https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Open Access
WIND ENERGY SCIENCE DISCUSSIONS

Determining the ideal length of wind speed series for wind speed distribution and resource assessment

Lihong Zhou[1], Igor Esau[1]

[1]Department of Physics and Technology, Faculty of Science and Technology, The Arctic University of Norway, Tromsø, 9010, Norway

Correspondence to: Lihong Zhou (lihong.zhou@uit.no)

Abstract. Accurate wind resource assessment depends on wind speed data that capture local wind conditions, crucial for energy estimates and site selection. The International Electrotechnical Commission (IEC) recommends at least one year of data collection, yet this duration may not fully account for interannual variability. While studies often maximize data length, guidance on the minimum duration required for reliable wind speed and power estimates remains limited. To address this gap, we propose a method to quantify the errors introduced by using wind speed series of different lengths for wind speed distributions fitting, relative to long-term data. This allows us to determine the minimum number of hourly observations needed to for a given accuracy level. We apply our method to in-situ weather station observations and ERA5 reanalysis data at 10-meter and 100-meter heights. Our results show that key parameters, including mean, standard deviation, and Weibull parameters, stabilize with relatively short records (~1 month of hourly data), whereas skewness requires at least 1.6 years, and kurtosis requires 88.6 years to stabilize. ERA5 data stabilize with fewer observations but differ from in-situ measurements, requiring careful use. Moreover, combining available hourly data for distribution fitting produces parameters comparable to those obtained when controlling for diurnal and seasonal effects, suggesting discontinuous data can be viable under certain conditions. These findings offer a practical framework for optimizing data collection in wind resource assessments, balancing accuracy and cost-effectiveness.

1 Introduction

Wind energy production critically depends on strengths and persistence of winds in the lower earth's atmosphere. Precise and cost-effective assessment of wind speed is crucial for evaluating wind energy potential and designing wind farms and power generators, because accurate assessments ensure that the selected site has adequate wind conditions, making the investment economically viable and optimizing energy production efficiency (Wang et al., 2022).

Quantifying wind speed characteristics, a crucial component of wind speed assessment, typically relies on analysing wind speed distribution from collected data. Ideally, long-term meteorological measurements at the proposed wind turbine locations are preferred, as they account for a broader range of wind variability. However, despite the high demand for such data,

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

collecting long-term datasets is often impractical due to the extensive time required and significant associated costs (Wais, 2016).

As a more practical alternative, wind energy potential is often assessed using wind speed data spanning a single year or several years (Ouarda et al., 2015). A review of 46 studies revealed that 31 of them (67.4%) used wind speed time series of six years or less. However, such datasets lack year-to-year (interannual) variability, which can significantly affect wind speed and, consequently, wind power output (Jung and Schindler, 2018). For example, decadal changes in wind speed can result in a 17 ± 2% variation in potential wind energy (Zeng et al., 2019). Since wind farms typically operate for 20 to 30 years (Pryor et al., 2020), relying on such short-term datasets without accounting for interannual variability can introduce significant biases in wind energy assessments. Additionally, short-term datasets may lack seasonal or diurnal characteristics due to sampling frequency or other factors that lead to data gaps. For instance, the Sentinel-1 Ocean wind product, aligning well with in-situ observations and reanalysis products (Khachatrian et al., 2024), revisits the same location only once every one or two days, making it unable to capture the diurnal characteristics of wind speed.

This discussion highlights a critical research gap: the optimal duration of wind observation time series required to adequately account for wind variability in resource assessments remains poorly quantified. Specifically, is one year of data, as recommended by IEC (International Electrotechnical Commission, 2019), sufficient to provide accurate assessments of wind distributions given the interannual variability of wind? Furthermore, considering the challenges in obtaining long-term observations, if we must reply on short-term datasets that may lack interannual, seasonal, or diurnal variability, how do errors vary with the length of data time series?

This research gap has been highlighted in previous studies. For instance, Barthelmie and Pryor, (2003) and Pryor et al., (2004) evaluated the accuracy of satellite sampling in representing offshore wind speed distributions. They quantified the numbers of satellite observations required to estimate key probability distribution parameters with an uncertainty of ±10%. Specifically, mean and Weibull scale parameter required about 60-70 random selected half-hourly observations, respectively. In contrast, the variance requires 150 observations, and the Weibull shape parameter and energy density require nearly 2000 observations, while skewness and kurtosis required 9712 and more than 10000 observations. However, these results are specific to satellite observations and may not directly apply to in-situ measurements without further analysis. To the authors' knowledge, relatively few studies have examined in-situ observations, particularly those from weather stations certified by the World Meteorological Organization (WMO). These stations are more widely distributed, accessible, and frequently used in wind energy studies (Ouarda et al., 2015; Wang et al., 2016).

Our study aims to evaluate the potential biases and uncertainties that arise when short-term data from WMO stations are used for wind energy assessments. Barthelmie and Pryor (2003) used the random sampling method to create wind speed datasets

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Wind Energy Science Discussions

under varying sampling density. However, this approach may overlook significant diurnal-cycle and seasonal effects commonly observed in terrestrial wind speeds from in-situ weather stations. As a result, it may introduce biases in wind energy assessments. Therefore, we also investigate whether random sampling can replace sampling that retains these temporal effects, and under what specific conditions this substitution would still yield reliable results.

We are also interested in investigating whether reanalysis products can replicate the results from meteorological observations. Reanalysis products become a primary alternative for wind resource assessment, especially given the spatial and temporal limitations of traditional meteorological data (Gil et al., 2021; Gualtieri, 2021). Reanalysis products offer consistent, comprehensive coverage of wind speed data because they are generated by integrating numerical weather prediction models with observational data from various sources, including satellite instruments, surface synoptic observations, ships, and drifting buoys (Hersbach et al., 2022). By focusing on ERA5, the most current and widely utilized reanalysis product, we can evaluate its potential to replace in-situ observations in the statistical distribution fitting process for wind speed analysis. ERA5 is chosen not only for its strong agreement with observational data on turbine heights, particularly in Europe and North America, in terms of mean values and interannual variability (Ramon et al., 2019), but also because it provides wind speed data at both 10-meter and 100-meter heights, which is crucial for wind turbine analysis. This allows for direct analysis at typical wind turbine hub heights, eliminating the need for extrapolation methods that are often required with other datasets. In contrast, other studies have commonly employed wind profile log or power-law extrapolations to estimate wind speeds at hub height (e.g., Soares et al., 2020; Jung and Schindler, 2019).

The main objectives of our study are as follows:

1. Investigate whether short-term wind speed data from WMO weather stations realistically represent the wind speed statistics.

2. Determine the optimal length of wind data series required for fitting accurate distribution fitting by identifying the error margins across different time series lengths.

3. Explore whether ERA5 reanalysis products, at both 10-meter and 100-meter heights, yield results like those from observations.

Through these objectives, we aim to enhance the understanding of the limitations and capabilities of short-term meteorological data in wind speed assessment, contributing to more reliable wind energy evaluations.

2 Data and Methods

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

2.1 Methods to identify optimal wind speed series length for accurate distribution

To find the optimal length of wind speed series for accurately representing wind speed distribution, we used the method from (Barthelmie and Pryor, 2003). We created datasets ranging from 720 hours (30 days) to 52,560 hours (6 years) in 240-hour (10-day) increments, comparing them to a full 16-year series. This was repeated 1,000 times per sample size to capture variability. These datasets were used to fit Weibull distributions, calculating seven parameters: six distribution parameters and Weibull wind power density. We compared these to the full series to assess differences and determine the minimum sample size needed for accurate parameter estimation within acceptable error margins.

We started with a minimum sample size of 720 hours, a common duration in wind studies (Jung and Schindler, 2019; Ouarda and Charron, 2018). The maximum of 52,560 hours was chosen to see if a six-year sample affects distribution stability, usually analysed over one to two years. Six years was selected based on preliminary findings that error margins stabilize below ±10% before this duration (Barthelmie and Pryor, 2004).

To find the effective sample size, we used percent error to measure differences between sample sizes and the full series. Since we increased sample size in 240-hour increments, we needed a precise threshold. Using least squares, we fitted an exponential function to the percent errors, creating equations that relate percent error (within a 90% confidence interval) to sample size. These equations help determine the sample size needed to achieve any specified error margin.

2.2 Probability density distributions

In this study, we exclusively employed the two-parameter Weibull probability density function to fit wind speed data. The function is expressed as Eq. (1):

$$p(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^{k}}, \tag{1}$$

where v represents the wind speed, k is the shape parameter, and c is the scale parameter. The Weibull distribution is characterized by two key parameters: the dimensionless shape parameter, which determines the curve's shape, and the scale parameter, which adjusts the distribution along the wind speed axis. The distributions vary with different values of k and c, making it a popular choice for approximating observed wind speed frequencies (Wais, 2017; Ouarda and Charron, 2018; Carta et al., 2009).

To estimate the Weibull parameters, we used the 'weibull_min.fit' function from Python's 'scipy.stats', employing the maximum likelihood estimation (MLE) method. MLE is preferred for its superior performances in parameter selection (Mohammadi et al., 2016). This 'weibull_min.fit' function is particularly useful for iterative experiments requiring repeated Weibull distribution fitting, such as those with thousands of iterations.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

We focused on the first four moments of the distributions: mean, standard deviation, skewness, kurtosis, and the Weibull shape and scale parameters, chosen for their importance in wind resource assessment. The standard deviation indicates wind speed variability, while skewness and kurtosis provide insights into asymmetry and extreme values in the distribution. We calculated the mean and standard deviation using Python's 'numpy' package, and the other parameters with 'scipy.stats'.

2.3 Wind resource assessment method

We used the Weibull wind power density to represent wind resources at a specific location. The Weibull wind power density is calculated using the estimated Weibull k and c parameters, and is given by the Eq. (2):

$$E = \frac{1}{2}\rho c^3 \Gamma\left(1+\frac{3}{k}\right), \quad (2)$$

where E represents the wind power density (W m^{-2}), ρ is air density (with 1.225 kg m^{-3}, the standard air density provided by IEC, used for calculation), and Γ is the gamma function.

We chose the Weibull wind power density in our study for two main reasons. First, wind power density measures the amount of kinetic energy in airflow passing through a unit area, which can be converted into wind energy. It is a critical metric for evaluating wind resources and has been widely adopted in previous studies (e.g., Wang et al., 2022; Mohammadi et al., 2016). Second, the Weibull wind power density can be easily derived from the scale and shape parameters of the Weibull distribution, simplifying the calculation process.

Given that our objective is to determine which dataset—specifically, which time series length—most accurately represents long-term wind conditions, the use of Weibull wind power density enables us to compare how the shape and scale parameters vary with datasets of different lengths. This approach helps us more effectively identify the time series that best captures long-term wind resource variability.

2.4 Data sources

2.4.1 In-situ observations from weather stations

In this study, we utilized weather station observations from the Norwegian Meteorological Institute (MET Norway). This data, accessed via their API (https://frost.met.no/observations/v0.jsonld?; last accessed 8 February 2025), offers hourly wind speed resolution over long periods, suitable for analysing interannual variability, as wind assessments typically need at least hourly resolution (Jung and Schindler, 2019).

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

We aimed to compare wind distribution parameters from short-term data with long-term series that include interannual variability. We prioritized weather stations with the longest hourly data series, retaining years with at least 8,600 hourly observations (97.9% of the possible 8,760 or 8,784 hours annually).

We identified five stations with over 16 years of hourly data: SN50500 (18 years), SN44080 (16 years), SN42160 (20 years), SN38140 (24 years), and SN35860 (17 years). Details are in Table 1, and their locations in southern Norway are shown in Fig. 1. We standardized the data to 16 years per station, omitting years with fewer observations for consistency.

Using the same years across all stations was not feasible due to data availability differences, so the years analysed varied. Table S1 details the selected years and hourly observations. The year with the fewest observations had 8,636 hours (98.32% coverage), and the average yearly count was 8,744 hours (99.54% coverage).

Table 1: Details of stations used in this study.

Station ID	WMO number	Latitude	Latitude of ERA5 grid point	Longitude	Longitude of ERA5 grid point	Height above mean sea level
SN50500	1311	60.2892° N	60.25°	5.2265° E	5.25°	48 m
SN44080	1412	58.6592° N	58.75°	5.5553° E	5.50°	24 m
SN42160	1427	58.109° N	58.00°	6.5675° E	6.50°	14 m
SN38140	1464	58.34° N	58.25°	8.5225° E	8.50°	6 m
SN35860	1467	58.6362° N	58.75°	9.1478° E	9.25°	4 m

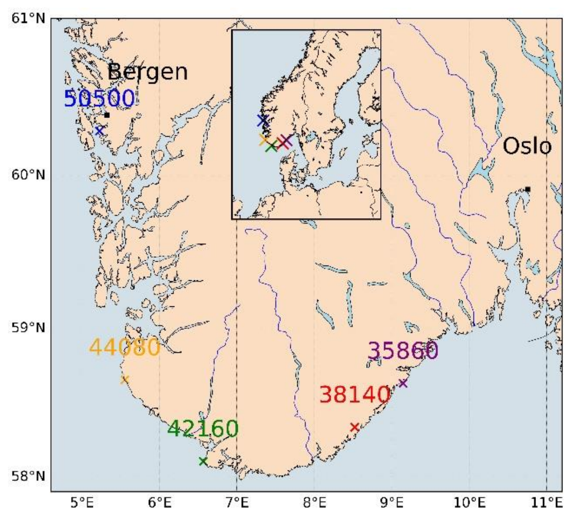


Figure 1: Location of the five weather stations used in this study.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

WIND ENERGY SCIENCE DISCUSSIONS

2.4.2 ERA5 reanalysis

For the ERA5 reanalysis products, we downloaded the "10m u-component of wind," "10m v-component of wind," "100m u-component of wind," and "100m v-component of wind" variables from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download; last accessed 8 February 2025). We calculated the wind speed at 10 m and 100 m by taking the square root of the sum of the squares of the u-component and v-component of wind. We used the ERA5 grid point closest to the location of each station, as indicated in Table 1.

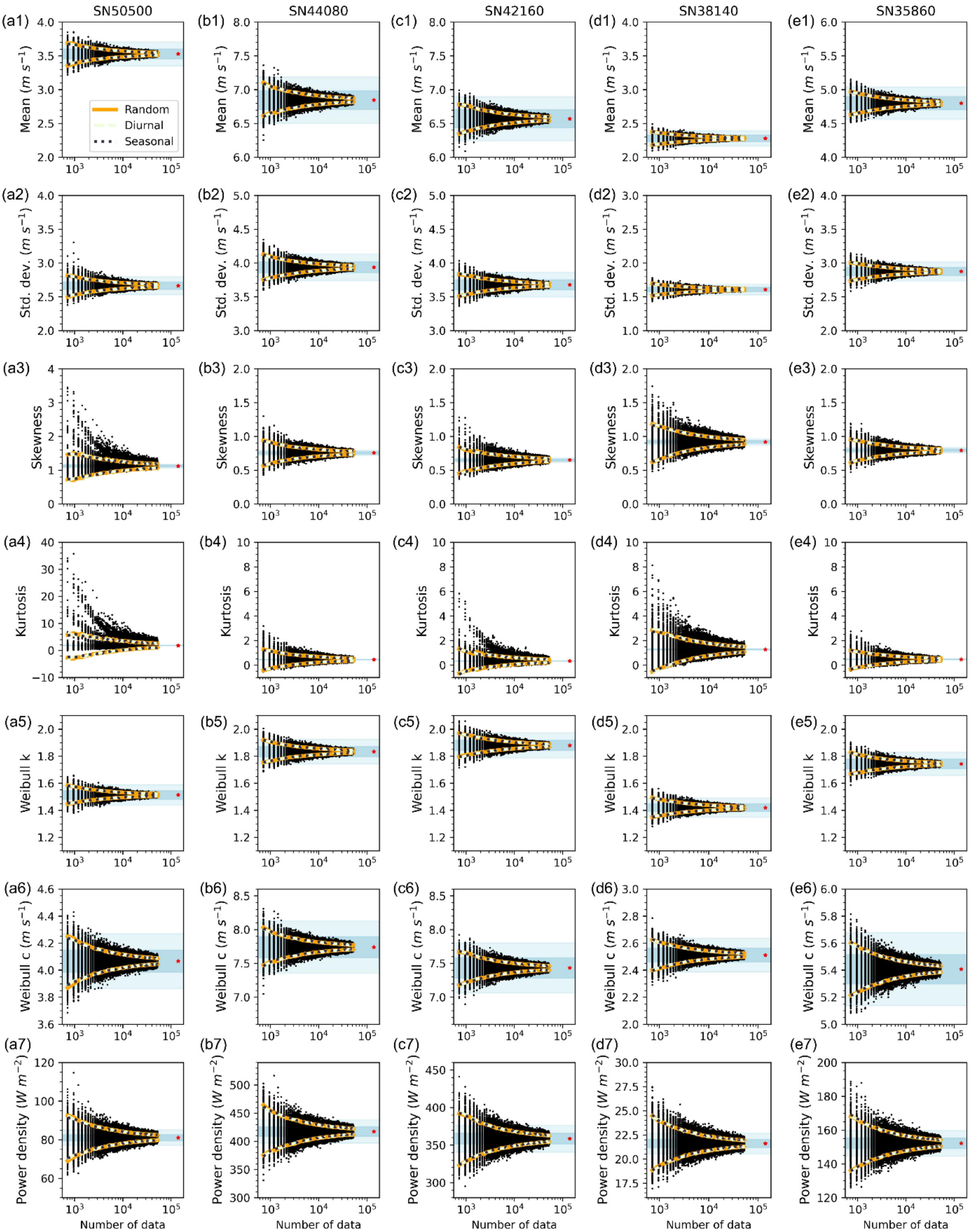
3 Results

The results section is organized into four parts. First, we assess the feasibility of using random sampling to investigate the uncertainty associated with different sample sizes for acquiring wind distribution parameters. Second, we examine the impact of sample size on the estimation of these parameters. Third, we identify the effective sample size necessary to capture overall wind characteristics, including interannual variability. Finally, we apply our methodology to ERA5 datasets at 10-meter and 100-meter heights to determine if they replicate the results observed in in-situ measurements.

3.1 Can random sampling replace diurnal cycle-retained or seasonality-retained sampling?

The five stations show significant diurnal and seasonal variations (Fig. S1-S2). We compared random sampling with diurnal and seasonality-retained sampling to evaluate its suitability. Diurnal cycle-retained sampling involved equal observations from four time intervals (0-5, 6-11, 12-17, 18-23) to capture daily variations. Seasonality-retained sampling ensured equal distribution across all 12 months. We compared these datasets to those from random sampling of the entire dataset.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025



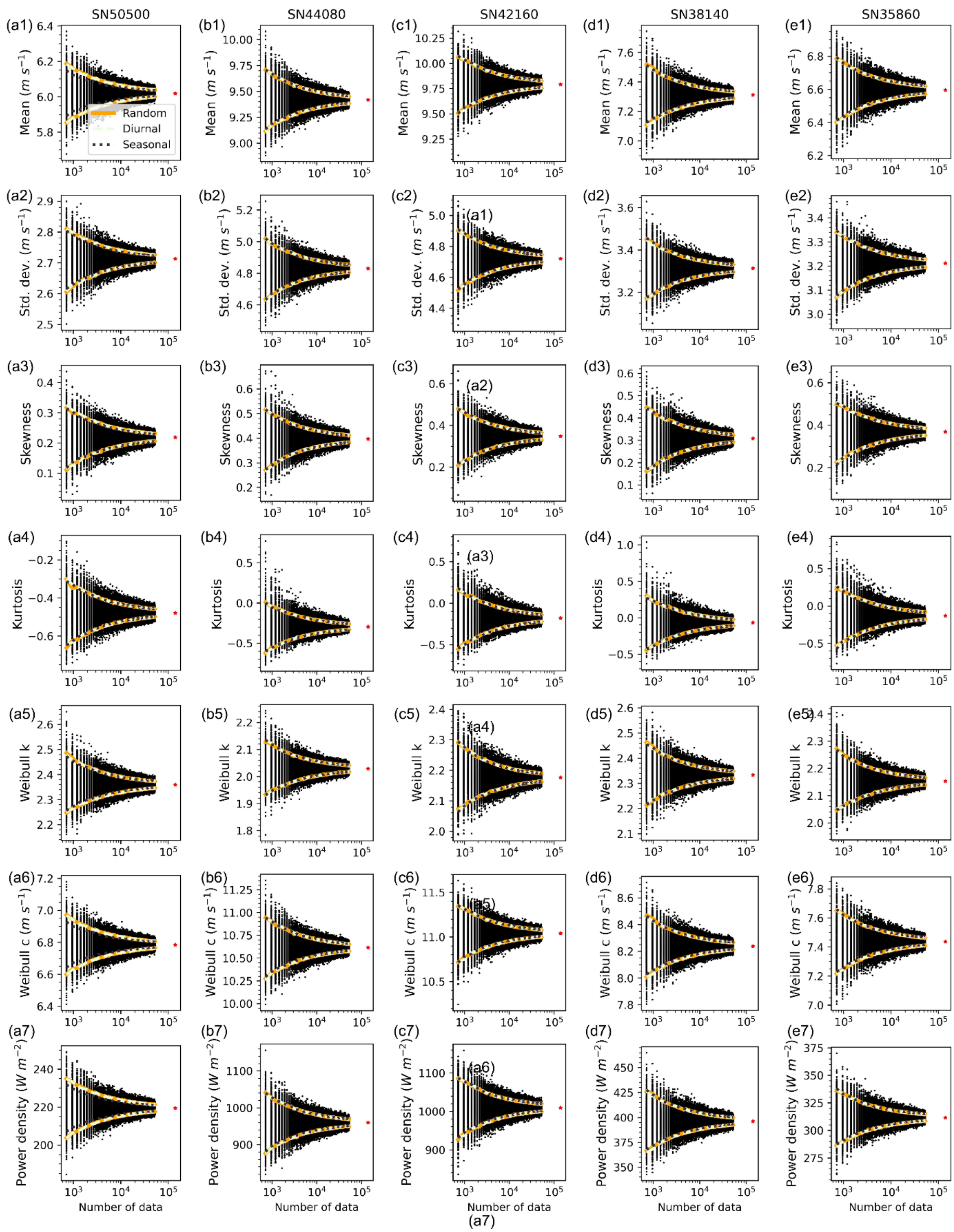
https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Figure 2: Distribution parameters and Weibull power density across randomly selected, diurnal-cycle-retained, and seasonality-retained sampling experiments for in-situ observations. Black dots represent the parameters calculated from each individual random sampling experiments. Each experiment utilized hourly observations, with sample sizes ranging from n=720 (30 days) to n=52,560 (6 years), increasing incrementally by 240 hours (10 days). For each sample size, 1,000 iterations were conducted. Red asterisks indicate the values derived from the entire 16-year hourly dataset, as detailed in Table 1. The dark blue and light blue shaded areas represent the ±2% and ±5% uncertainty range, respectively, for the values of the entire dataset. The 90% confidence intervals (CIs) are shown for each sampling method: randomly selected (orange lines), diurnal-cycle-retained (light green dashed lines), and seasonality-retained (dark grey dotted lines).

Figure 2 shows that the 90% confidence intervals (CIs) for random sampling overlap with those for diurnal and seasonality-retained methods across six distribution parameters and power density at all stations, indicating no significant differences. The average root mean square error (RMSE) is 0.2866 for random vs. diurnal sampling and 0.3904 for random vs. seasonality sampling. Power density has the largest RMSE, while the shape parameter has the smallest (Table S2). Differences in 90% CIs are small, fluctuating around zero, with larger deviations at low data density, stabilizing as density increases. Parameter differences are within ±0.2, while power density differences range from ±3.

We also analysed ERA5 100-meter wind speed data to assess random sampling at altitudes relevant to wind turbines, addressing the lack of high-altitude observational data. Similar CI overlaps were observed in the 100-meter data (Fig. 3). Average RMSE values are comparable to in-situ observations (Fig. S4) but slightly higher due to larger power density differences: 0.4895 for diurnal and 1.1010 for seasonality sampling (Table S3). These findings confirm random sampling as a viable method for analysing wind speeds at both surface and elevated levels. Thus, we used random sampling in further analyses to determine the optimal sample size for capturing overall wind characteristics.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025



https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

WIND ENERGY SCIENCE DISCUSSIONS

Figure 3: Distribution parameters and Weibull power density across randomly selected, diurnal-cycle-retained, and seasonality-retained sampling experiments for ERA5 100-meter data. Each experiment utilized hourly observations, with sample sizes ranging from n=720 (30 days) to n=52,560 (6 years), increasing incrementally by 240 hours (10 days). For each sample size, 1,000 iterations were conducted. The 90% confidence intervals (CIs) are shown for each sampling method: randomly selected (orange lines), diurnal-cycle-retained (light green dashed lines), and seasonality-retained (dark grey dotted lines). Black dots represent the parameters calculated from each individual random sampling experiments. Red asterisks indicate the values derived from the entire 16-year hourly dataset, as detailed in Table 1. The dark blue and light blue shaded areas represent the ±2% and ±5% uncertainty range, respectively, for the values of the entire dataset.

3.2 Effects of sample size on estimating wind distribution parameters

We studied how sample size affects the accuracy of wind distribution parameters. Figure 2 shows how six distribution parameters and power density change with increasing sample size, with full dataset values in Table 2. Despite different locations and wind speeds, the five stations showed consistent results.

Table 2: Distribution parameters and Weibull power density of five stations derived from the entire datasets.

Data products	Station ID	Mean (m s^{-1})	Std. dev. (m s^{-1})	Skewness	Kurtosis	Shape k	Scale c (m s^{-1})	Power density (W m^{-2})
In-situ weather stations	SN50500	3.53	2.66	1.12	1.81	1.51	4.07	81.08
	SN44080	6.85	3.94	0.76	0.45	1.83	7.74	417.34
	SN42160	6.57	3.68	0.65	0.34	1.88	7.43	358.49
	SN38140	2.28	1.61	0.92	1.28	1.42	2.51	21.61
	SN35860	4.80	2.88	0.79	0.47	1.74	5.41	152.15
ERA5 (10 meter)	SN50500	4.82	2.45	0.30	-0.68	2.07	5.44	126.73
	SN44080	7.58	3.74	0.35	-0.36	2.13	8.55	478.87
	SN42160	8.04	3.74	0.32	-0.28	2.28	9.07	539.59
	SN38140	4.74	2.27	0.45	-0.15	2.20	5.35	113.61
	SN35860	4.50	2.19	0.48	-0.06	2.16	5.08	98.77
ERA5 (100 meter)	SN50500	6.02	2.71	0.22	-0.48	2.36	6.78	219.44
	SN44080	9.42	4.83	0.40	-0.29	2.03	10.61	959.38
	SN42160	9.79	4.72	0.35	-0.18	2.18	11.04	1009.61
	SN38140	7.31	3.31	0.31	-0.07	2.33	8.24	396.08
	SN35860	6.60	3.21	0.37	-0.13	2.15	7.44	311.57

As hourly observations increased, the absolute range for all parameters decreased, though robustness varied. The mean, standard deviation, and Weibull k and c parameters were most robust, with 90% confidence intervals within ±5% from the start with 720 observations (Fig. 2). In contrast, power density had a larger range, and skewness and kurtosis were less robust. Even with six years of data (n = 52,560), some skewness and kurtosis values exceeded the ±5% margin due to their sensitivity to data distribution tails and extreme values, requiring larger sample sizes.

Previous studies noted systematic bias in distributions with low data density (e.g., 21 observations) (Barthelmie and Pryor, 2003). We calculated the median of 1,000 resampling groups for each parameter (Fig. S5) and found skewness and kurtosis,

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

especially kurtosis, showed significant biases under low data density, aligning with past findings. At 720 observations, median skewness was over 2% lower, and kurtosis over 25% lower than full dataset values. Kurtosis bias improved to within 10% with over 2,160 observations. SN50500 had the largest kurtosis underestimation, needing at least 22,080 observations to reduce error to 10%. Other parameters, including power density, showed minimal variation, staying within 1% of full dataset values.

3.3 Determine an effective sample size for capturing overall wind characteristics

To determine the optimal sample size for capturing wind characteristics, we evaluated percent errors across different sample sizes (Fig. 4-5). Percent error measures discrepancies between parameters from the full dataset and smaller subsets, helping identify the minimum observations needed for target accuracy. The equations for percent errors are in Table S2.

As observations increase, percent error decreases, but different parameters need varying sample sizes to meet specific error thresholds. For most stations, 720 hourly observations keep percent errors for the mean, standard deviation, and Weibull parameters within ±7% (Fig. 4). However, power density, skewness, and kurtosis show larger errors with the same observations, with errors of at least ±10% to ±150% depending on the station. Variability is greater for these parameters across stations, with error differences of 4.6% for power density, 18.1% for skewness, and 154.2% for kurtosis, compared to less than 1.5% for others.

Figure 5 shows percent error changes with fewer observations. Errors decrease quickly below 400 observations and more slowly above. About 200 observations can achieve ±10% error for the mean, standard deviation, and Weibull parameters.

Table 3 details sample sizes needed for error margins of ±10%, ±5%, ±2%, and ±1% for each parameter at each station. For ±5% error, the mean and Weibull scale need 459 and 470 observations (20 days), respectively. Standard deviation requires 796 observations (34 days), and the Weibull shape needs 681 observations (28 days). Power density needs 4,031 observations (168 days). Achieving ±2% error requires six times more observations than ±5%, and ±1% needs 24 times more.
Skewness and kurtosis need significantly more data due to sensitivity to distribution tails. For instance, SN38140 needs 177,390 observations (20 years) for ±10% error, while SN50500 needs 1,541,437 observations (176 years). These differences reflect distinct wind speed distributions at each station. Sample density requirements increase significantly with precision.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

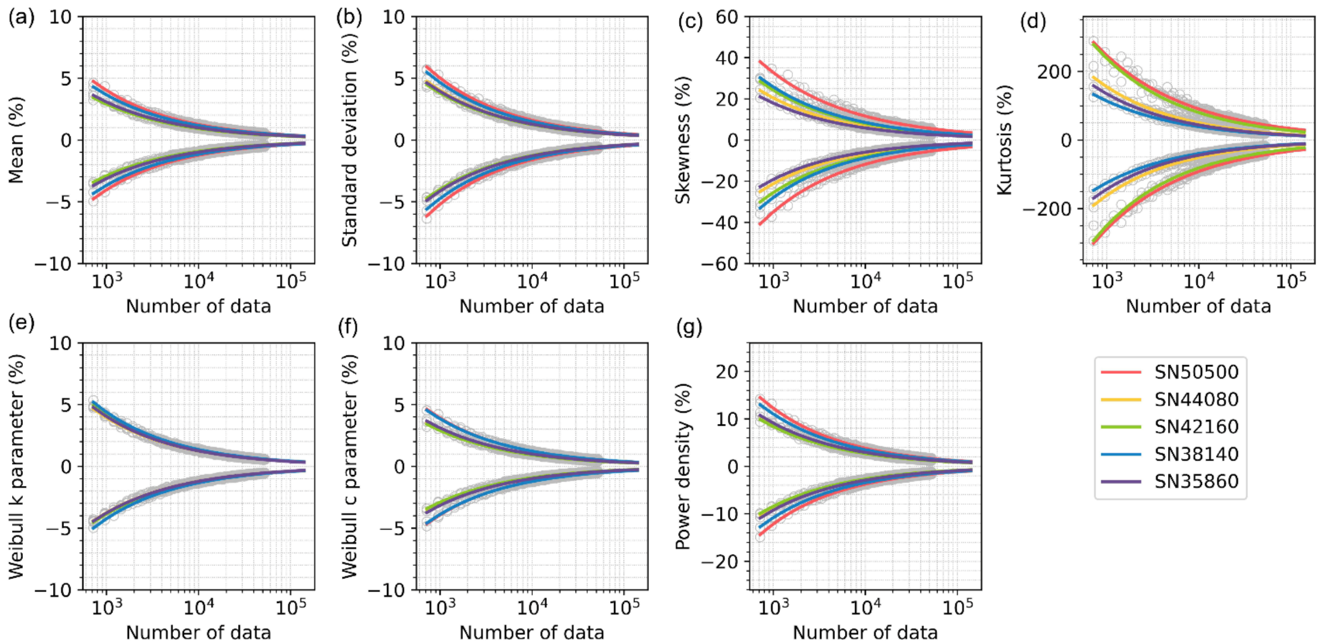


Figure 4: 90% confidence intervals for the percent error in the mean, standard deviation, skewness, kurtosis, Weibull k and c parameters, and energy density, based on hourly observations ranging from n = 720 (30 days) to n = 140,160 (16 years) across five stations. Grey circles indicate the values used to fit the 90% confidence intervals for the percent error shown. The equations of fits here are shown in Table S4.

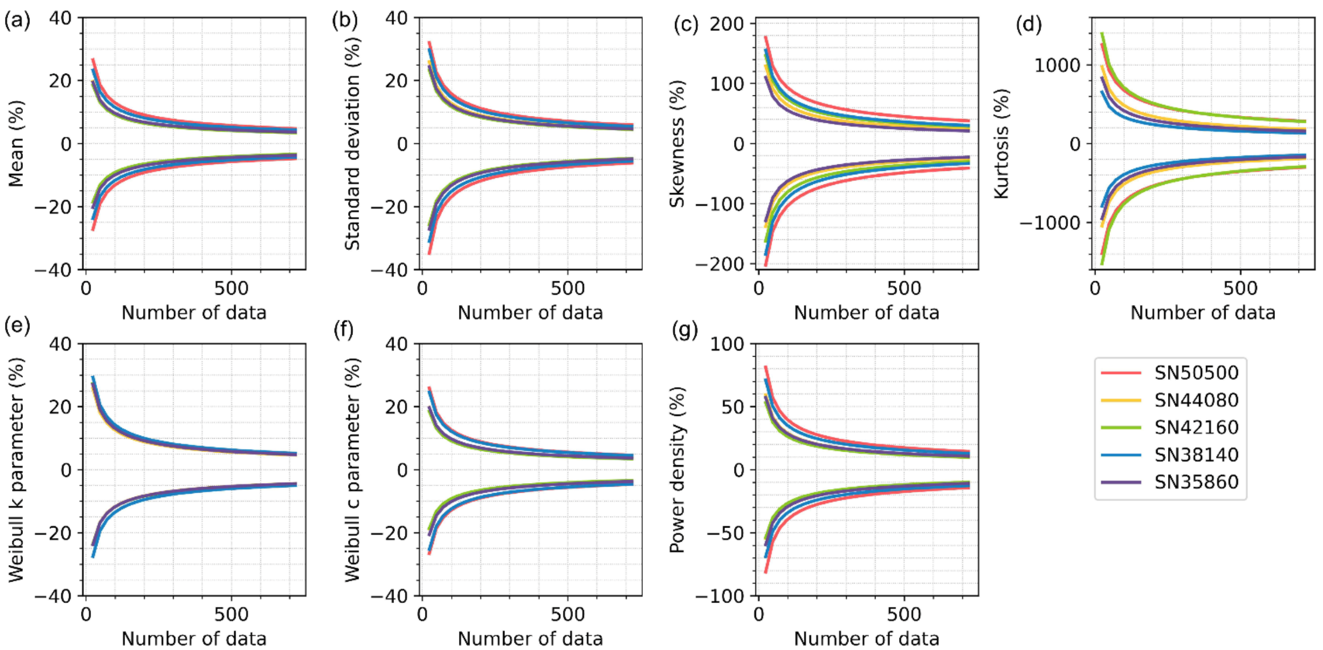


Figure 5: Same as Fig. 4, but the hourly observations ranging from n= 24 (1 day) to n= 720 (30 days) across five stations. These intervals are calculated using the same fits as shown in Fig. 4.

Stations with higher wind speed variability but lower skewness and kurtosis need fewer observations for the same error margins. For example, SN50500 and SN38140, with the highest skewness and kurtosis, require more observations.

All parameters except skewness and kurtosis show moderate regional differences. Power density has the largest regional difference (ratio of 2.1), while the shape parameter has the smallest (ratio of 1.2). Skewness shows significant regional differences, increasing from 3.96 to 6.1 times, and kurtosis from 8.69 to 13.16 times, as error margins decrease from ±10% to ±1%. This highlights skewness and kurtosis's sensitivity to regional variability and data distribution tails.

Table 3. Required number of randomly selected in-situ observations (unit: hours) to obtain an estimate within ±10%, ±5%, ±2%, and ±1% of the parameters from the entire observed time series (157,465 data points), calculated at the 90% confidence level. The fits to get the required data density are shown in Table S2.

Error margins	Location	Mean	Std. dev.	Skewness	Kurtosis	Shape k	Scale c	Power density
±10%	SN50500	170	279	14297	1541437	166	162	1489
	SN44080	92	162	4505	262169	157	93	813
	SN42160	83	160	6658	801270	177	84	709
	SN38140	135	228	7673	177390	198	153	1211
	SN35860	98	175	3611	204844	169	101	853
	average	116	201	7349	597422	174	119	1015
±5%	SN50500	659	1087	63795	7545102	649	629	5836
	SN44080	365	655	17944	1058755	623	368	3202
	SN42160	335	640	26968	3458621	700	338	2859
	SN38140	541	905	30229	777573	774	610	4840
	SN35860	393	691	14084	847284	657	404	3417
	average	459	796	30604	2737467	681	470	4031
±2%	SN50500	3956	6576	484327	61581562	3936	3770	35501
	SN44080	2256	4165	111517	6790761	3853	2276	19931
	SN42160	2113	4008	174520	23905124	4321	2131	18057
	SN38140	3379	5593	200542	5484926	4689	3793	30218
	SN35860	2445	4262	88940	5535245	3956	2513	21623
	average	2830	4921	211970	20659524	4151	2897	25066
±1%	SN50500	15531	25766	2244402	301432368	15383	14785	139117
	SN44080	8944	16876	444166	27700221	15295	9032	81625
	SN42160	8503	16046	733004	103184595	17126	8585	72806
	SN38140	13574	22191	844568	24042683	18315	15117	120783
	SN35860	9757	16870	368113	22895088	15391	10011	88205
	average	11262	19550	926851	95850991	16302	11506	100507

3.4 Does ERA5 reanalysis (10 m and 100 m) show similar results with in-situ observations?

We analysed the ERA5 dataset to assess its deviations from in-situ observations. Four out of five stations showed that ERA5 overestimated the mean wind speed for both the full series (Table 2) and sampling experiments (Fig. 6), likely due to a higher

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

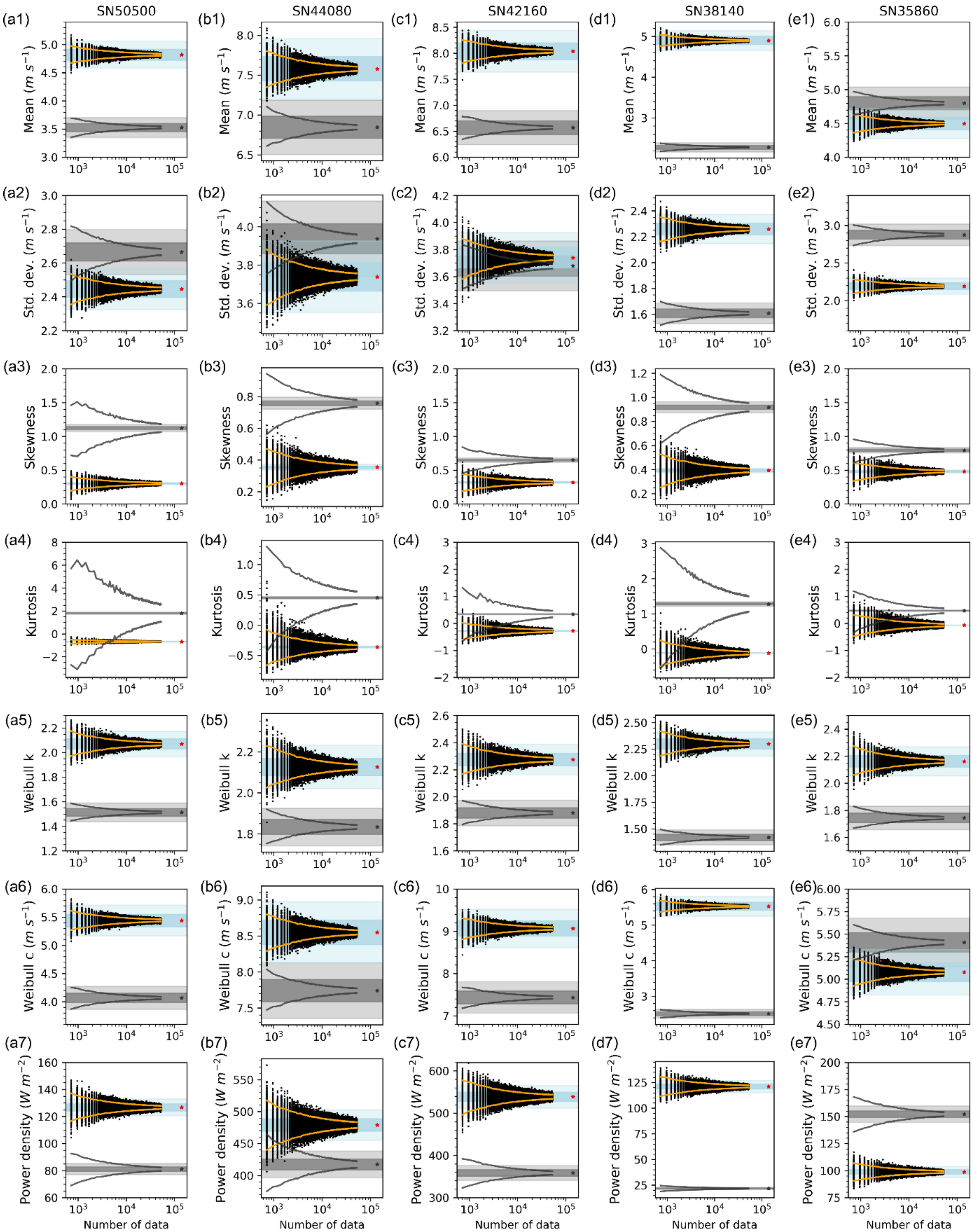
frequency of lower wind speeds at these locations (Fig. S6). Similarly, ERA5 overestimated the scale parameter for stations with higher wind speeds and underestimated it for others. This could be due to the higher frequency of lower wind speed values observed at the same locations (Fig. S6). The shape parameter was consistently higher in ERA5, often exceeding 2, indicating a potential bias in overestimating high wind events. These biases affected the Weibull power density calculations, causing systematic discrepancies (Table 2 & Fig. 6).

Both in-situ and ERA5 distributions were positively skewed, but in-situ data had higher skewness (Table 2). ERA5 samples consistently showed lower skewness (Fig. 6). For kurtosis, ERA5 had negative values across all stations, while in-situ observations had positive kurtosis (Table 2), indicating more peaked distributions around the mean. In-situ kurtosis varied widely, especially at SN50500 and SN38140 (Fig. 6a4 & 6d4), whereas ERA5 had flatter distributions with less variability (Fig. 6a4-e4).

Due to differences in skewness and kurtosis, ERA5 (10m) requires fewer data points for the same error margins in parameters like mean, standard deviation, Weibull scale, and power density (Table 4). However, for tail-sensitive parameters like shape, skewness, and kurtosis, ERA5 needs more samples. Differences among locations are smaller in ERA5, shown by greater overlap in percent error lines (Fig. S7-S8).

We also examined the ERA5 100-meter dataset to see if it requires similar data densities as the 10-meter data, given its relevance to turbine heights. Figures S9-S10 show that for most parameters, the 100-meter dataset needs similar observations as the 10-meter dataset, though data density can vary by station. For instance, SN42160 had the highest error in the 10-meter dataset, while SN35860 showed nearly double the error under the same density. Table 5 shows that for mean, standard deviation, scale, and power density, both datasets have similar requirements, but the 100-meter dataset consistently needs more data for the shape parameter.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025



https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Figure 6: Distribution parameters and Weibull power density from experiments using ERA5-10m data (black dots) based on randomly selected samples. Each experiment was conducted with hourly observations ranging from n=720 (30 days) to n=52,560 (6 years, incrementing by 240 (10 days), with 1,000 iterations for each sample size. The 90% confidence intervals (CIs) for the randomly selected ERA5-10m (orange lines) and in-situ observations (grey lines) are presented. Red asterisks indicate the values for the entire 16-year hourly ERA5-10m dataset. The dark blue and light blue shaded areas represent ±2% and ±5% uncertainty margins around the ERA5-10m dataset values, respectively, while the dark grey and light grey shaded areas represent the corresponding uncertainty for in-situ observations.

Table 4: Required number of randomly selected ERA5 10-meter reanalysis (unit: hours) to obtain an estimate within ±10%, ±5%, ±2%, and ±1% of the parameters from the entire observed time series (157,465 data points), calculated at the 90% confidence level. The fits to obtain the required data density are shown in Table S5.

Error margins	Location	Mean	Std. dev.	Skewness	Kurtosis	Shape k	Scale c	Power density
±10%	SN50500	73	96	8172	5016	180	73	471
	SN44080	66	117	8313	44143	185	67	472
	SN42160	57	126	11723	95190	194	56	427
	SN38140	60	134	8735	711310	195	59	460
	SN35860	64	139	6207	3540359	185	64	508
	average	64	123	9262	944804	188	64	468
±5%	SN50500	290	378	32016	19838	695	288	1856
	SN44080	264	461	32714	178285	730	266	1877
	SN42160	229	495	46455	392676	761	227	1711
	SN38140	238	528	34605	2908557	751	232	1825
	SN35860	254	547	24898	14867900	716	254	2041
	average	255	482	34138	3673452	731	254	1862
±2%	SN50500	1780	2314	200956	124202	4155	1777	11362
	SN44080	1642	2826	208777	1128607	4469	1649	11743
	SN42160	1443	3016	298655	2556252	4626	1424	10706
	SN38140	1461	3244	221711	18715159	4468	1430	11298
	SN35860	1587	3343	165203	99101050	4294	1587	12890
	average	1583	2949	219061	24325054	4403	1574	11600
±1%	SN50500	7030	9113	809645	498171	16071	7032	44916
	SN44080	6548	11134	848415	4558267	17597	6563	47679
	SN42160	5802	11843	1220400	10544961	18114	5721	43071
	SN38140	5777	12805	903642	76526556	17220	5660	45063
	SN35860	6368	13141	691404	416179369	16643	6348	51972
	average	6305	11608	894702	101661465	17129	6265	46541

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Table 5: Required number of randomly selected ERA5 100-meter reanalysis (unit: hours) to obtain an estimate within ±10%, ±5%, ±2%, and ±1% of the parameters from the entire observed time series (157,465 data points), calculated at the 90% confidence level. The fits to obtain the required data density are shown in Table S6.

Error margins	Location	Mean	Std. dev.	Skewness	Kurtosis	Shape *k*	Scale *c*	Power density
±10%	SN50500	56	110	16201	8729	198	54	374
	SN44080	73	123	7056	81022	189	74	521
	SN42160	61	133	11263	328841	205	62	468
	SN38140	58	137	15661	2453346	222	57	435
	SN35860	64	137	11069	795574	211	64	480
	average	63	128	12230	701703	205	63	456
±5%	SN50500	223	434	65875	38941	767	215	1501
	SN44080	289	483	27566	329399	745	294	2067
	SN42160	247	523	44785	1367095	803	247	1867
	SN38140	239	528	39510	2240186	816	234	1808
	SN35860	255	535	44939	3346344	815	255	1916
	average	251	501	44535	1464393	790	249	1832
±2%	SN50500	1391	2651	427303	248311	4604	1347	9434
	SN44080	1786	2950	176226	2103464	4560	1819	12841
	SN42160	1551	3187	290902	8991336	4889	1552	11635
	SN38140	1481	3272	247668	14218455	4903	1457	11209
	SN35860	1587	3244	296038	22351593	4884	1590	12125
	average	1560	3061	287628	9582632	4768	1553	11449
±1%	SN50500	5556	10417	1757931	1008422	17854	5394	37889
	SN44080	7091	11598	717060	8551751	17952	7217	51955
	SN42160	6236	12509	1198029	37379775	19172	6231	47065
	SN38140	5891	12995	998600	57540275	19027	5801	44825
	SN35860	6341	12685	1232216	94015313	18917	6340	48981
	average	6223	12041	1180767	39699108	18585	6197	46143

4 Discussions and Implications

It is claimed that the uncertainty bounds acquired by the methods in this study provided exhibit robustness and are applicable to all remotely sensed wind speed data series (Barthelmie and Pryor, 2003). Specifically, they reached this conclusion by finding a similar required sample size with an uncertainty of ±10% from five different locations, including Denmark, eastern North Pacific, the Gulf of Mexica, the Gulf of Alaska, and the western Atlantic (Barthelmie and Pryor, 2003; Pryor et al., 2004). However, upon replicating their methods using in-situ wind speed measurements from WMO stations, we are reluctant to draw the same conclusion. Although when using the same error margin (±10%) as Barthelmie and Pryor, (2003), we obtain similar results. As the error margins narrow (from ±10% to ±1%), the discrepancy among stations becomes significant. Therefore, we suggest that the uncertainty bounds presented in Table 3 exhibit robustness and are applicable only under higher error margins, such as those exceeding ±10%. Additionally, lower moments and two Weibull parameters showed higher robustness.

Furthermore, although we provided the uncertainty bounds for datasets with fewer than 720 samples, it is important to note that we calculated these values based on an exponential function fitted to the results derived from 720 to 52,560 points. As a result, the curve may be biased due to the potential asymmetry in the distribution of the parameters (Barthelmie and Pryor, 2003).

Our results indicated that ERA5 tends to overestimate the mean and Weibull scale parameters. Discrepancies between ERA5 and observational data are unsurprising, as previous studies have noted differences in magnitude and trends (Zhou et al., 2021; Torralba et al., 2017). These discrepancies can be partly attributed to ERA5 not assimilating in-situ land observations and the inherent limitations of the ERA5 reanalysis (Hersbach et al., 2020), such as its inability to accurately reproduce mesoscale dissipation rates (Bolgiani et al., 2022). Additionally, modern data assimilation systems still struggle to adequately correct the inevitable errors in model-generated guess fields at these smaller scales (Wang and Sardeshmukh, 2021). Consequently, ERA5 may underestimate variability and fail to capture local extremes observed in in-situ data, leading to discrepancies in parameters like skewness and kurtosis. For instance, at stations SN50500 and SN38140, in-situ data show significantly more wind observations close to zero compared to ERA5 datasets, resulting in distinct wind characteristics such as differing skewness and kurtosis.

4.1 Implications

Both onshore and offshore sites exhibit seasonal variations, with onshore and near-coast locations often experiencing significant diurnal cycles (Barthelmie and Pryor, 2003; Barthelmie et al., 1996; Ashkenazy and Yizhaq, 2023). Our findings indicate that random sampling can effectively analyse wind distribution parameters, even when dealing with discontinuous data that lacks explicit diurnal or seasonal cycle information. This is particularly important given the challenges associated with accurately collecting data that reflects these cycles; factors such as anemometer malfunctions, site relocations, and other disruptions can create gaps in the wind speed data series, leading to non-continuous records (Liu et al., 2024). For instance, the Sentinel-1 Level 2 OCN ocean wind field product (1 km resolution), while performing well in offshore areas, has a revisit frequency of one to two days that may not sufficiently capture rapid temporal variations (Khachatrian et al., 2024).

It was noted that this finding is drawn from analyses utilizing a 90% confidence interval. This confidence level indicates that while minor discrepancies may exist in the data, they are considered negligible under specific statistical assumptions. Therefore, we argue that random sampling provides a practical and statistically robust alternative, particularly in scenarios where it is not feasible to retain the characteristics of diurnal cycles or seasonality.

4.2 Limitations of this study

Our study reveals several uncertainties that need to be acknowledged. The geographic scope of our data is limited; all the weather stations used in our study are in Norway. This is because the required wind speed data need to have long-term series but with hourly resolution at the same time, and such a long-term time series is rarely available publicly. We encourage researchers from other regions with access to high-quality wind speed data to replicate our study and compare the results, to verify the generalizability of our findings.

Our results may not accurately reflect the real situations for offshore sites, because our study is based on on-land weather stations, though they are located along the coast. Further, offshore wind can differ significantly from onshore. For example, we showed that ERA5 data shows an overestimation of the frequency of high wind events, while a recent study indicates that ERA5 underestimates strong wind speed offshore (Gandoin and Garza, 2024). Therefore, further studies focused specifically on offshore winds are needed.

Another limitation is the time resolution of the wind speed data we used. We utilized hourly data instead of higher temporal resolution data, such as 10-minute intervals, for wind distribution assessments. Despite this, Yang et al., (2024) demonstrated that hourly wind speed data provide sufficiently accurate estimations of wind power density, with errors smaller than ±2% when compared to 10-minute resolution data. This suggests that hourly data are suitable for such analyses. Additionally, Effenberger et al., (2024) showed that three- or six-hourly instantaneous wind speed data can effectively preserve the distribution characteristics of 10-minute wind speeds. Therefore, it is reasonable that hourly wind speed can adequately represent the characteristics of 10minute wind speeds.

It is worth noting that the hourly data provided by MET Norway represent the average wind speed over the last ten minutes of each hour rather than the entire hour. Despite this, previous research found that Weibull distribution parameters remain consistent across different averaging periods (e.g., 1 minute and 30 minutes) (Barthelmie and Pryor, 2003). Based on these findings, we believe that our use of last 10-minute averages is unlikely to significantly impact the accuracy of the Weibull distribution parameters compared to full-hour averages.

Additionally, our study focuses on near-surface wind speeds (10 m), raising questions about whether our conclusions hold at turbine-height winds. Prior studies indicate a height dependency for Weibull distribution parameters, with higher altitudes typically showing higher means (and scale parameter), variances, skewness, and kurtosis, while the shape parameter remains height-independent (Barthelmie and Pryor, 2003; Dixon and Swift, 1984). Due to the absence of observational data at heights other than 10 meters, we utilized the ERA5 dataset to compare distribution parameters at 10-m and 100-m heights. For the five locations studied, only the mean (and Weibull scale parameter), and variance show height dependency, with other parameters (skewness, kurtosis, Weibull shape parameter) showing independence from height.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

WIND ENERGY SCIENCE DISCUSSIONS
Open Access
eawe european academy of wind energy

5 Conclusions

Our study quantifies errors in wind speed distribution fitting using series of varying lengths, accounting for interannual variability. We find that skewness and kurtosis, particularly kurtosis, are systematically underestimated with limited data, especially in datasets with higher skewness and kurtosis levels, necessitating significantly longer observation periods for accurate estimates. For example, mean and standard deviation stabilize within weeks, while skewness requires over 1.6 years and kurtosis over 88.8 years for a ±5% error margin. Our findings highlight the critical influence of distribution shape on data requirements, with regional variations becoming more pronounced as precision demands increase, particularly for higher-order statistical properties like skewness and kurtosis.

This has important implications for wind resource assessment, particularly in regions with highly variable wind regimes. For such areas, extended data collection periods or advanced techniques like data fusion or machine learning may be necessary to accurately capture higher-order statistical properties. Additionally, our analysis suggests that random sampling can provide comparable accuracy to strict diurnal or seasonal sampling, offering a flexible alternative for data collection in resource-constrained settings.

Our analysis of ERA5 reanalysis data reveals that while they require fewer data points for the same error margin, they exhibit systematic biases, such as underestimating skewness and overestimating shape parameters, compared to in-situ measurements. This underscores the need for caution when using reanalysis data in wind resource assessments, particularly in regions with complex wind regimes.

Future studies should explore methods to mitigate the systematic underestimation of skewness and kurtosis, such as through data fusion or bias-correction models. Furthermore, the applicability of these findings to different geographic regions and turbine heights should be investigated to enhance the generalizability of wind resource assessment practices.

Code availability

The code used in this paper can be obtained from the author upon request.

Data availability

The observed wind speed dataset from MET Norway is available for download from at MET Norway's FROST platform (https://frost.met.no/index.html; last access: 8 February 2025). The ERA5 datasets is available at Copernicus Climate Data Store (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download; last accessed 8 February 2025).

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Author contributions

LH conceptualized the article, wrote it, and conducted the analysis, while IE supervised the project and contributed to the interpretation of the results and the writing.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

The work is part of the project "UiT - Intermittent character of wind energy resources on different spatial and temporal scales", funded by the Faculty of Science and Technology, University of Tromsø. Igor Esau acknowledges a contribution from the ESA project MAXSS 4000132954/20/I-NB.

References

Ashkenazy, Y., and Yizhaq, H.: The diurnal cycle and temporal trends of surface winds, Earth Planet. Sci. Lett., 601, doi:10.1016/j.epsl.2022.117907, 2023.

Badger, M., Peña, A., Hahmann, A. N., Mouche, A. A., and Hasager, C. B.: Extrapolating satellite winds to turbine operating heights, J. Appl. Meteorol. Climatol., 55(4), 975–991, doi:10.1175/JAMC-D-15-0197.1, 2016.

Barthelmie, R. J., Grisogono, B., and Pryor, S. C.: Observations and simulations of diurnal cycles of near-surface wind speeds over land and sea, J. Geophys. Res. Atmos., 101(16), 21327–21337, doi:10.1029/96jd01520, 1996.

Barthelmie, R. J., and Pryor, S. C.: Can Satellite Sampling of Offshore Wind Speeds Realistically Represent Wind Speed Distributions?, J. Appl. Meteorol., 42(1), 83–94, doi:10.2307/26185389, 2003.

Bolgiani, P., Calvo-Sancho, C., Díaz-Fernández, J., et al.: Wind kinetic energy climatology and effective resolution for the ERA5 reanalysis, Clim. Dyn., 59(3), 737–752, 2022.

Carta, J. A., Ramírez, P., and Velázquez, S.: A review of wind speed probability distributions used in wind energy analysis. Case studies in the Canary Islands, Renew. Sustain. Energy Rev., 13(5), 933–955, doi:10.1016/j.rser.2008.05.005, 2009.

Dixon, J. C., and Swift, R. H.: The dependence of wind speed and Weibull characteristics on height for offshore winds, Wind Eng., 87–98, 1984.

Effenberger, N., Ludwig, N., and White, R. H.: Mind the (spectral) gap: How the temporal resolution of wind data affects multi-decadal wind power forecasts, Environ. Res. Lett., 19(1), doi:10.1088/1748-9326/ad0bd6, 2024.

Gandoin, R., and Garza, J.: Underestimation of strong wind speeds offshore in ERA5: Evidence, discussion, and correction, Wind Energy Sci. Discuss., 1–22, 2024.

Gil Ruiz, S. A., Barriga, J. E. C., and Martínez, J. A.: Wind power assessment in the Caribbean region of Colombia, using ten-minute wind observations and ERA5 data, Renew. Energy, 172, 158–176, doi:10.1016/j.renene.2021.03.033, 2021.

Hersbach, H., Bell, B., Berrisford, P., et al.: The ERA5 global reanalysis, Q. J. R. Meteorol. Soc., 146, 730, doi:10.1002/qj.3803, 2020.

International Electrotechnical Commission: Wind energy generation systems - Part 12: Power performance measurements of electricity producing wind turbines - Overview (IEC 61400-12:2022), Int. Electrotech. Comm., 2022.

Jung, C., and Schindler, D.: On the inter-annual variability of wind energy generation – A case study from Germany, Appl. Energy, 230, doi:10.1016/j.apenergy.2018.09.019, 2018.

Jung, C., and Schindler, D.: Wind speed distribution selection–A review of recent development and progress, Renew. Sustain. Energy Rev., 114, 109290, doi:10.1016/j.rser.2019.109290, 2019.

Khachatrian, E., Asemann, P., Zhou, L., et al.: Exploring the potential of Sentinel-1 Ocean Wind Field Product for near-surface offshore wind assessment in the Norwegian Arctic, Atmosphere, 15(2), doi:10.3390/atmos15020146, 2024.

Liu, Y., Zhou, L., Qin, Y., et al.: Impacts of anemometer changes, site relocations, and processing methods on wind speed trends in China, Atmos. Meas. Tech., 17(3), doi:10.5194/amt-17-1123-2024, 2024.

Mohammadi, K., Alavi, O., Mostafaeipour, A., Goudarzi, N., and Jalilvand, M.: Assessing different parameters estimation methods of Weibull distribution to compute wind power density, Energy Convers. Manag., 108, 322–335, doi:10.1016/j.enconman.2015.11.015, 2016.

Ouarda, T. B. M. J., and Charron, C.: On the mixture of wind speed distribution in a Nordic region, Energy Convers. Manag., 174, 33–44, doi:10.1016/j.enconman.2018.08.007, 2018.

Pryor, S. C., Barthelmie, R. J., Bukovsky, M. S., et al.: Climate change impacts on wind power generation, Nat. Rev. Earth Environ., 1(12), 627–643, doi:10.1038/s43017-020-0101-7, 2020.

Pryor, S. C., Nielsen, M., Barthelmie, R. J., and Mann, J.: Can Satellite Sampling of Offshore Wind Speeds Realistically Represent Wind Speed Distributions? Part II: Quantifying Uncertainties Associated with Distribution Fitting Methods, J. Appl. Meteorol. Climatol., 43(5), 739–750, 2004.

Ramon, J., Lledó, L., Torralba, V., Soret, A., and Doblas-Reyes, F. J.: What global reanalysis best represents near-surface winds?, Q. J. R. Meteorol. Soc., 145(724), 3236–3251, doi:10.1002/qj.3616, 2019.

Soares, P. M. M., Lima, D. C. A., and Nogueira, M.: Global offshore wind energy resources using the new ERA5 reanalysis, Environ. Res. Lett., 15(10), doi:10.1088/1748-9326/abb10d, 2020.

Torralba, V., Doblas-Reyes, F. J., and Gonzalez-Reviriego, N.: Uncertainty in recent near-surface wind speed trends: A global reanalysis intercomparison, Environ. Res. Lett., 12(11), doi:10.1088/1748-9326/aa8a58, 2017.

Wang, J. W., and Sardeshmukh, P. D.: Inconsistent global kinetic energy spectra in reanalyses and models, J. Atmos. Sci., 78(8), 2589–2603, 2021.

Wang, J., Hu, J., and Ma, K.: Wind speed probability distribution estimation and wind energy assessment, Renew. Sustain. Energy Rev., 60, 881–899, doi:10.1016/j.rser.2016.01.057, 2016.

https://doi.org/10.5194/wes-2025-25
Preprint. Discussion started: 27 February 2025

Wang, W., Chen, K., Bai, Y., Chen, Y., and Wang, J.: New estimation method of wind power density with three-parameter Weibull distribution: A case on Central Inner Mongolia suburbs, Wind Energy, 25(2), 368–386, doi:10.1002/we.2677, 2022.

Yang, X., Tao, Y., Jin, Y., et al.: Time resolution of wind speed data introduces errors in wind power density assessment, Energy Convers. Manag. X, 24, doi:10.1016/j.ecmx.2024.100753, 2024.

Zhou, L., Zeng, Z., Azorin-Molina, C., et al.: A continuous decline of global seasonal wind speed range over land since 1980, J. Clim., 34(23), doi:10.1175/JCLI-D-21-0112.1, 2021.