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RELEVANCE OF ERA5 REANALYSIS FOR WIND ENERGY APPLICATIONS: COMPARISON WITH SODAR OBSERVATIONS

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ABSTRACT. ERA5 reanalysis is one of the most trusted climate data sources for wind energy modeling. However, any reanalysis should be verified through comparison with observational data to detect biases before further use. For wind verification at heights close to typical wind turbine hub heights (i.e. about 100 m), it is preferable to use either in-situ measurements from meteorological towers or remote sensing data like acoustic and laser vertical profilers, which remain independent of reanalysis. In this study, we validated the wind speed data from ERA5 at a height of 100 m using data from four sodars (acoustic profilers) located in different climatic and natural vegetation zones across European Russia. The assessments revealed a systematic error at most stations; in general, ERA5 tends to overestimate wind speed over forests and underestimate it over grasslands and deserts. As anticipated, the largest errors were observed at a station on the mountain coast, where the relative wind speed error reached 45%. We performed the bias correction which reduced absolute errors and eliminated the error dependence on the daily course, which was crucial for wind energy modeling. Without bias correction, the error in the wind power capacity factor ranged from 30 to 50%. Hence, it is strongly recommended to apply correction of ERA5 for energy calculations, at least in the areas under consideration.

KEYWORDS: ERA5, bias correction, reanalysis verification, wind energy modeling

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INTRODUCTION

Nowadays, a rapid transformation in the energy sector implies making policy decisions for long-term energy planning under numerous uncertainties. Energy modeling is the key tool for providing evidence to support decision-making processes. A rapidly increasing share of the climate-governed renewable generation determines the demand for accurate climate data. At the same time, climate information is not only used for renewables but also for traditional energy sources. Energy models rely on climate data covering a wide spatial range, from point-wise observations for individual power plants to global energy system models that include all types of energy and require global-scale climate datasets. Among various energy problems that require climate information are the assessment of the renewable energy potential, the planning of new power plants and power grids, optimization cost evaluation of technology mix for energy systems, and the assessment of the climate change impact on existing power plants. Therefore, high-quality climate data for diverse energy applications is in great demand.
Modern reanalysis datasets belong to the most widely used sources of climate inputs for energy modeling. Reanalysis involves numerical simulations with atmospheric or Earth system models over a rather long period (>10 years, typically 40-70 years), initialized from past data and updated with observational data interpolated onto the model grid every few hours or days.

Reanalysis offers both advantages and disadvantages, and the latter primarily include inaccuracies in meteorological data compared to observed values, especially in areas with complex topography and surface types. These inaccuracies are associated with numerical model imperfections, errors in assimilated observational data, and coarse horizontal and vertical resolution. Reanalysis errors are usually associated with incorrect reproduction of orography (Dörenkämper et al. 2020) and underlying surface types (Gualtieri 2021). However, currently, there is no real alternative to reanalysis in terms of both spatial and temporal coverage.

In this study, we assessed the quality of climate information on wind, a critical climate input for various energy models. For correct work of energy models, climate information on wind should realistically reflect statistical wind characteristics, namely the probability distribution function of wind speed and seasonal and diurnal wind speed courses. The wind in the lower atmosphere is largely determined by the turbulent structure of the atmospheric boundary layer, which is tolerably reflected only in measurements with high vertical and temporal resolution (for example, in measurements on meteorological masts or using acoustic profilers), but is usually poorly reproduced by reanalysis. In this context, verification of wind data in reanalysis does not seem far-fetched, but a necessary task. However, utilization of the original (uncorrected) reanalysis data without verification and correction remains quite widespread in the energy modeling domain (Craig et al. 2022). Verification of reanalysis datasets is partly hampered by the rarity of the so-called independent data, i.e. those that are not assimilated in reanalysis. Independent data on wind includes local and typically short-term measurements on meteorological masts, sodars, and other means of ground-based remote sensing, ground-based networks of local stations, and some others.

Uncertainties associated with reanalysis data usage vary regionally, which means that the applicability of the reanalysis datasets should be assessed for specific regions of interest. Currently, research on reanalysis uncertainties is predominantly focused on Europe and the Americas (e.g., Molina et al. 2021; Thomas et al. 2021; Kubik et al. 2013; Santos et al. 2019; Staffell and Pfenninger 2016; Olauson 2018; Jourdier 2020; Dörenkämper et al. 2020). However, even for these regions, it is impossible to obtain unambiguous conclusions about the quality of wind data in particular reanalysis cases because quality evaluations depend on specific tasks, orographic complexity and land use of the site, and the verification method. At the same time, other areas of the world are much less studied at the time being. This knowledge gap is becoming crucial from the perspective of the global energy transition. The regions facing the most serious challenges in the implementation of renewable generation are least covered with the quality assessment of key climate inputs for energy planning studies.

The primary objective of this study is to assess the viability of using wind speed data at the 100 m level from the modern ERA5 reanalysis for energy modeling across European Russia. We selected ERA5 because of its popularity within the energy community and its use in creating other products, including both global (GWA) and European (NEWA) wind atlases, which use ERA5 as input data for mesoscale and microscale models to produce high-resolution outputs (Dörenkämper et al. 2020). However, the error in the initial data usually propagates further along the chain and can be found in the output fields. Therefore, we decided to validate the original ERA5 reanalysis to get a quantification of its performance in the context of energy modeling. Most comparative studies ((Ramon et al. 2019; Santos et al. 2019; Olauson 2018; Thomas et al. 2021), however, not all of them, e.g. (Calisir et al. 2021)) have shown that ERA5 outperforms other reanalyses in terms of wind speed and calculated wind power generation.

We compared ERA5 against measurements from acoustic locators (sodars) across central and southern parts of European Russia. Most sodar locations are situated in the southern regions, which are known for their high wind energy potential (Spravochnik 2007), where this industry is actively developing with new wind turbines being constructed. While ERA5 was previously verified against different sources of wind data in many regions across the world (Gualtieri 2021; Ramon et al. 2019; Santos et al. 2019; Olauson 2018; Molina et al. 2021; Calisir et al. 2021), its performance depends heavily on individual site characteristics and averaging periods. For instance, correlation coefficients of ERA5 with observations vary from 0.2-0.3 for stations with complex terrain to almost 1 for flat sites (Molina et al. 2021; Ramon et al. 2019; Santos et al. 2019; Jourdier 2020). Especially high correlation coefficients of 0.9-0.95 are obtained with increasing averaging time (Santos et al. 2019; Molina et al. 2021).

The spread of wind speed bias is very large across estimates reported by different studies: from -5 m s^{-1} to 4 m s^{-1} (Dörenkämper et al. 2020; Ramon et al. 2019; Molina et al. 2021; Jourdier 2020). Generally, the reanalysis performs better over the sea, while its quality is often not suitable for energy problems on land. This is explained, firstly, by the fact that the roughness of the sea surface depends on wind speed in a rather straightforward way, while the assessment of the land surface roughness is quite ambiguous. Secondly, reanalyses assimilate satellite wind observations only available over the ocean. Over the sea surface, ERA5 may slightly overestimate the wind speed (Ramon et al. 2019; Gualtieri 2021). Over the land, the wind speed, especially for strong winds, is underestimated and the frequency of weak winds is overestimated (Molina et al. 2021; Jourdier 2020; Santos et al. 2019; Gualtieri 2021). The only exception is forest areas, over which wind speed is overestimated (Gualtieri 2021), which is usually explained by the difficulty of determining the roughness length for a forest.

The hourly resolution of the ERA5 data allows us to consider the daily course of wind speed. Still, there is no clear dependence of the reanalysis quality on the time of day – at some stations, the error is greater at night, and at others during the day (Jourdier 2020). All these errors naturally affect the accuracy of wind power generation calculations, and, due to the nonlinear dependence of wind generation on wind speed, even with a small error in wind speed, the error in wind generation estimates becomes significant (Andersen et al. 2015; Gualtieri 2021). Wind power generation calculated from ERA5 data is usually slightly overestimated over the sea (e.g., Gualtieri 2021) and underestimated on the land by 5-20% in flat areas (except in forested areas, where it is overestimated (Gualtieri 2021)) and by more than 30% in areas with complex terrain (Dörenkämper et al. 2020; Gualtieri 2021; Jourdier 2020). However, with monthly averaging and in areas such as Scandinavia, great agreement can be achieved between reanalysis-calculated and observed power generation (Olauson 2018). Generally, the more estimates of reanalysis quality for sites in various natural conditions are obtained, the more complete picture of the quality of the reanalysis can be acquired and the higher the probability of finding the dependence of the error on these conditions.

Another aim of this study was to test the bias-correction method to correct the reanalysis of wind speed using sodar observations. The correction was performed in two ways: with and without the daily course of wind speed errors. The original and corrected wind speed series from the reanalysis were used to assess the relevance of the bias correction for quantifying the propagation of wind speed error into wind energy production, expressed as the capacity factor error. In general, the study is focused not on planning wind energy construction at specific locations, but on the development of the operation of universal methods that can be applied to any other area. The universality of the methods means that they can be applied to any region and reanalysis grid node. Although their application requires non-universal scaling factors that depend on local conditions, we assume that in the future it will be possible to obtain the dependence of these scaling factors on external conditions, which will make the bias correction method completely universal. This study also aims to supply energy modelers with a power-relevant estimation of uncertainty associated with errors of the modern reanalysis for natural conditions typical for various natural zones of Russia. Therefore, it is not of primary importance that not all sites we are considering are located in areas with high wind energy potential.

The rest of the article is organized as follows. The section Materials and Methods describes the sodar observations and ERA5 wind data, methods of reanalysis verification and correction, and capacity factor calculation. The Results and Discussion section presents the results of reanalysis verification and correction and considers the propagation of the wind speed error into errors in energy modeling. In conclusion, the main findings and limitations of the study are presented.

MATERIALS AND METHODS

Sodar data

Sodar (SOnic Detection And Ranging) is an acoustic locator providing vertical profiles of wind vector components within the lowest 500-m layer of the atmosphere. In this study, sodar observations from four locations were used (Table 1, Fig.1). Continuous measurements up to 300 m in height were carried out in the Zvenigorod area at the observation station of the Obukhov Institute of Atmospheric Physics (IAP) from 2009 to 2021. The IAP station is predominantly surrounded by mixed forest and occasional low-rise buildings (Fig.1b). Sodar measurements for steppe, arid, and coastal regions were obtained in short-term expeditions organized by the IAP (for Tsimlyansk and Kalmykia) and Lomonosov Moscow State University (for the Gelendzhik area). Measurements up to 200 m were conducted on the northern edge of Tsimlyansk (in a flat steppe area) in July-August, with a vertical resolution of 10 m . Measurements in dunes near Narynkhuduk in Kalmykia, 80 km northwest of the Caspian Sea, were carried out in late July–early August. In the Gelendzhik area, the measurements were carried out on the base of the Institute of Oceanology, at the end of a long pier, essentially over the sea surface (Fig.1e).

The Sodar LATAN-3, developed at IAP (Kuznetsov 2007), was employed in Zvenigorod, Kalmykia, and Tsimlyansk. The wind speed measurement accuracy was 0.3 m/s. In Gelendzhik, the measurements were carried out with a Scintec sodar (co-production of Germany, the USA, and some other countries), with a declared wind speed measurement accuracy of 0.1-0.3 m/s.

Data processing was performed to eliminate erroneous measurements. At the IAP base in Zvenigorod, trees and individual buildings contributed to the "blind zone" of the sodar, resulting in a higher occurrence of erroneous registrations of the echo signal from fixed objects ("fixed echoes"). To ensure maximum data availability at all levels, the lower measurement level ("blind zone") was set at 40 meters for Zvenigorod site and 30 meters for arid and steppe sites. The presence of "fixed echoes" led to

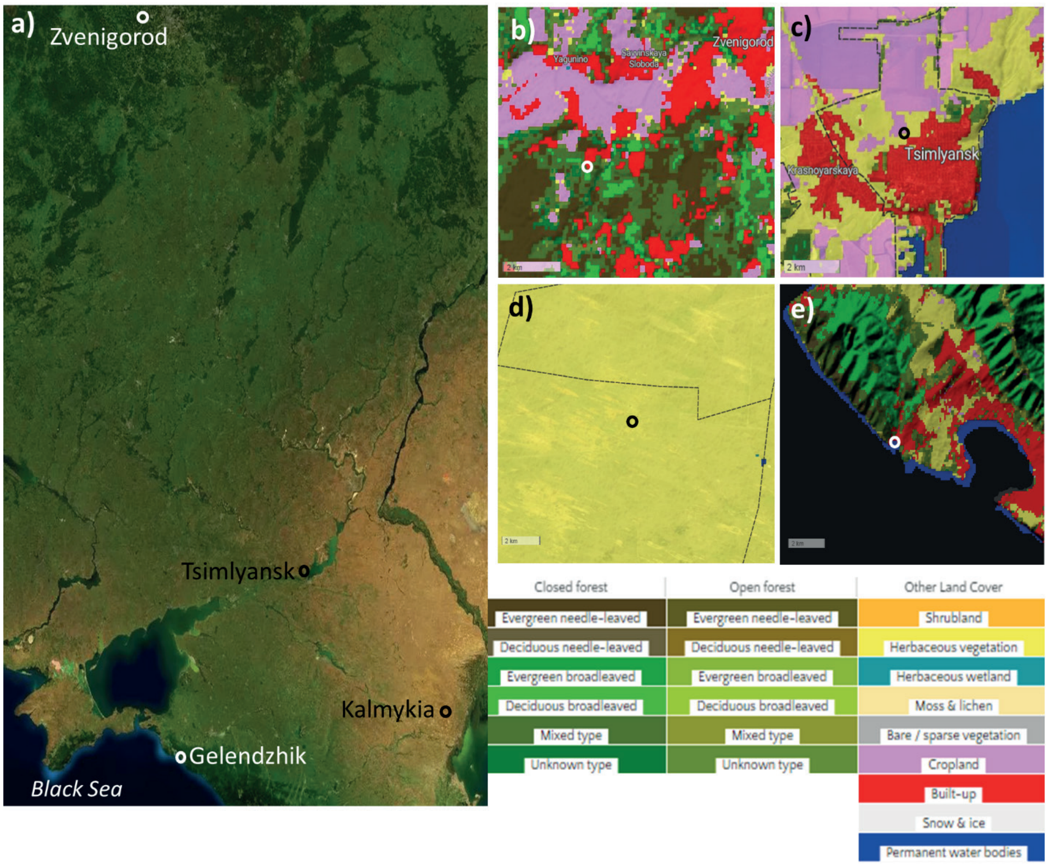

Fig. 1. Satellite image of the study area (a) and types of land cover (from Global Land Cover database, available at https://lcviewer.vito.be) around sodar locations (white and black circles) in Zvenigorod (b), Tsimlyansk (c), Kalmykia (d) and Gelendzhik (e)

an increase in the number of near-zero wind speeds at altitudes up to 300 m, significantly distorting wind statistics at this station. To remove the influence of obstacles from the data, a two-stage filtering algorithm was applied. In the first stage, instantaneous sounding profiles were analyzed, and intervals with zero wind speed at heights exceeding 40 meters and intervals with a significant excess of the echo signal level (> 3 dB) relative to adjacent intervals were excluded from averaging. Subsequently, in the second stage, the averaged data were filtered to eliminate sharp peaks in the vertical profiles. For this purpose, outliers in the vertical profiles of horizontal wind speed were filtered out if they exceeded 2 m/s compared to adjacent vertical levels.

Reanalysis and its processing

In this study, we compared the wind speed from ERA5 reanalysis (Hersbach et al. 2020) with observations taken at a 100-m height. This height is commonly used in wind energy studies, as it corresponds to the typical hub height of wind turbines. In reanalysis, wind speed values at heights of 100 m above ground level (a.g.l.) and below are considered diagnostic, meaning they are not directly calculated in the atmospheric model but rather interpolated from the lowest model level to the desired height using a wind profile approximation (logarithmic or power law). However, this approximation is valid only for neutral temperature stratification and moderate to strong wind. Vertical interpolation also requires the surface roughness length (or power law exponent), which is set constant on land (depending on the type of land cover) and dependent on wind speed over water. Thus, the values of the diagnostic wind speed contain errors associated with the deviation of the real wind profile from the approximation and with the inaccuracy in determining the roughness length/power law exponent.

The ERA5 reanalysis has 137 hybrid sigma levels from 10 m to 80 km above the surface, with 14 levels located in the lowest 500-m layer. This high resolution, coupled with the low placement of the lowest level (on average at 10 meters above ground level), minimizes errors in interpolation at both 10 and 100 meters, making ERA5 advantageous for wind generation studies compared to other reanalyses.

To compare observations with ERA5 reanalysis, we employed two approaches. The first one involved the interpolation of the reanalysis of 100-m wind horizontally to sodar locations. The series of observations were averaged over an hourly interval based on the following assumptions. The value in a reanalysis cell was the average over the area occupied by that cell. Since one reanalysis cell occupied 0.25°x0.25°, i.e. about 25 x 18 km at middle latitudes, then at an average speed of 5 m/s (characteristic speed for all the studied points), the airflow passed the entire cell in 1-1.5 h. This means that the reanalysis value averaged over the area of the cell could be compared with the 1-h mean of observations at one point.

The interpolation was carried out by the two most popular methods: the bilinear interpolation method and the nearest neighbor method. The latter implies that the reanalysis values are not interpolated, but are taken from the grid node closest to the observation station. Hence the verification results should significantly depend on how close the underlying surface in the reanalysis area is classified in comparison to the reality. In Zvenigorod, the nearest reanalysis nodes were occupied by forests (80% forest cover). The roughness coefficient in the reanalysis was plausibly high (around 0.9 m). For the Tsimlyansk station, land cover at the nearest node corresponded to crops (see Fig.1c), with a roughness length of around 0.3 m (which was quite high, since the roughness length for low grass is typically a few centimeters (Zilitinkevich 1972)). Other nodes to the east were partially occupied by water (Tsimlyansk reservoir). In Kalmykia, the land cover of nearby nodes was indicated as grass. The surrounding nodes were also classified as crops and sediments. The roughness coefficient was around 0.15 m, which was quite high for a relatively smooth dune surface. In Gelendzhik, the closest reanalysis node to the station was in the sea, and the cell that corresponded to it was 70% occupied by water. The cell average roughness coefficient was around 0.3 m. However, in reality, the land cover near the station was represented by a low pine forest, while the water roughness in the absence of waves is usually less than 1 cm. In Gelendzhik, the dependence of the reanalysis error on the wind direction (from the sea or land) was quite possible. In general, the surface types in the reanalysis nodes corresponded to reality.

The second approach to comparing reanalysis and observations involved averaging the reanalysis data over the area around the cell where the station point was located (hereafter, "averaging method"). Averaging was carried out over the area of 3 x 3 cells (approximately 75 x 55 km). An increase in the averaging area from 1 cell to 3 cells also led to an increase in the averaging period of observations from 1 h to 3 h. From general considerations, the verification results should improve with this approach, although the value of the obtained information decreases due to smoothing.

Table 1. Observation sites and characteristics of sodar measurements

	Coordinates, elevation	Land use; topography	Sodar system	Period	Vertical resolution; maximum height of measurements; averaging period
Zvenigorod	55.696ºN, 36.775ºE, 180 m a.g.l.	Mixed forest with few buildings	LATAN-3	2009-2021	20 m; 300 m; 30 min
Tsimlyansk	46.657ºN, 42.08ºE, 86 m a.g.l.	Steppe (low grass) with low-rise buildings to the south; flat topography	LATAN-3	2012, 2015-2021 (July-August)	10 m; 200 m; 30 min
Kalmykia	45.423ºN, 46.53ºE, -20 m a.g.l.	Dunes (desert); flat topography	LATAN-3	2016, 2020, 2021 (July-August)	10 m; 200 m; 30 min
Gelendzhik	44.575ºN, 37.979ºE, 4 m a.g.l.	Sea; mountains to the north	Scintec	2012 (June-July), 2012-2014 (January-February)	5 m; 300 m; 10-20 min

Verification methods

An interesting issue that requires further investigation is the problem of the criteria for the quality of wind data, specifically for wind energy applications. Since wind energy performance is very sensitive to wind speed, it can be expected that the quality criteria should also be quite strict. However, in the absence of such tailored criteria, we used a set of standard ones: bias, normalized bias (NB), mean absolute error (MAE), the standard deviation (scatter) of errors (SDE), normalized root mean square error (NRMSE), normalized standard deviation of wind speed in reanalysis (NSD), and correlation coefficient (CC), which are commonly used in practical energy-related climate data quality assessments. We also considered the empirical probability distribution function of errors, wind speed, and direction, and the dependence of the error on the wind speed and direction.

Typically, wind speed error is deemed acceptable if it does not exceed 10% of the value for speeds greater than 5 m/s, or if the error is less than 0.5 m/s for wind speeds less than 5 m/s (WMO 2014). Although these criteria were developed for standard wind measurements at ground-based weather stations, they can also be applied to assess the quality of wind in reanalysis when other strict criteria are lacking. We calculated the percentage of errors within acceptable accuracy (PEAA) based on these criteria, with a higher PEAA indicating better performance. Additionally, we used the ratio of the error value to the standard deviation of wind speed from observations (SDW) as a criterion for the reanalysis quality: if the error is comparable to or greater than SDW, which represents the natural variability of wind speed, then the quality of wind in the reanalysis is considered low.

Bias correction method

When systematic errors are detected in reanalysis data or climate model outputs, they are usually corrected using various methods. One commonly used method for correcting wind speed data is the Quantile Mapping based on the Weibull Distribution bias correction method (Haas et al. 2014). The method involves calculating the corrected wind speed u_{cor} using the following formula, which transforms the reanalysis's probability distribution function to match the observed distribution:

$$u_{cor} = c_o\left[-\ln\left(1-\left(1-e^{-\left(\frac{u_r}{c_r}\right)^{k_r}}\right)\right)\right]^{k_o^{-1}} \quad (1)$$

Here, the subscripts $_o$ and $_r$ mean observations and reanalysis, and the shape parameter k and scale parameter c are calculated from the mean μ and standard deviation σ of wind speed:

$$k = \left(\frac{\mu}{\sigma}\right)^{1.086} \quad (2)$$

$$c = \frac{\mu}{\Gamma\left(1+\frac{1}{k}\right)} \quad (3)$$

where Γ is the gamma function.

In many studies (e.g., Li et al. 2019, Akperov et al. 2022, Akperov et al. 2023), the parameters *k* and *c* were calculated separately for each month. However, due to limited year-round data at stations (except Zvenigorod), we initially calculated these parameters for the entire data series rather than for each month. Subsequently, we further calculated these coefficients for each hour of the day and each month for Zvenigorod owing to the abundance of observations there, and for each hour of the day in July-August for Tsimlyansk. This approach was adopted to account for the daily (and annual in Zvenigorod) variation of the reanalysis wind speed error when performing corrections.

Capacity factor calculation

Wind speed dynamics affects wind generation performance most directly. This implies that uncertainties of the wind speed are being translated into uncertainties in wind power generation. A common method to convert wind speed into generated power is by using a so-called working curve of a wind turbine (Andresen et al. 2015). A wind turbine working curve is the relationship between the harnessed power and the wind speed. Typically, working curves are nonlinear, exhibiting higher sensitivity to speed variation at lower speed values. Working curves provided by manufacturers are derived from testing procedures conducted on a hub height under conditions reflective of wind generation unit operation.

We calculated the propagation of the ERA5 uncertainties on the operation of modern wind turbines using various approaches to bias correction. Calculations were performed based on the assumption of a realistic working curve of modern wind turbines. An example of such a curve is provided in Fig. 2.

The combination of a wind turbine power curve with actual wind speed values determines the wind power

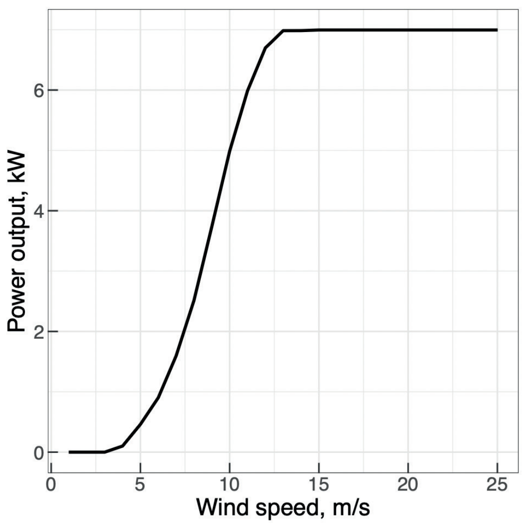

Fig. 2. A working curve for "Vestas V164" wind turbine

generation achievable at any particular location. The economic feasibility of wind generation can be roughly assessed using a capacity factor which is defined as the ratio of the actual harnessed power to the nominal power of a turbine. Additionally, we assumed that turbine construction is viable if its annual average capacity factor matches with typical values reported for wind generation.

Relevance of the wind speed values for wind power generation was addressed for each considered location using a linear scaling approach for the wind speed time series, which involved increasing wind speed values using a constant multiplier. This artificial approach aimed to account for the fact that the available measurement locations were not selected to maximize wind power output. Capacity factor values based on the "original" reanalysis data served as a reference point to match with a situation when the reanalysis data are utilized directly in energy simulations omitting any correction procedures. Indeed, the applied linear scaling procedure is a simplification intended only for a robust estimation of the broad effects that reanalysis errors may have on energy modeling outcomes. The scaling factor values were determined through a fitting procedure to achieve multiannual average capacity factors consistent with typical values for modern onshore wind generation, assumed to range from 0.25 to 0.35 based on global statistics (Boretti and Castelletto 2020; Jung and Schindler 2022).

The calculated capacity factors were averaged over the entire available observation period and compared against the assumed typical annual average values. To account for the nonlinear sensitivity of wind turbine performance to wind speed, the scaling factor was varied within the assumed typical capacity range. This scaling approach was applied to wind speed data for all considered stations except Gelendzhik. The ERA5-extracted wind speed values for Gerendzhik were high enough to yield capacity factors exceeding 0.35, the assumed upper boundary of the typical capacity factor range.

The range of the fitted scaling factor values depended primarily on the annual average wind speed and was found to be 1.15 to 1.30 for Zvenigorod and Tsimlyansk, and 1.25 to 1.43 for Kalmykia, with no scaling needed for Gelendzhik. These obtained scaling factor ranges were compared against wind speed values within approximately a 50 km radius around each station location, corresponding to the correlation length for wind speed aggregated with hourly time resolution and combined with a potential to vary the hub height between 70 and 200 m, following current standards.

RESULTS AND DISCUSSION

Verification

Statistical characteristics of the wind speed reanalysis error are shown in Table 2 and Figure 3. Notably, there is minimal difference between the verification results when using bilinear and the nearest neighbor interpolation methods. Previous studies (Ramon et al. 2019) also demonstrated the same independence of estimates from the interpolation method for ERA5, although the difference between methods arises for reanalyses with coarser spatial resolution. Therefore, we focus on the results obtained using the bilinear interpolation method.

It should be kept in mind that the amount of data available in Zvenigorod is several orders of magnitude higher than for other sites (Table 2), making the statistical estimates for Zvenigorod the most reliable. Systematic errors are observed at most stations (except for Gelendzhik). The Mean Absolute Error (MAE) varies from 1.4 to 2.1 m/s, with errors consistently lower than the standard deviation of the wind speed at all locations (Table 2). On average, 59% of errors fall within acceptable accuracy criteria. The average correlation coefficient between reanalysis and observations is 0.7. Across all locations except Zvenigorod, the reanalysis underestimates the frequency of wind speeds over 8-10 m/s (Fig. 4). The frequency of wind directions in the reanalysis roughly corresponds to the observed values (Fig. 5).

Variations in verification results among the stations can be attributed to the differences in the "complexity" of the areas where the stations are located. The highest errors are observed in Zvenigorod, despite its larger sample size, due to the presence of a high and heterogeneous forest which disrupts the logarithmic wind profile. At the same time, Tsimlyansk demonstrates the best results among all stations (i.e. the smallest MAE and SDE, the largest correlation coefficient), which is explained by the favorable location (the absence of significant obstacles nearby).

In Zvenigorod, the largest errors occur during weak winds of any direction (Fig.4a, 5a). In general, the wind speed probability distribution is shifted towards higher wind speeds in the reanalysis compared to observations (Fig. 4). This systematic overestimation may stem from the underestimation of roughness length and the deviation of the wind profile observed over the forest from the logarithmic profile, especially evident during weak winds.

In Tsimlyansk, there is a slight systematic underestimation of wind speed, particularly noticeable during the night (Fig.6b), possibly due to the absence of night low-level jet streams or an inaccurate description of momentum transfer processes under stable boundary layer stratification in the reanalysis. The largest underestimations, up to 7 m/s, are observed when the wind speed exceeds 7 m/s , and with errors reaching 5 m/s during weak winds. There is no clear dependence of the error on wind direction (Fig.5b).

In Kalmykia, the reanalysis similarly tends to underestimate wind speed, which can be explained with local effects, particularly the frequent sandstorms. During sandstorms, the roughness length becomes highly dependent on wind speed (Semenov 2020), similar to the sea surface, with values changing by four orders of magnitude. Additionally, flow acceleration may occur due to the influence of sand in the air, which disrupts the logarithmic wind profile (Semenov

Table 2. Statistical characteristics of wind speed reanalysis errors following bilinear interpolation method (BIM) and nearest neighbor method (NNM)

	Bias, m/s		MAE, m/s		SDE, m/s		SDW, m/s	CC		PEAA, %		Number of values
	BIM	NNM	BIM	NNM	BIM	NNM		BIM	NNM	BIM	NNM	
Zvenigorod	1.0	1.0	1.4	1.4	1.6	1.6	2.0	0.73	0.73	34	34	67352
Tsimlyansk	-0.8	-0.8	1.5	1.5	1.7	1.7	2.8	0.79	0.79	71	71	1765
Kalmykia	-1.1	-1.1	1.8	1.8	2.2	2.2	2.9	0.66	0.66	67	67	209
Gelendzhik	0.1	0.0	2.1	2.1	2.7	2.7	3	0.48	0.47	42	44	782

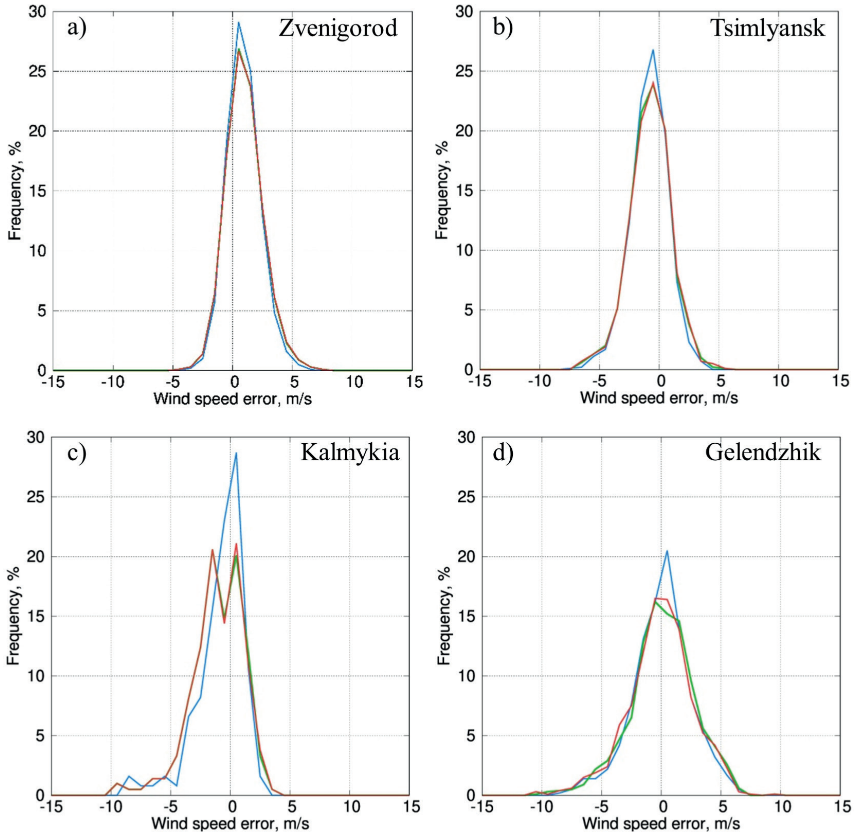

Fig. 3. Probability distribution of wind speed reanalysis errors when using bilinear interpolation (green line), nearest neighbor interpolation (red line), and averaging method (blue line) speed in Zvenigorod (a), Tsimlyansk (b), Kalmykia (c), and Gelendzhik (d)

2000). The largest errors, up to 10 m/s, correspond to strong southeast winds (Fig. 6c). However, there are insufficient observational data for a reliable assessment of reanalysis errors for different wind directions.

For the station in Gelendzhik, the largest spread of errors is observed due to the complexity of the surrounding orography and surface types (the combination of land and sea). This complexity leads to deviations of the wind profile from the logarithmic profile, which makes it impossible to accurately determine the roughness length in simplified parametrizations in the reanalysis. The largest errors, up to 11 m/s, occur at wind speeds exceeding 10 m/s with northeast, south, and southeast directions (Fig.5d). Strong northeastern winds in Gelendzhik are caused by the local Novorossiysk bora, a downslope windstorm (Shestakova et al. 2018). Strong southerly winds from the sea are also characteristic of the Gelendzhik area.

When using the "averaging method", the magnitude of MAE and SDE slightly decreases (by 0.2 m/s on average for all locations) compared to interpolation methods (Table 3). The error probability distribution becomes narrower for the "averaging method", with an increased frequency of small errors (Fig. 3). That error will continue to decrease with an increase in the area and period of averaging (Molina et al. 2021; Thomas et al. 2021), but this leads to a loss of useful information about the temporal variability of the wind field.

Our estimates of reanalysis's wind speed error are generally consistent with other similar estimates made previously for ERA5 (Gualtieri 2021; Ramon et al. 2019; Molina et al. 2021; Santos et al. 2019; Thomas et al. 2021; Dörenkämper et al. 2020; Jourdier 2020). According to the listed studies, the spread of the NSD varies from 0.3 to 2, the correlation coefficient from 0.2 to almost 1, and the bias from -5 to 3.8 m/s. Gualtieri (2021) examined the quality of the ERA5 reanalysis at several points on land, three of which can be compared with our points by land use type. For the Australian point Wallaby Creek situated in the forest, as well as in Zvenigorod, the reanalysis overestimated wind speed; the average NB and NRMSE practically coincided in Wallaby Creek and Zvenigorod. A point Humansdrop in South Africa, located on a flat grassland, can be compared with Tsimlyansk. The estimates for these two points also practically coincide, with the wind systematically being overestimated by 12-14% (Table 4). Conversely, the estimates for the point with desert land type in Iran (Ghoroghchi) do not coincide with our estimates for Kalmykia. The wind at the Iranian point, as well as in Kalymkia, is also underestimated by the reanalysis, but in higher proportions (the NB and NRMSE are 0.5 and 0.8 instead of 0.2 and 0.4 in Kalmykia, respectively).

Correction of reanalysis

Once the reanalysis had been verified, the next step was to evaluate how the obtained errors in wind speed propagated into wind energy modeling. However, we first needed to obtain "perfect" wind data so that we could compare it to the "original" reanalysis. To achieve this, we applied the bias correction method described earlier to the reanalysis data series.

Initially, we calculated the shape and scale parameters of the bias-correction method using formulas (2) and (3) for the entire data series due to its relatively small length. The wind speed probability distribution obtained after this correction is shown in Fig. 3 by a dotted line. Statistical analysis of the errors in the corrected wind speed (Table 4, 5) reveals that the correction not only eliminated the systematic error but also slightly decreased the MAE and NRMSE at most stations (Zvenigorod, Gelendzhik, and Tsimlyansk), with the standard deviation of wind speed in the corrected reanalysis being equal to the observed values. However, other statistical characteristics of the errors changed minimally, and the percentage of errors within acceptable accuracy for the corrected values even decreased.

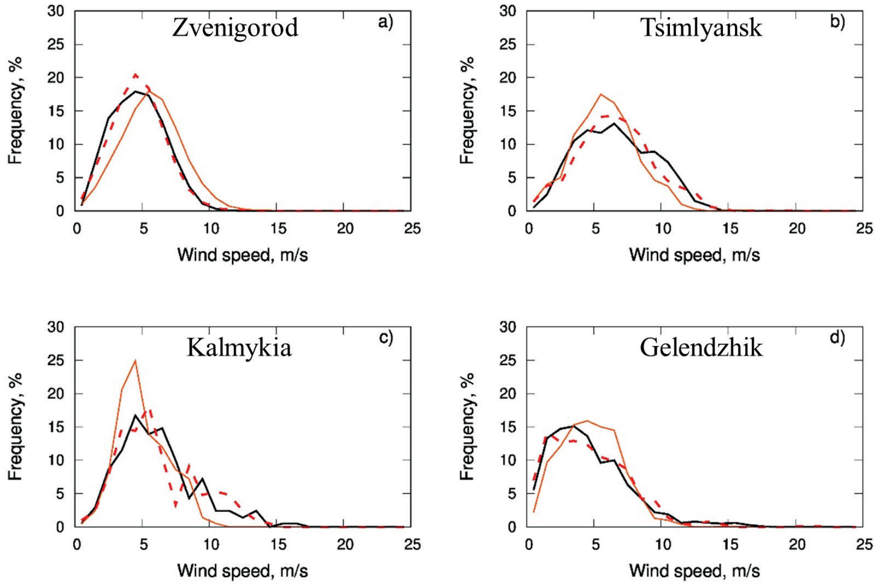

Fig. 4. Probability distribution of wind speed in Zvenigorod (a), Tsimlyansk (b), Kalmykia (c), and Gelendzhik (d) according to observations (black line), "original" reanalysis (red solid line) and corrected reanalysis (red dashed line)

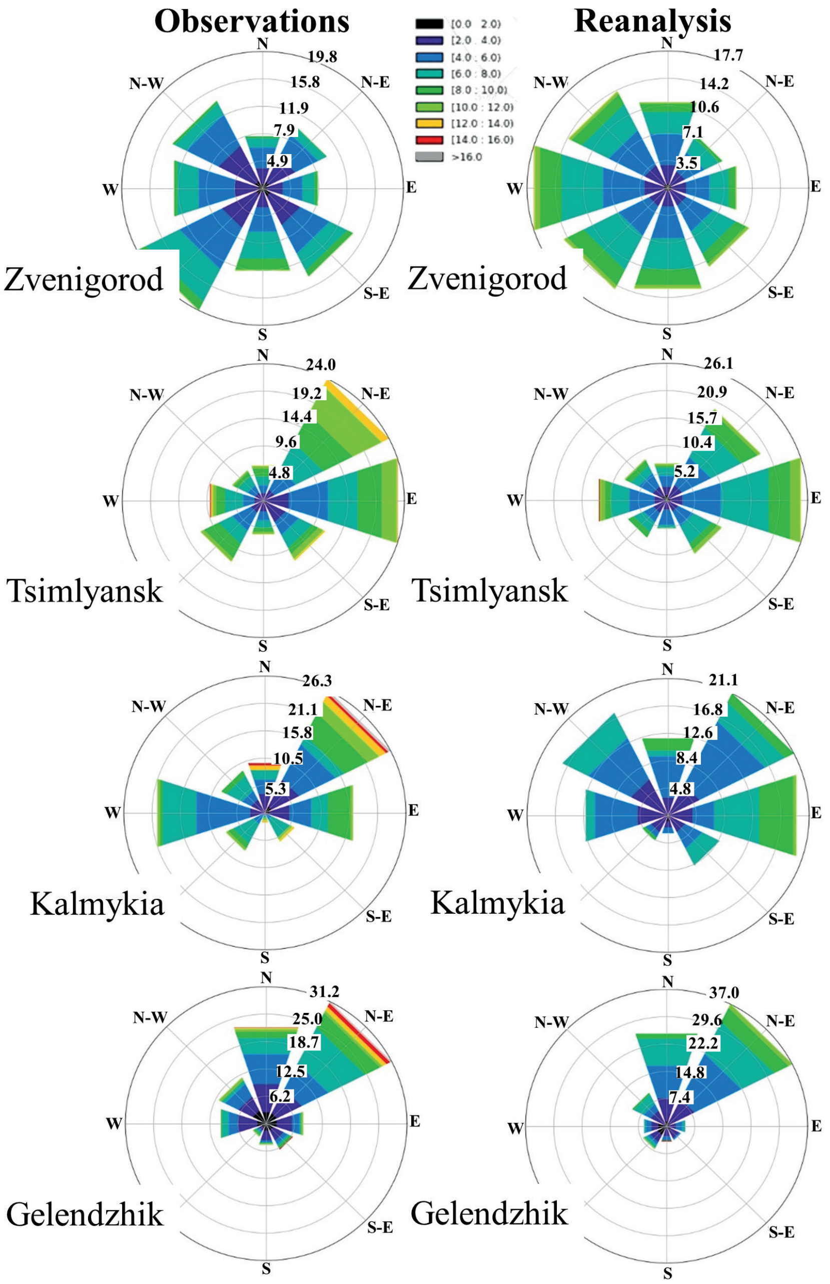

Fig. 5. Probability of wind of various speed categories from different directions in Zvenigorod , Tsimlyansk , Kalmykia, and Gelendzhik according to observations (left column) and reanalysis (right column)

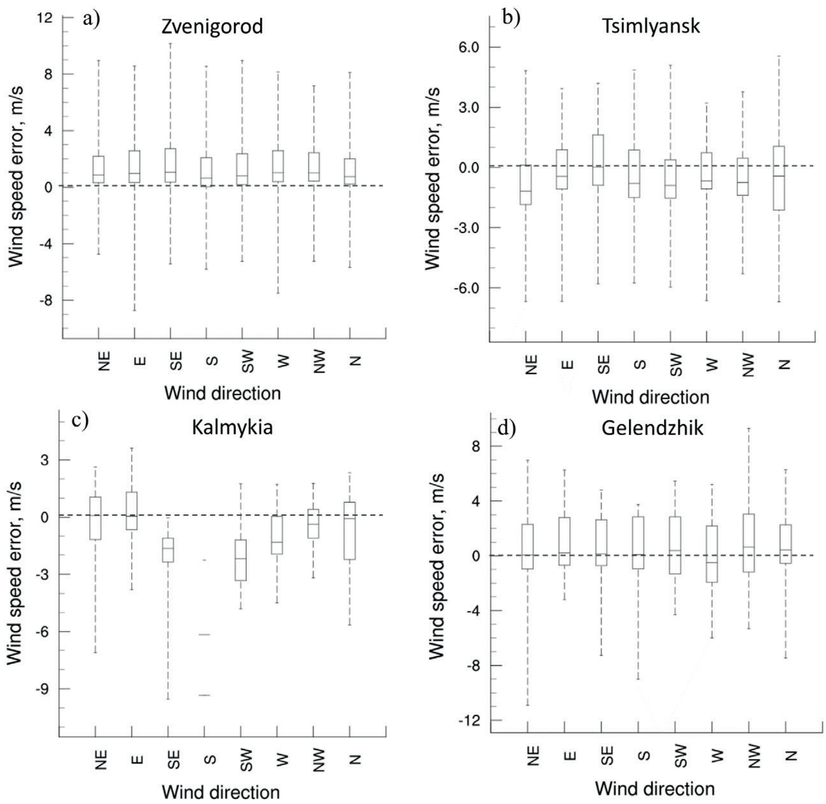

Fig. 6. The dependency of wind speed error of "original" reanalysis on wind direction in Zvenigorod (a), Tsimlyansk (b), Kalmykia (c), and Gelendzhik (d). Whiskers indicate minimum and maximum errors

Table 3. Statistical characteristics of wind speed reanalysis errors when using "averaging method"

	Bias, m/s	MAE, m/s	SDE, m/s	SDW, m/s	CC	PEAA, %	Number of values
Zvenigorod	0.9	1.3	1.4	1.8	0.77	35	55267
Tsimlyansk	-0.8	1.4	1.6	2.7	0.82	72	1468
Kalmykia	-0.8	1.4	2.0	2.5	0.59	70	122
Gelendzhik	0.0	1.9	2.4	2.5	0.45	43	649

Table 4. Comparison of NB, NRMSE and NSD before and after bias correction

	NB		NRMSE		NSD	
	original	corrected	original	Corrected	original	corrected
Zvenigorod	0.21	0	0.38	0.29	1.1	1
Tsimlyansk	-0.12	0	0.29	0.26	0.9	1
Kalmykia	-0.18	0	0.39	0.39	0.7	1
Gelendzhik	0.02	0	0.59	0.54	0.7	1

Table 5. Statistical characteristics of wind speed reanalysis errors after bias correction

	Bias, m/s	MAE, m/s	SDE, m/s	SDW, m/s	CC	PEAA, %	Number of values
Zvenigorod	0.0	1.1	1.4	2.0	0.73	53	67352
Tsimlyansk	0.0	1.4	1.8	2.8	0.79	58	1765
Kalmykia	0.0	1.8	2.4	2.9	0.67	53	209
Gelendzhik	0.0	2.3	3.0	3	0.49	41	782

Moreover, this correction method does not account for the features of the wind speed distribution associated with terrain features or intra-diurnal variability. For example, in Zvenigorod during summer, the reanalysis errors (namely, the overestimation of wind speed) are the smallest in the middle of the day and night. At this time of day, the regime of stratification and mixing of the boundary layer becomes more steady than in the transition hours. In the transition hours – in the morning and in the evening – the errors increase sharply (Fig 7.a), which is associated with the change from nighttime to daytime turbulence regime and vice versa (which may not occur simultaneously in reanalysis and observations). The transition from nocturnal to daytime boundary layers and vice versa is a rather subtle process, especially under conditions of a complex underlying forested surface, considering the low spatial resolution of the reanalysis and the complex nature of turbulence. Such features are typical for summer, when the differences between the daytime (convective) and nocturnal (stably stratified) boundary layers are highest, and hence the transitions between them are the sharpest. In addition, the change in the form of the daily course of wind speed in this region occurs at a height of about 100 m (Lokoshchenko 2014): the maximum speed is observed during the day below 100 m and at night above 100 m. This happens due to thermal stratification and features of the vertical transfer of momentum between the layers. In the reanalysis, this boundary (reversal of the daily course) can be higher or lower than the observed one, which adds to the reanalysis inaccuracy. After the correction procedure, morning and evening errors decreased, but at the same time a rather strong negative bias appeared in the middle of the day and night (Fig 7a).

The dependence of the reanalysis error on the time of day is not universal. There are small errors in the daytime in Tsimlyansk (Fig.7b), with the magnitude of errors significantly increasing at night, similar to the previously described underestimations. The correction procedure "spreads" the error evenly over the daily course, although the usefulness of such solution from the energy production point of view is questionable.

To address this, we performed another correction procedure for Zvenigorod and Tsimlyansk (at other stations, the length of the data series was insufficient for the calculation of the mean and standard deviation), considering the daily variation of wind speed error. After this correction, we eliminated biases in the reanalysis for both the entire series and individual hours. At both locations, MAE decreased by 0.1 m/s compared to the values in Table 5, and the correlation coefficient slightly increased, to 0.82 in Tsimlyansk and 0.76 in Zvenigorod. However, even with these corrections, the formal criteria of reanalysis quality outlined above were not fully met: the ratio of SDE to SDW was quite high, while PEAA was rather low. Such data are rarely "perfect". However, as demonstrated in the next section, even with bias correction alone, acceptable results for wind energy applications can be achieved.

Manifestation in energy modeling

Having evaluated the corrected reanalysis data, which we have assumed to be accurate, we could quantify the effects of the reanalysis uncertainties on the accuracy of the wind power modeling.

We assessed two main mechanisms for the propagation of the reanalysis uncertainty into energy modeling:

1. The difference in average capacity factors of the renewable generation on a long-term time scale associated with applying different approaches to the ERA5 bias correction. This uncertainty defines a difference between the wind power output values assumed by planning studies compared with values harnessed during the operation of real power systems.

2. Discrepancies between the power system regime parameters corresponding to the reanalysis-extracted wind speed values compared to the use of the "perfect" climate data.

Both climate-related energy modeling uncertainties were found to depend on the assumed wind speed scaling factor. Lower scaling values were linked to higher sensitivity of the energy modeling output to the underlying uncertainty of climate data. This effect should be expected and is explained by the nonlinear shape of the working curve mentioned earlier. It was shown that using the "original" ERA5 reanalysis data could lead to errors in the wind power capacity factor up to 0.10 to 0.15 on the "original" reanalysis data for all considered locations except Gelendzhik, where the errors could be up to 0.40. Keeping in mind that the typical capacity factor is about 0.3, the uncertainties associated with the reanalysis biases may seriously compromise the results of the investment planning if not corrected. The error value drops to as low as 0.01...0.02 when the proposed hourly-resolved bias correction procedure is applied (Fig. 8).

We considered several types of wind turbines (Vestas V80, Vestas V164, Siemens 82, Siemens 107, Repower 82, and Nordex N90) to ensure the obtained results are robust against wind turbine design. Power curves of each turbine type were approximated with a Weibull cumulative distribution function model (Bokde et al. 2018). The resulting relationship was used to compare the capacity factors of wind turbines corresponding to different approaches to climate data processing. Vestas 164, a 10 MW nominal class that is widely used in Russian wind farms, was selected for further calculations presented in the paper.

The obtained capacity factor errors (30-50%) when using the "original" ERA5 data as input are consistent with previously obtained estimates for different locations in Europe and the world (Staffell and Pfenninger 2016; Gualtieri 2021), although errors usually do not exceed ±10% on flat land or over the sea (Jourdier 2020; Gualtieri 2021). For some locations (for example, in regions with complex orography or forested areas), capacity factor errors calculated from ERA5 data can be even larger and reach 70-120% (Gualtieri 2021).

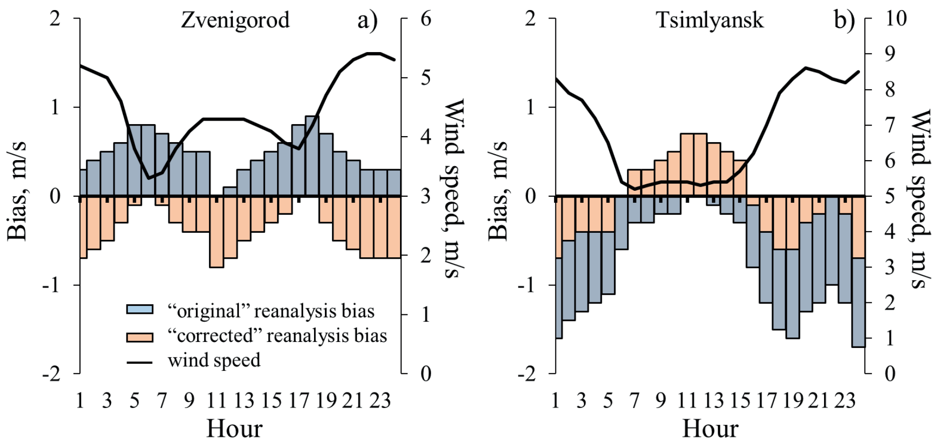

Fig. 7. Daily course of wind speed and wind bias in "original" and corrected reanalysis data series in Zvenigorod (a) and Tsimlyansk (b)

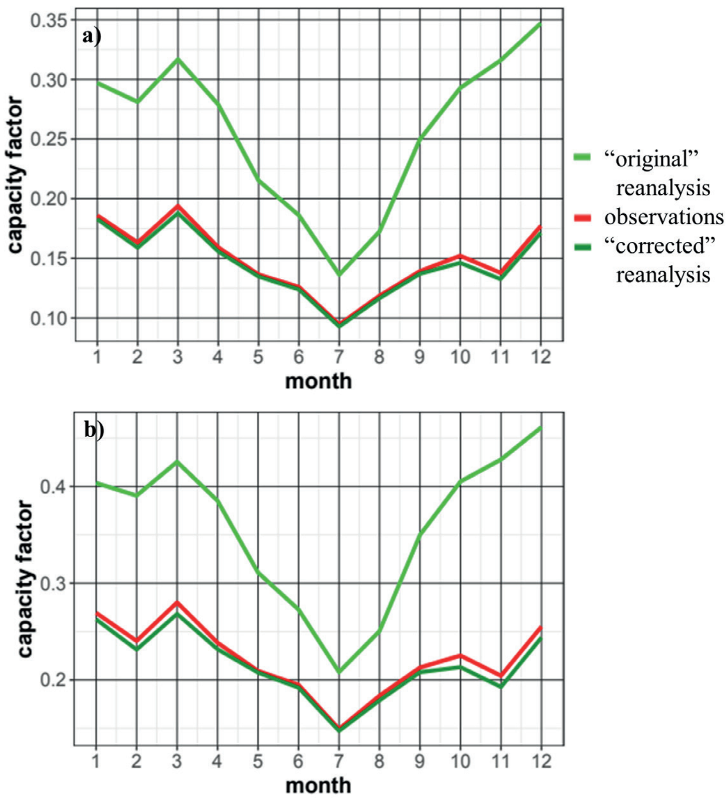

Fig. 8. The effect of ERA5 biases on the simulated multi-annual wind power capacity factor calculated using different approaches to the ERA5 biases correction with the average power capacity factor being 0.25 (a) and 0.35 (b) (Zvenigorod, turbine type «Vestas V164»)

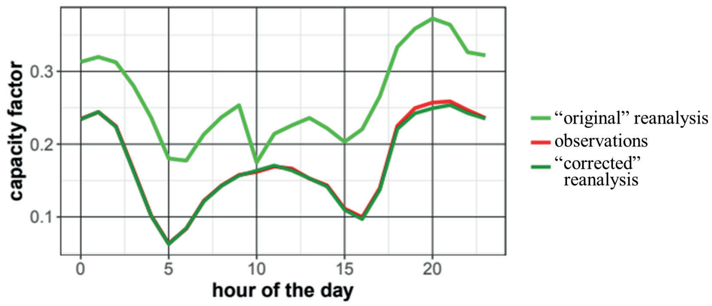

Fig. 9. Typical daily course of the simulated wind power capacity factor in May calculated using different approaches to the ERA5 biases correction (average power capacity factor on the reanalysis data is 0.30, Zvenigorod, scaling factor = 1.5, turbine type «Vestas V164»)

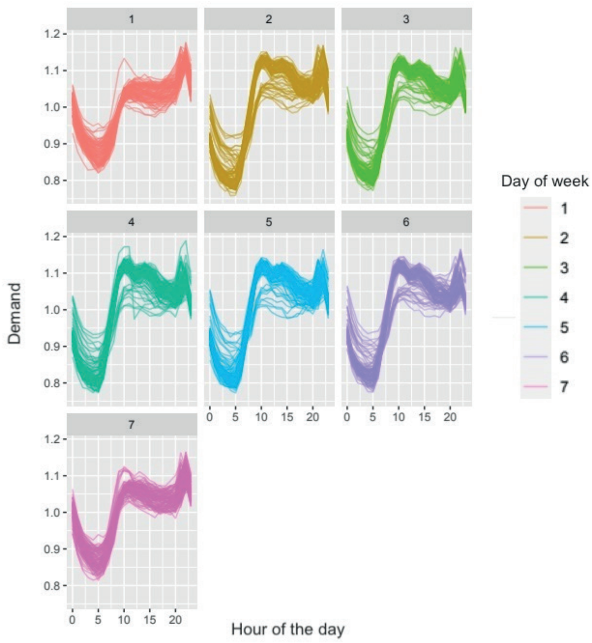

Fig. 10. Normalised daily power demand profiles for the Center power system in May for each day of the week (calculated using the System Operator data (so-ups.ru, 2005) data for 2000 – 2020)

It is worth emphasizing that the overestimation of harnessed wind power (as observed in Zvenigorod and Gelendzhik) by ERA5 may not be quite obvious from reviewing the current state-of-the-art of climate-energy research. Most published works report the underestimation of real wind potential by reanalysis data and consider energy simulation results obtained on original reanalysis data as conservative estimates of wind generation performance. This bias is linked to the fact that intensive wind generation development and applicable regional wing-energy research are currently concentrated in a few geographical regions of the world. Such a situation obviously leads to some research biases if a priori knowledge.

Diurnal patterns of reanalysis accuracy determine variations in climate-related uncertainties of simulated wind power throughout the day, particularly during peak demand hours when failing to provide the power needed to cover the actual electricity demand can lead to the most dramatic consequences for the power system. Inadequate modeling of the power system behavior during peak hours may lead to increasing risks for the power supply reliability. From this perspective, the local increase of reanalysis errors linked to the change of the boundary layer regime in the morning and evening hours poses a serious concern for energy modeling's practical use.

For example, in Zvenigorod during late spring (Fig. 8), the reanalysis error increases between 17:00 and 21:00 due to the transition between the daytime and nighttime boundary layer regimes. This timeframe is overlaid with the peak hours of the Center power system where Zvenigorod is located (see Fig. 10), which are typically between 19:00 and 21:00. If "original" reanalysis data are utilized to calculate the wind power available in the system, it can lead to an almost 50% overestimation of wind power for the evening load peak. Such discrepancy questions any conclusions which can be derived from energy models regarding power system reliability. Applying bias-corrected procedures significantly decreases this modeling error and is recommended for improving the reliability of energy models.

CONCLUSIONS

In this paper, we verified the wind speed and direction in the ERA5 reanalysis by comparing it with sodar measurements at 100 m above ground level. These measurements were carried out in various climatic zones and landscapes across European Russia. The presence of systematic errors in the reanalysis prompted us to correct the reanalysis data, considering the intradiurnal variation of wind speed error at each station. Since ERA5 reanalysis is often used as input climate data in energy modeling, we examined how wind speed bias translates into wind power capacity factor error and how this error can be eliminated with reanalysis bias correction.

Here are the main conclusions from the verification:

The systematic error of wind speed in ERA5 can be both positive and negative, ranging from -18% to 21% for the considered stations. The mean absolute wind speed error varies from 1.4 to 2.1 m/s, and the relative error ranges from 23% (on flat grassland in Tsimlyansk) to 45% (in the topographically complex area in Gelendzhik). The wind rose, representing the frequency and intensity of wind from different directions, is satisfactorily reproduced by ERA5.

There is no clear universal dependence of wind speed quality in ERA5 on a particular type of landscape and topography, as previously mentioned by other researchers (e.g., Molina et al. 2021). However, when comparing our results with those from other studies (Gualtieri 2021), ERA5 tends to overestimate wind speed over forest landscapes and underestimate it over steppe (grasslands) and desert landscapes.

There is a dependence of reanalysis error on the time of day, but this dependence varies among different stations.

In general, wind speed errors in ERA5 are significant, especially in Zvenigorod and Gelendzhik, where the percentage of errors within acceptable accuracy is less than 50%, and the absolute error approaches the standard deviation of wind speed. Therefore, reanalysis correction is necessary, especially if these data is used in energy modeling.

Bias correction not only eliminates the systematic error in wind speed but also slightly decreases the absolute error at most locations.

Our simplified wind energy modeling approach allowed us to assess the propagation of reanalysis biases into energy modeling. The energy modeling assumptions are based on the usage of working curves of wind turbines, which implies neglecting possible wake effects or the influence of mesoscale topography features. The analysis demonstrated that using "original" reanalysis data as inputs can produce misleading results. The main concerns include:

Reanalysis can both under and overestimate wind power capacity factors on a long-term time scale, depending on the area. Using "original" ERA5 data instead of observations can lead to capacity factor errors of 30-50%. This effect means that the wind energy modeling results can be misleading when used to support investment decisions. It should be recommended to assess the reanalysis uncertainty at least quantitatively, especially if an area is not well studied from the perspective of wind power development.

An important mechanism for the propagation of the reanalysis uncertainty into the energy model was identified when analyzing diurnal patterns of the reanalysis errors. High reanalysis errors associated with transient regimes of the atmospheric boundary layer can coincide with peak load periods of regional power systems. Failing to account for this effect in energy modeling can compromise power system reliability.

Utilizing the bias-correction approach is an effective measure to ensure meaningful energy modeling outputs. The capacity factor error is reduced by a factor of 10 compared to using original reanalysis data, and is less than 10% of its typical value. The developed bias-correcting approach accounting for the daily course of wind speed error was found to be an effective measure that allows to ensure a proper quality of climate inputs for energy modeling.

The main limitations of our study include the absence of wind measurements at a height of 100 m in southern European Russia during the cold season, when wind speed is highest. This limits a full assessment of reanalysis error over steppes and deserts, suitable areas for wind power plants. Additionally, the used correction method depends strongly on natural conditions, which may be unknown in advance. Further assessments of reanalysis quality for various natural conditions will help to obtain such dependences and apply them globally, not only for individual regions. Such in-depth assessments are crucial for accurate energy planning studies accommodating an increasing share of wind generation in power systems cost-effectively.

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