Valdes J, Macia YM, Dorner W. Assessment of on-site steady electricity generation from hybrid renew-able energy systems in Chile, year = 2019. Appl Energy Oct. 2020;250:1548–58.

[26] Technical University of Denmark (DTU). (Oct. Global wind atlas 3.0. 2019. https://globalwindatlas.info/.

[27] González-Aparicio I, Monforti F, Volker P, Zucker A, Careri F, Huld T, Badger J. Simulating European wind power generation applying statistical downscaling to reanalysis data. Appl Energy Aug. 2017;199:155–68.

[28] Bloomfield H, Gonzalez P, Lundquist J, Stoop L, Browell J, Dargaville R, Felice MD, Gruber K, Hilbers A, Kies A, Panteli M, Thornton H, Wohland J, Zeyringer M, Brayshaw D. The importance of weather and climate to energy systems: a workshop on Next Generation Challenges in Energy-Climate Modelling. Bull Am Meteorol Soc Oct. 2020:1–23.

[29] Goić R, Krstulović J, Jakus D. Simulation of aggregate windfarm short-term production variations. Renew Energy Nov. 2010;35(11):2602–9.

[30] Santos-Alamillos F, Pozo-Vázquez D, Ruiz-Arias J, Bremen LV, Tovar-Pescador J. Combining wind farms with concentrating solar plants to provide stable renewable power. Renew Energy Apr. 2015;76:539–50.

[31] Gelaro R, McCarty W, Suárez MJ, Todling R, Molod A, Takacs L, Randles CA, Darmenov A, Bosilovich MG, Reichle R, Wargan K, Coy L, Cullather R, Draper C, Akella S, Buchard V, Conaty A, da Silva AM, Gu W, Kim G-K, Koster R, Lucchesi R, Merkova D, Nielsen JE, Partyka G, Pawson S, Putman W, Rienecker M, Schubert SD, Sienkiewicz M, Zhao B. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). J Clim

Jul. 2017;30(14):5419−54.
[32] Copernicus Climate Change Service. ERA5 monthly averaged data on single levels from 1979 to present. ECMWF; 2019.
[33] Badger J, Sempreviva AM, Söderberg S, Costa PA, Simoes T, Estanqueiro A, et al. Report on link to global wind atlas and national wind atlases (deliverable D4.7). Tech Rep 2019. https://doi.org/10.5281/zenodo.3243193.
[34] Technical University of Denmark (DTU). GWA2.1. In: Davis N, editor; 2020. https://silo1.sciencedata.dk/shared/cf5a3255eb87ca25b79aedd8afcaf570?path=%2FGWA2.1.
[35] ANEEL. Agência nacional de energia elétrica. https://www.aneel.gov.br/; 2020.
[36] ANEEL. Big - banco de Informações de Geração. http://www2.aneel.gov.br/aplicacoes/capacidadebrasil/capacidadebrasil.cfm; 2020.
[37] ANEEL. Download de Dados. https://sigel.aneel.gov.br/Down/; 2019.
[38] New Zealand Wind Energy Association. NZ wind farms operating and under construction, [online]. http://www.windenergy.org.nz/operating-&-under-construction; 2020.
[39] Department of Energy, The IPP Office, and Eskom. Location and contracted capacities, [online]. http://redis.energy.gov.za/power-producers/; Feb. 2020.
[40] Hoen B, Diffendorfer JE, Rand J, Kramer LA, Garrity CP, Roper AD, Hunt H. United States wind turbine database. U.S. Geological Survey; 2018.
[41] International Energy Agency. Data and statistics, [online]. https://www.iea.org/data-and-statistics/data-tables; Dec. 2020.
[42] The Wind Power. The wind power. Wind power Market intelligence. https://www.thewindpower.net/; 2020.
[43] Operador Nacional do Sistema Elétrico (ONS). Histórico da Operação. 2020. http://www.ons.org.br/Paginas/resultados-da-operacao/historico-da-operacao/geracao_energia.aspx.
[44] Electricity Market information, generation output by plant. Electricity Authority, 2020. [Online], https://www.emi.ea.govt.nz/Wholesale/Datasets/Generation/Generation_MD/.
[45] Department of energy, the IPP office, and eskom, load factors for provincial data. http://redis.energy.gov.za/electricity-production-details/.
[46] U.S. Energy Information Administration. Electricity data browser [online]. 2020. https://www.eia.gov/electricity/data/browser/#/topic/0?agg=1,0,2&fuel=008&geo=vvvvvvvvvvvvo&sec=o3g&linechart=ELEC.GEN.WND-OK-99.M~ELEC.GEN.WND-IA-99.M~ELEC.GEN.WND-TX-99.M~ELEC.GEN.WND-LA-99.M~~~&columnchart=ELEC.GEN.WND-US-99.M~ELEC.GEN.WND-IA-99.M~ELEC.GEN.WND-TX-99.M&map=ELEC.GEN.WND-US-99.M&freq=M&start=200101&end=201911&ctype=linechart&ltype=pin&rtype=s&pin=&rse=0&maptype=0.
[47] ISO New England. Net energy and peak load. 2020.
[48] Electric Reliability Council of Texas. Hourly aggregated wind output. 2020.
[49] Bonneville Power Administration. WIND GENERATION & total load in the BPA balancing authority. 2020.
[50] Ryberg DS, Caglayan DG, Schmitt S, Linßen J, Stolten D, Robinius M. The future of European onshore wind energy potential: detailed distribution and simulation of advanced turbine designs. Energy Sep. 2019;182:1222−38.
[51] Borsche M, Kaiser-Weiss AK, Undén P, Kaspar F. Method-ologies to characterize uncertainties in regional reanalyses. Adv Sci Res Oct. 2015;12(1):207−18.
[52] Chambers J, Cleveland W, Kleiner B, Tukey P. In: Bickel P, Cleveland W, Dudley R, editors. Graphical methods for data analysis. Murray Hill. New Jersey: Bell Telephone Laboratories Incorporated; 1983.
[53] C. C. C. Service. (Aug. 2020). ERA5: data documentation, [Online]. Available: https//confluence.ecmwf.int/display/CKB/ERA5:%20data%20documentation#ERA5:datadocumentation-Observations.
[54] Gonzalez-Aparicio I, Zucker A, Carei F, Monfori-Ferranio F, Huld T, Badger J. EMHIRES dataset Part I: wind power generation. European Meteorological derived HIgh resolution RES generation time series for present and future scenarios. " European Union: JRC-Joint Research Center; 2016.
[55] Gruber K, Klöckl C, Regner P, Baumgartner J, Schmidt J. Assessing the Global Wind Atlas and local measurements for bias correction of wind power generation simulated from MERRA-2 in Brazil. Energy Dec. 2019;189:116−212.
[56] Gruber K, Regner P, Wehrle S, Zeyringer M, Schmidt J. Towards global validation of wind power simulations: a multi-country assessment of wind power simulation from MERRA-2 and ERA-5 re-analyses bias-corrected with the Global Wind Atlas. 2021.
[57] Gruber, Katharina. windpower_GWA. https://github.com/KatharinaGruber/windpower_GWA; 2020.