Can Satellite Sampling of Offshore Wind Speeds Realistically Represent Wind Speed Distributions?

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(Manuscript received 30 January 2002, in final form 8 July 2002)

ABSTRACT

Wind speeds over the oceans are required for a range of applications but are difficult to obtain through in situ methods. Hence, remote sensing tools, which also offer the possibility of describing spatial variability, represent an attractive proposition. However, the uncertainties inherent in application of current remote sensing methodologies have yet to be fully quantified. Aside from known issues regarding absolute accuracy and precision, there are a number of biases inherent in remote retrieval of wind speeds using satellite-borne instrumentation that lead to overestimation of the wind resource and are demonstrated here to be of sufficient magnitude to merit further consideration. As an interim measure, error bounds are proposed for the wind speed probability distribution parameters, which may be applied to sparse datasets such as those likely to be obtained from satellite-borne instrumentation.

1. Introduction

a. *The need for wind speed observations over the sea surface*

A number of applications ranging from evaluation of climate variability and models (e.g., Isemer and Hasse 1991) to estimation of air–sea exchange (e.g., Erickson et al. 1999) and wind energy resources (e.g., Barthelmie et al. 2000) rely upon estimation of wind speeds over the sea surface. Hence, significant effort has been expended to develop robust and homogeneous datasets from historical shipboard observations of sea state (e.g., Isemer and Hasse 1991). Difficulties in quantitatively reconciling measured winds and visual observations are the subject of a long and unresolved debate (Bumke and Hasse 1989; Ive 1987). Further, visual observations of the sea surface were taken infrequently or at irregular intervals (Lindau et al. 1990), giving similar interpretation problems (Peterson and Hasse 1987) to those currently being experienced by users of remotely sensed wind speeds. Hence, despite reanalysis of the historical data and recent supplementation of measurements from ships and buoy networks with data from a few offshore meteorological masts (Barthelmie 1999a), marine winds are typically less reliable and are undersampled in historical and current datasets relative to land surfaces.

Remote sensing offers the potential to develop more comprehensive and spatially resolved datasets over the oceans, but the adequacy and robustness of these data remain uncertain. Wu (1995) presented an analysis of remotely sensed (altimeter) wind speeds relative to model output and coincident in situ observations and determined large, systematic deviations in the resolved mean flow fields.

In the case of wind energy applications, available wind power density is related to the cube of the wind speed. Hence, to develop wind resource estimates for any location it is necessary not only to adequately characterize the mean wind speed but also the higher moments or other descriptive parameters of the wind speed probability distribution (Pryor and Barthelmie 2002). Wind energy, therefore, represents a stringent test of remotely sensed (and in situ) observations.

b. *Wind speed probability distributions*

A number of probability distribution functions have been fitted to, or used to represent, wind speed data (Justus et al. 1976). However, the most commonly used

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is the two-parameter Weibull distribution, which has been shown to give a good fit to observed wind speed distributions particularly over water surfaces (Pavia and O'Brien 1986; Isemer and Hasse 1991). The two parameters of the Weibull distribution are k, the dimensionless shape parameter, and c, the scale parameter. The shape parameter (k) is inversely related to the variance of wind speed (U) around the mean value, and the scale parameter (c) is related to the mean of the time series; both are a function of the data averaging period (Conradsen et al. 1984). The Weibull cumulative probability distribution is

$$P(U) = 1 - \exp\left[-\left(\frac{U}{c}\right)^{k}\right]. \quad (1)$$

The available wind power density (E, which is proportional to the cube of the wind speed) may be calculated from the Weibull distribution parameters as follows:

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

where ρ is the air density and Γ is the gamma function.

In the subsequent analysis we use the first–fourth moments of the distribution (described using the mean, standard deviation, skewness, and kurtosis) (Rice 1995) and the Weibull distribution (shape and scale parameters) to describe the probability density functions of wind speed datasets, and we calculate the energy density as shown in (2) from each Weibull fit to the wind speed probability distributions. The Weibull parameters are calculated here from the mean and median of the dataset and are validated based on the variance according to the following taken from Troen and Petersen (1989):

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

$$\text{median} = c(\ln 2)^{1/k}, \quad \text{and} \quad (4)$$

$$\text{variance} = c^{2}\left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^{2}\left(1 + \frac{1}{k}\right)\right]. \quad (5)$$

c. Remote sensing of wind speed distributions offshore

Currently, wind resource information is obtained by deploying instrumentation on an in situ meteorological mast for a period of at least 1 yr, as well as by using statistical models to develop a climatological dataset from those observations, which is then used to compute the probability distribution descriptors and power output predictions. Given the obvious difficulties and expense of monitoring wind resources offshore (Barthelmie 1999a), satellite observations are an attractive proposition since in principle they also offer the potential to assess spatial variability of wind speed and direction (see special issue of the *Journal of Geophysical Research: Oceans,* 1998, vol. 103, No. 4).

Synthetic Aperture Radar (SAR) images are currently available from the *European Remote-Sensing Satellite-2* (*ERS-2*) and the Canadian *Synthetic Aperture Radar Satellite-1* (*RADARSAT-1*). The *ERS-2* orbits such that at the midlatitudes a region is sampled approximately three times a month. The SAR sensors are cloud penetrating and have a resolution of 30 m $\times$ 30 m or better, although the signal may be quenched by thick clouds or heavy precipitation, and complex flow (atmospheric or oceanic) may lead to additional difficulties in signal interpretation. However, typically 100 cells are composited to reduce noise; hence, the operational resolution is on the order of 300 m $\times$ 300 m. The SAR sensors operate at a wavelength of approximately 5 cm and most of the backscatter is derived from capillary waves on the sea surface. Because capillary waves are dependent on atmospheric forcing, the backscatter coefficient is a function of wind direction and speed (in addition to incidence angle), and lookup tables or empirical algorithms are used to relate the observed backscatter to wind speed at a nominal height of 10 m (Korsbakken et al. 1998). The accuracy of SAR has been reported to be ± 2 m s^{-1} in the range of wind speeds of 2–24 m s^{-1}, although the absolute error may be higher at the extremes of the range (Kerbaol et al. 1998), especially if the wind direction is not known a priori (Korsbakken et al. 1998) or the spatial resolution is high ($\gtrsim$2 km) (Lehner et al. 1998).

d. Reconciling remotely sensed wind speeds with in situ observations

Aside from questions regarding the absolute accuracy of wind speeds derived from remote sensing (e.g., Wu 1995; Stoffelen 1998), difficulties in reconciling remotely sensed wind speeds and in situ observations arise from several factors, described below.

1) Differing averaging periods of the observations

For example, SAR uses a wavelength of 5 cm and responds most strongly to reflection at a wavelength of the wave spectra (capillary waves) that is almost instantaneously coupled to the atmospheric flow (equilibrium is reached in $<$1 min), whereas most in situ observations of wind speed are typically averaged over 10-, 30-, or 60-min periods.

2) Dataset density

In common with meteorological observations, satellite processing may occur over a short time period in climatological terms. In the case of in situ meteorological observations, assuming the data period is not less than 1 yr and does not reflect seasonal bias, a measure of the interannual variability from nearby sites is typically used to provide an estimate of the error associated with disregarding longer-timescale variability. However, in the case of remotely sensed observations, dataset density is limited not only by sampling time (the time series length), but by the number of observations that can realistically be derived from remotely sensed images because of a limited number of satellite passes and limitations imposed by image processing time [a schematic of the processing steps is given in Korsbakken et al. (1998)]. For example, in the Wind Energy Mapping Using Synthetic Aperture Radar (WEMSAR) project sponsored by the European Union (Johannessen et al. 2000), fewer than 28 images will be processed to assess the resource at each potential wind farm location.

3) Temporal biases

Remote sensing data may exhibit temporal selectivity introduced as the satellite orbits the globe. Despite the common belief that offshore areas do not exhibit diurnal wind patterns, these cycles have been shown to exist in coastal areas, although they may be inverted or shifted as compared with typical onshore diurnal wind patterns (Barthelmie et al. 1996b). Hence, if the area under investigation is subject to a distinct diurnal cycle and the satellite pass occurs at a fixed time (or times) of the day, the remotely sensed wind speeds may be biased relative to data collected throughout the entire day.

4) Truncation of the actual wind speed distribution

The observations obtained by any technique may reflect only a portion of the actual data distribution because of limitations in the operational range of both in situ meteorological instrumentation (e.g., anemometers) and the algorithms used to derive wind speeds from the satellite-borne instrumentation. In the case of the data presented here, the cup anemometers have an operational range of 0.2–70 m s^{-1}. The operational range of the SAR calibration is assumed to be 2–24 m s^{-1}.

5) Selection criteria applied for image processing

A number of criteria may be used for image selection, including exclusion of satellite passes where a front was observed to pass (to avoid highly complex wind fields) (Korsbakken et al. 1998) or for preferential selection for high wind speeds (low wind speeds are associated with low radiation scatter and hence higher uncertainty in the SAR interpretation). Because image selection criteria are subjective and are therefore operator-dependent we shall neglect biases associated with image selection in this analysis.

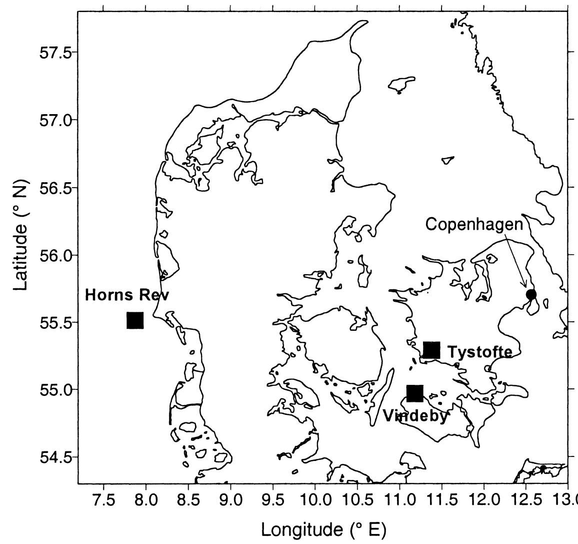

FIG. 1. Location of the meteorological masts from which data are presented.

e. This research

In this manuscript we quantify the biases in derived wind speed distribution parameters (moments and parameters from the Weibull distribution) and forecast wind power potential resulting from the points given in sections 1d(1)–1d(4). It is important to note that this analysis is not an evaluation of the accuracy of SAR retrieval of wind speeds; rather it is an analysis focusing on the biases relative to in situ measurements introduced by differing sampling protocols. These biases would remain even if the remotely sensed observations were perfectly accurate with respect to in situ measurements.

The analysis presented is based on in situ datasets collected at two offshore sites in the waters around Denmark:

1) An offshore mast in the Vindeby offshore wind farm located 2 km from the coast (Fig. 1) (Barthelmie et al. 1996a). Half-hourly mean wind speeds and the standard deviation of scalar wind speed have been collected on an offshore mast (SMW) at a height of 48 m MSL over the period November 1993 to August 2001 giving a database of 111 557 records (82% data recovery). Data from other measurement heights and at higher temporal resolution (1 min) are available for shorter time periods.
2) A meteorological mast at Horns Rev, the site of a prospective wind farm, located 16 km west of the coast of Denmark (Fig. 1; Neckelmann and Petersen 2000). The data record from Horns Rev is considerably shorter than that from Vindeby (from June 1999 onward). These data are used here to evaluate whether the results of the analyses conducted using the Vindeby dataset are significantly biased by near-coastal effects. Horns Rev is also one of the sites undergoing an evaluation of the application of SAR

TABLE 1. Probability distribution descriptive parameters for data from the Vindeby site conditionally sampled as described in the first column.

Conditional sampling criteria	Height (m)	Data averaging period (min)	Moments: Mean (m s^{-1})	Moments: Std dev (m s^{-1})	Moments: Skewness	Moments: Kurtosis	Weibull parameters: Shape (k)	Weibull parameters: Scale (c) (m s^{-1})	Energy density (W m^{-2})
Entire dataset	48	30	7.99	3.64	0.466	0.177	2.26	9.02	522
Coincident measurement: 1-min avg	48	1	7.54	3.25	0.471	−0.244	2.32	8.52	431
Coincident measurement: 30-min avg	48	30	7.54	3.20	0.434	−0.375	2.34	8.51	427
1100–1200 and 2200–2300 DST	48	30	8.06	3.65	0.457	0.229	2.35	9.09	519
0300–0400 DST	48	30	7.80	3.54	0.535	0.302	2.14	8.81	509
U_{48} = 2–24 m s^{-1}	48	30	8.19	3.48	0.573	0.103	2.16	9.25	585
Cumulative SAR criteria: 1100–1200 and 2200–2300 DST, U_{48} = 2–24 m^{-1}	48	30	8.26	3.49	0.554	0.103	2.26	9.33	577
Coincident measurements: two heights	10	30	6.81	3.09	0.468	0.130	2.29	7.69	320
	48	30	7.87	3.57	0.494	0.325	2.29	8.88	493

to provide offshore wind resource estimates within the WEMSAR project (Johannessen et al. 2000).

Data from the Tystofte mast on the Danish island of Zealand (Fig. 1), which has been operating continuously since 1983, are used to present an assessment of the Vindeby dataset distribution parameters in a climatological context.

To examine the impact that the sampling that characterizes SAR (and other remote sensing of wind speeds over oceans) has on the resulting observations relative to in situ observations, we conditionally sample in situ data records to replicate data that might reasonably be obtained via remote sensing tools. We first present an analysis of the difference in wind speed distribution parameters derived using a dataset containing 1-min-average observations and derived from coincident observations recorded as 30-min averages. Then we present an analysis of the 30-min-average wind speed datasets from Vindeby and Horns Rev in which we degrade the observational datasets with respect to the items in sections 1d(2)–1d(4) and repeatedly resample the data to determine the ‘‘new’’ distribution parameters and to derive uncertainty bounds applicable for use with probability distribution parameters from a sparse wind speed dataset. Last, we present an assessment of the uncertainties in this analysis and document the implications for wind resource estimation.

2. Data analysis

a. *Sensitivity of the wind speed distribution parameters to averaging period*

The influence of sampling period on resulting mean wind speed has long been an issue in meteorology, and for marine wind sampling in particular. As indicated by Børreson (1987), shorter sampling periods (e.g., 1 min) lead to higher gusts and means than long averaging periods (e.g., 1 h). While differences in the mean wind speed estimated using different averaging periods are small (and $\rightarrow 0$), if a long time series is used, differences in the variance and skewness are important to wind power estimation (Petersen et al. 1981).

To examine the differences in wind speed probability distribution parameters derived from remote sensed SAR pseudoinstantaneous realizations of the wind field versus 30-min-average data derived from in situ measurements, probability distribution parameters from the Vindeby mast were computed for 1-min- and 30-min-average wind speeds. To ensure that any differences in the distribution parameters are due to differences in the data averaging period, coincident measurements from the datasets containing 1-min- and 30-min-average observations from the Vindeby SMW at 48-m height were selected and analyzed with respect to the distribution parameters. The results are summarized in Table 1 and indicate that the 30-min-average data capture most of the variability present in the 1-min data series and that the Weibull distribution parameters for the two datasets are equivalent. This result is not unexpected since the two dataset blocking (or averaging) periods span part of what is commonly referred to as the spectral gap (Stull 1988); as Petersen et al. (1981) note, differences in statistics generated from 10-minute to 1-h averages tend to be small due to the shape of the variance spectrum.

b. *Dependence of the wind speed distribution parameters on dataset density (number of observations)*

To examine the dependence of the distribution parameters on dataset density (i.e., number of observations in the time series) the dataset from Vindeby SMW was randomly and multiply resampled for a range of number of observations from $n = 21$ (assumed to be the lower bound on the dataset likely to be obtained using remote sensing) to $n \sim 0.1$ of the actual number of observations available from Vindeby for the entire data collection period (i.e., $n = 10\,000$). The resampling was undertaken with sample replacement (so the same observation could be selected multiple times within one resampling

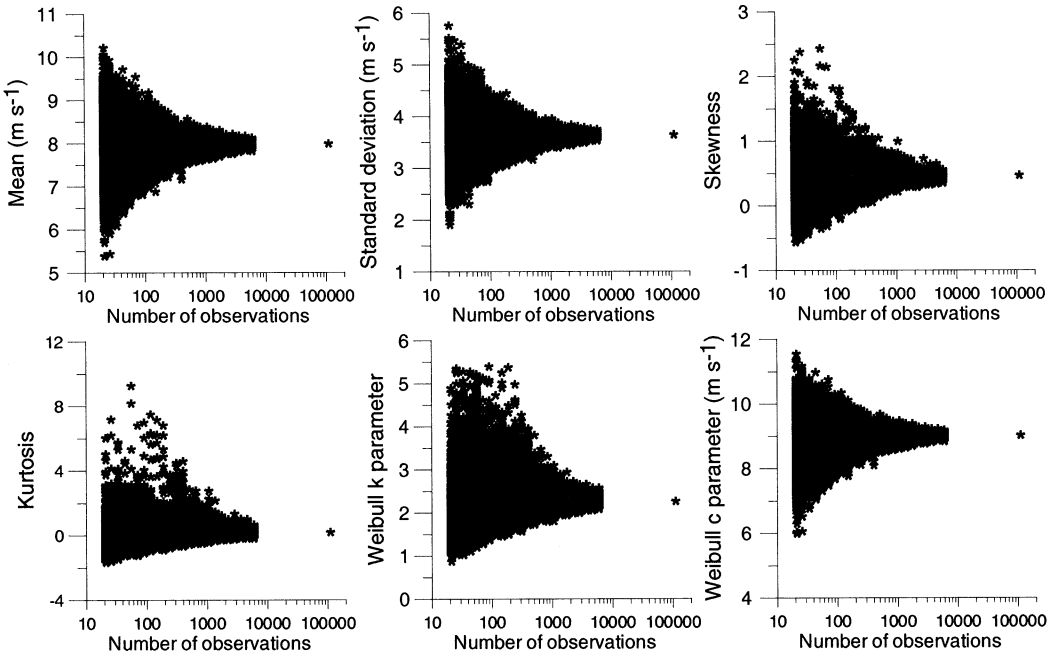

FIG. 2. Six wind speed distribution parameters (mean, standard deviation, skewness, kurtosis, and the Weibull k and c parameters) shown for each of the 1000 iterations for each number of observations (from $n = 21$ to $n = 0.1$ of the total number of observations in the dataset), plus the value of each parameter calculated for the entire dataset (i.e., for $n = 111\,557$). As shown, the absolute range of mean (m s^{-1}), std dev (m s^{-1}), skewness, and kurtosis calculated for each of the 1000 resampled groups is 5.39–10.22, 1.90–5.76, −0.57–2.25, and −1.66–6.02, respectively; the maximum percent error is −33–28, −48–58, −221–383, and −1040–3303, respectively.

group and/or in two or more of the 1000 resampling groups for each n) using the Park and Miller ''Minimal Standard'' random number generator. The results are presented in Fig. 2 for the four moments of the distribution and the Weibull parameters for 1000 resampling iterations for each n. As expected, the mean wind speed is the most robust characteristic of the dataset, and both the random error associated with each resampled group and the systematic error (or bias) in estimation of the mean are low, even for small n. The error is larger for the standard deviation (maximum difference in median standard deviation, and the time series value is −0.12 m s^{-1} indicating the standard deviation is, on average, slightly underestimated for $n = 21$). Again, the error reduces rapidly with increasing n. The higher moments are, as expected, less robust with low sample numbers. The median skewness for $n = 21$ is 0.375 (i.e., 20% lower than the time series value), while the median kurtosis is −0.649 for $n = 21$ (relative to the time series mean of 0.177). These results indicate that for low n each of the moments of the probability distribution is, on average, underestimated (i.e., there is a systematic bias in the calculated moments). The results further indicate a very large range in the estimated distribution parameters for the resampling groups and hence high uncertainty at low n. The errors in the moments for all of the 1000 samples for each n decline to below ±10% at $n = 200$ for the mean, $n = 600$ for the standard deviation, and $n > 9000$ for the skewness and kurtosis. The c parameter of the Weibull distribution is related to the distribution mean, and like the mean is relatively well characterized even at low n. The k parameter is related to the variability about the mean and shows both a high degree of uncertainty and significant bias even for $n > 500$. Table 2 summarizes the number of randomly distributed observations (i.e., observations taken without diurnal or seasonal bias) required to obtain an estimate of the distribution parameters within ±10% of the actual time series value at a confidence level of 90%.

TABLE 2. The number of randomly distributed observations required to obtain an estimate of the distribution parameters within ±10% of the actual time series value for a confidence level of 90% calculated from the half-hourly average wind speeds measured at 48 m at Vindeby SMW computed with statistics derived from the initial database of 111 557 observations.

Mean	Std dev	Skewness	Kurtosis	Weibull k	Weibull c	Energy density
56	150	9712	>10 000	1744	71	1744

Table 3 shows the upper and lower bounds on the 90% confidence interval for the wind speed distribution parameters for varying numbers of observations (n). These confidence intervals are specified such that 90% of realizations were within ± the specified error from the actual dataset mean (computed without conditional sampling). As shown, the confidence intervals exhibit a power form with increasing n:

TABLE 3. Here are shown 90% confidence intervals calculated for the wind distribution parameters and energy density, such that an observation will approximate the actual mean value for the entire dataset ± the specific error (Y) (expressed as the percentage of the mean value) for a given number of observations (n). These equations were calculated using data from Vindeby SMW for $n = 21$ to 1061.

Parameter: Error bar	Equation (derived from 48-m data from Vindeby, entire dataset)	Equation (derived from 10-m data from Vindeby, SAR criteria)
Wind speed: negative	$Y = -\exp[-0.497 \ln(n) + 4.246]$	$Y = -\exp[-0.512 \ln(n) + 4.293]$
Wind speed: positive	$Y = \exp[-0.497 \ln(n) + 4.246]$	$Y = \exp[-0.508 \ln(n) + 4.146]$
Std dev: negative	$Y = -\exp[-0.517 \ln(n) + 4.900]$	$Y = -\exp[-0.470 \ln(n) + 4.734]$
Std dev: positive	$Y = \exp[-0.493 \ln(n) + 4.740]$	$Y = \exp[-0.554 \ln(n) + 5.020]$
Weibull k: negative	$Y = -\exp[-0.393 \ln(n) + 5.092]$	$Y = -\exp[-0.360 \ln(n) + 5.025]$
Weibull k: positive	$Y = \exp[-0.301 \ln(n) + 5.017]$	$Y = \exp[-0.280 \ln(n) + 4.999]$
Weibull c: negative	$Y = -\exp[-0.545 \ln(n) + 4.622]$	$Y = -\exp[-0.540 \ln(n) + 4.454]$
Weibull c: positive	$Y = \exp[-0.468 \ln(n) + 4.069]$	$Y = \exp[-0.488 \ln(n) + 4.012]$
Energy density: negative	$Y = -\exp[-0.294 \ln(n) + 4.604]$	$Y = -\exp[-0.239 \ln(n) + 4.181]$
Energy density: positive	$Y = \exp[-0.628 \ln(n) + 6.813]$	$Y = \exp[-0.619 \ln(n) + 6.672]$

$$\ln(Y) = \ln(n) + \text{const}, \tag{6}$$

where Y is the percent error and n is the number of observations.

As also shown, the error bars for the higher moments are asymmetric, reflecting the average bias in estimation of parameters at low sample numbers due to the non-Guassian underlying probability distribution.

c. Dependence of the wind speed distribution parameters on diurnal bias

Because synoptic-scale systems exhibit no significant diurnal cycle, on climatological timescales midlatitude offshore locations experience homogenous forcing and hence exhibit no significant diurnal cycle. However, as shown in Fig. 3, wind speed observations at both the Vindeby (2 km from the closest shoreline) and Horns Rev (16 km from the closest shoreline) masts exhibit significant diurnal cycles due largely to advective effects (see Barthelmie et al. 1996b). Since the timing of the satellite overpasses is unlikely to be chosen specifically for wind resource analysis, careful analysis of the diurnal cycle of wind speeds is appropriate for locations within the coastal zone, particularly in complex areas such as archipelagos or where the thermal regime produces sea breezes or low-level jets.

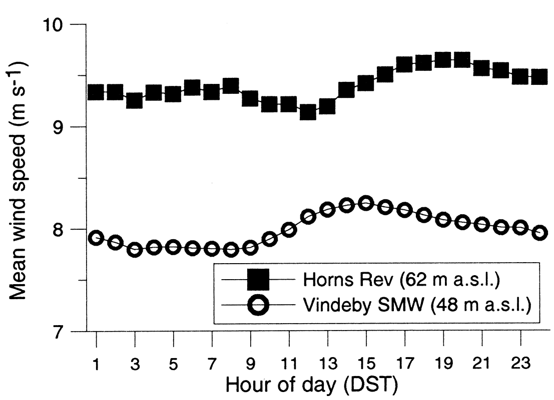

FIG. 3. Diurnal cycles of mean wind speed at Vindeby SMW computed using 30-min-average data collected at a height of 48 m MSL for the entire data record and at Horns Rev for 10-min-average data collected at a height of 62 m MSL.

The European satellite carrying the SAR instrumentation passes over Denmark at 1030 or 2130 UTC with a repeat track of approximately 10 days. To determine the influence on the wind speed distributions resulting from this diurnal bias, the observational data from Vindeby were conditionally sampled, where records were only selected if the data record start time fell between 1100 and 1200 or 2200 and 2300 Danish standard time (DST). The resulting wind speed distribution parameters are shown in Table 1. As shown, selection of time periods associated with the *ERS-2* passage over Denmark tends to lead to slightly higher mean wind speeds than those calculated using the dataset from Vindeby SMW, but otherwise the distribution parameters are well characterized. However, if the satellite passed only at 0300–0400 DST then, as shown in Table 1, the wind speed distribution parameters would significantly deviate from those calculated for the data series as a whole.

d. Dependence of the wind speed distribution parameters on the operational range of the SAR algorithms

SAR has a reported operational range of 2–24 m s^{-1}. To determine the influence on the wind speed distributions resulting from this truncation of the actual wind speed distribution, the data collected at a height of 48 m at Vindeby SMW were conditionally sampled for this wind speed range and the distribution parameters were recomputed. As shown in Table 1, the bias introduced by exclusion primarily of low wind speeds (few 0.5-h-average observed wind speeds exceed 24 m s^{-1}) is manifest as an increase in the mean and positive skewness, and reduced variance and kurtosis. In terms of the Weibull parameters, the shape parameter is reduced and the scale is increased. The impact on the mean and skewness by truncation of the wind speed dataset is more pronounced than any of the other sampling criteria and, as will be discussed later, has a profound impact upon the estimated wind resource.

e. *Cumulative impact of sampling bias on wind speed distributions*

Sections 2a–d report the individual effects of sampling bias upon the wind speed distribution as manifest in the data collected at Vindeby. However, the bias resulting from these effects need not be additive, and so to assess the cumulative effect of biases associated with nonrandom temporal allocation of data acquisition, low sampling number, and truncation of the wind speed distribution, the dataset from Vindeby was conditionally sampled such that observations were selected only if they represented data collected between 1100 and 1200 or 2200 and 2300 DST and had values between 2 and 24 m s^{-1} (Table 1). These data were then multiply resampled (for $n = 21$ to $n = 0.1$ times the number of observations) to generate the wind speed parameters for varying n shown in Fig. 4. As shown, while the errors for individual resampled groups are large for all parameters, the systematic bias is larger for the higher moments and the Weibull k parameter. As also shown in Fig. 4 and Table 1, the cumulative impact of selecting data that most closely represent those that might be obtained from SAR for this region is to overestimate wind speeds, and hence energy density.

f. *Analysis for Horns Rev*

To assess the generalizability of the results presented earlier for other midlatitude locations and for regions less strongly influenced by the coastal discontinuity, data from Horns Rev measured at a height of 62 m MSL during the period June 1999 to May 2000 were subjected to the conditional sampling as described in section 2e. As shown in Fig. 5, qualitatively similar results were found for the Horns Rev data to those articulated for the Vindeby data, in that the selection of data that most closely replicate remotely sensed observations leads to a high degree of uncertainty in the wind speed distribution parameters and, on average, to overestimation of the wind speed.

To assess the applicability of the 90% confidence intervals derived for the mean, standard deviation, and Weibull distribution parameters based on sparse resampling of the Vindeby dataset, the entire Horns Rev dataset was resampled for varying n and the 90% confidence interval from the data was compared with that predicted by the fits described in Table 3. The results, shown in Fig. 6, indicate generally good agreement between the uncertainty bounds derived from the Vindeby dataset and those determined from the Horns Rev data. The least-well-predicted parameter is the Weibull shape parameter because of its relationship with data variance. Based on this analysis, it may be inferred that the uncertainty bounds described in Table 3 have general applicability.

3. Discussion and implications

a. *Summary of the effect of sampling bias on wind speed probability distributions and limitations of the research*

Prior to discussion of biases in the wind speed probability distribution parameters inherent in remotely sensed marine wind speed datasets (by SAR), it is worthy of note that Justus et al. (1978) showed evidence of a height dependence of the Weibull scale and shape parameters over relatively high roughness surfaces. Wind speeds derived from SAR equate to a nominal measurement height of 10 m MSL while the data from Vindeby represent a measurement height of 48 m MSL. To assess the magnitude of the difference in nominal measurement height on the wind speed distribution parameters, 0.5-h-average wind speed data from Vindeby for the period when anemometers were operated at two measurement heights, 48 and 10 m MSL, (1996 to date) were used to calculate the distribution parameters summarized in Table 1. As shown, the distribution parameters all exhibit height dependence except the Weibull shape parameter (k), which is equal at the two heights. The latter is in accord with the analysis of Dixon and Swift (1984) who suggested the shape parameter in the Weibull distribution is independent of height over water surfaces. However, the height dependencies of the other distribution parameters are large, with the lower measurement height indicating lower mean (and c parameter), variance, skewness, and kurtosis. Hence, the uncertainty bounds calculated using the in situ observations from 48-m height are not directly applicable to remotely sensed data for a nominal height of 10 m. For this reason, the analysis was repeated using a shorter dataset available for a height of 10 m at Vindeby (May 1996–August 2001). The results are summarized in Table 3 and Fig. 7 in terms of the 90% confidence interval that can be applied to the wind speed distribution parameters and energy density estimates derived for sparse datasets as would be derived from SAR analysis. As shown in Table 3, the asymmetries in the uncertainty bounds and the form of the power-law fits to the uncertainty bounds are very similar to those derived for the data from 48 m.

It should be noted that a critical aspect of the applicability of the results (and uncertainty bounds) presented here is that the datasets are randomly drawn from the time series with respect to seasonality. It should further be noted that it is well known that mean wind speeds vary on an interannual basis and that while this variability is small in comparison with the intraannual variability, sampling for 1 yr does not provide a sufficient basis for a wind resource estimate. A number of statistical methods [such as measure-correlate-predict

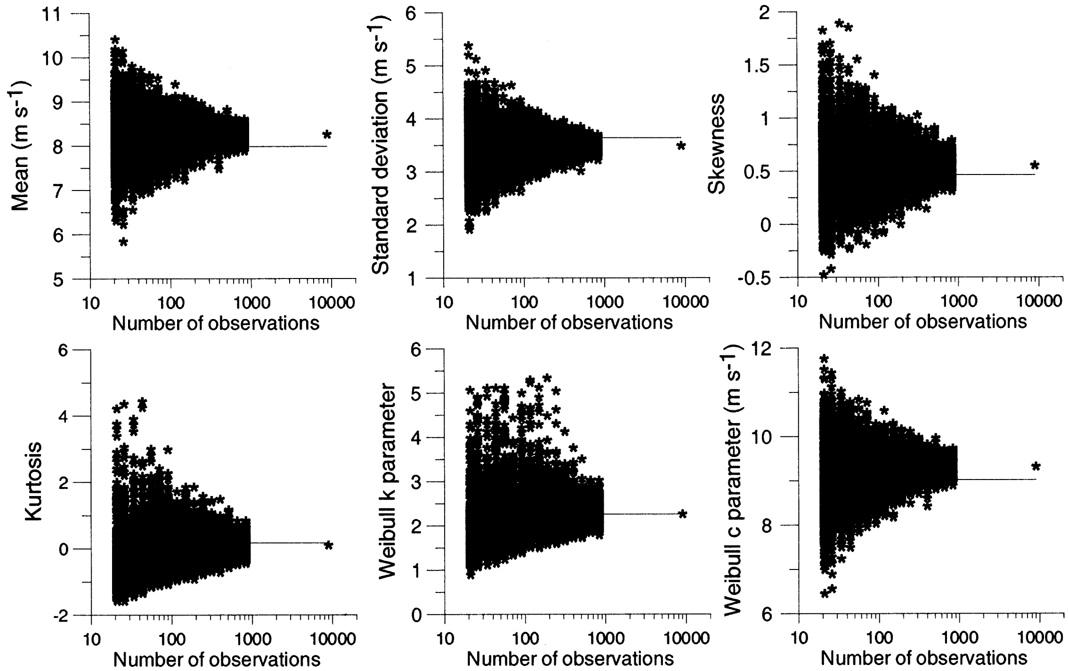

FIG. 4. Six wind speed distribution parameters (mean, std dev, skewness, kurtosis, and the Weibull k and c parameters) shown for each of the 1000 iterations for each number of observations (from $n = 21$ to $n = 0.1$ of the total number of observations that meet the criteria described in section 2e). Data are from Vindeby SMW. The horizontal lines indicate the parameter estimates derived from the entire dataset.

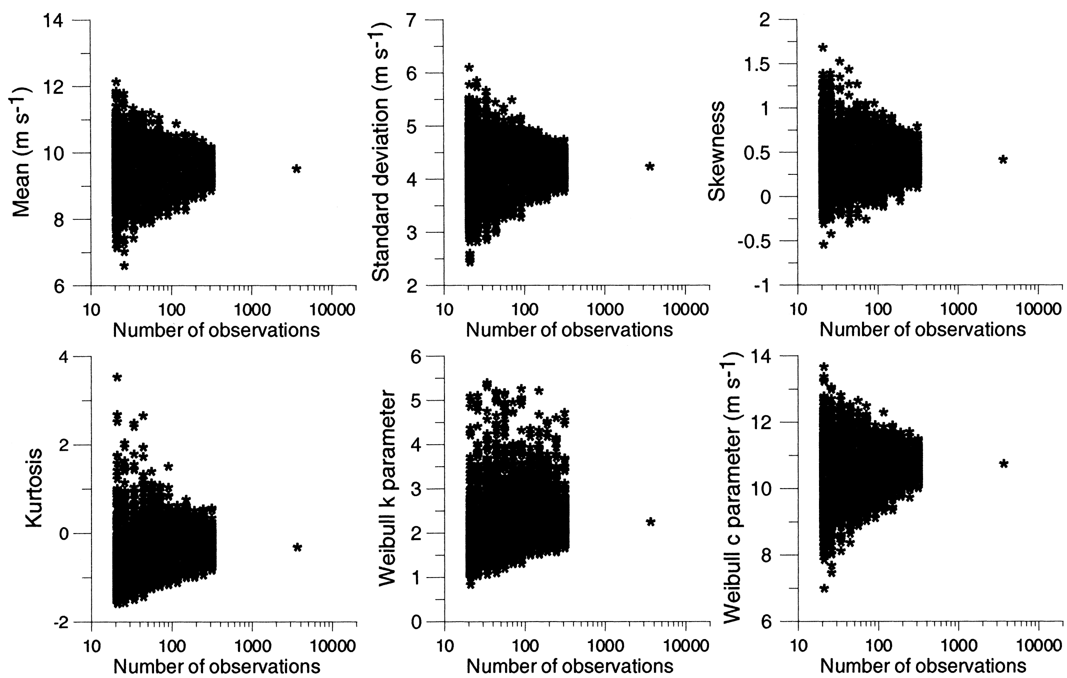

FIG. 5. Six wind speed distribution parameters (mean, std dev, skewness, kurtosis, and the Weibull k and c parameters) shown for each of the 1000 iterations for each number of observations (from $n = 21$ to $n = 0.1$ of the total number of observations that meet the criteria described in section 2e). Data are from Horns Rev.

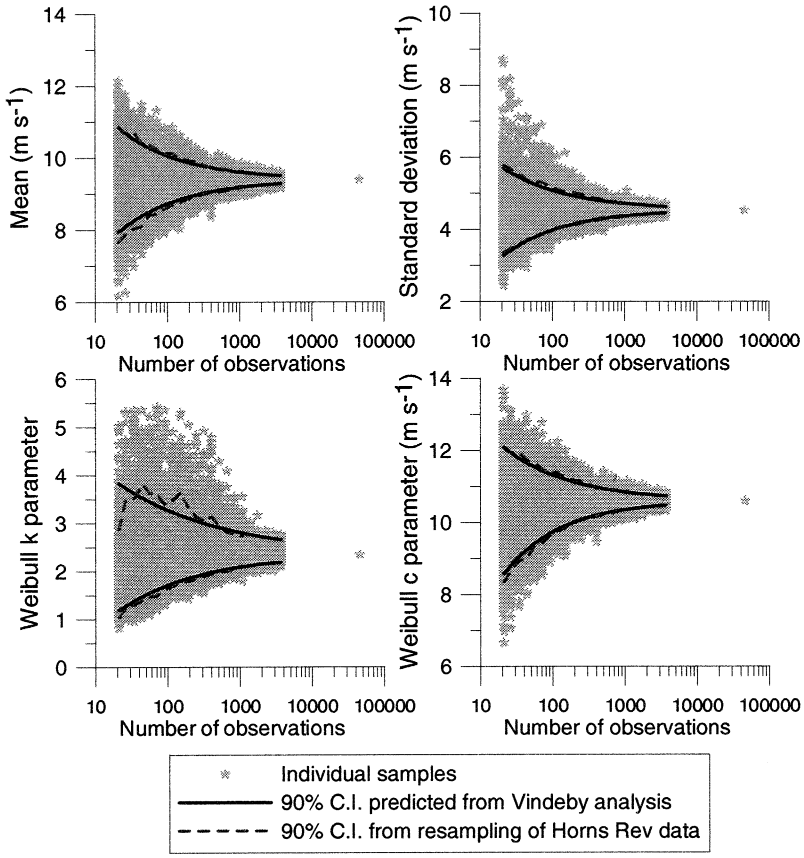

FIG. 6. The mean, std dev, and Weibull *k* and *c* parameters from the resampling of the entire Horns Rev dataset. The lines show the 90% confidence interval based on the data from Horns Rev (labeled "90% C. I. from resampling . . .") and the 90% confidence interval predicted from the fits described in Table 3 and calculated from the Vindeby SMW dataset (labeled as "90% C. I. predicted . . .").

(Woods and Watson 1997)] or models [such as Wind Analysis and Application Program (WASP; Mortensen et al. 1993)] may be used to link short-term records with longer-term datasets, thus producing climatologically representative statistics (Barthelmie 1999b). As shown in Fig. 8, annual mean wind speeds at Tystofte and Vindeby were below average during 1999 (about 3% lower than the mean for the data series). Additionally, there is some evidence that the dataset mean for the period 1994–2000 slightly underestimates the climatological mean (based on the Tystofte data from 1983–2000; see Table 4). The implication of the relatively low mean wind speeds during the last 7 yr in Denmark relative to the preceding 10 for the present analysis is that the uncertainty bounds presented in section 2 may slightly underestimate those calculated from a climatological data series.

b. Implications for predicted power output for offshore wind farms

As shown in Fig. 9, there is a distinct asymmetry in the distribution of energy density calculated for each of the randomly sampled (sparse) wind speed distributions derived in section 2b. This indicates that in addition to very large uncertainty for low *n*, on average, the wind power density as calculated from the Weibull distribution is likely to be overpredicted in excess of 10% for $n < 90$, as a result of poor fitting of the *c* and *k* parameters.

Table 1 summarizes wind power (or energy) density calculated from the Weibull parameters, as shown in (2), for each of the selective sampling analyses. The results indicate that, in terms of wind resource estimation for Vindeby, there is a small diurnal signal with slightly lower average energy density in the early morning (0300–0400 DST). Although the 1- versus 30-min data comparison differs from the long-term average because of the dominance of summer data in the subsample, the higher-temporal-resolution data do not differ significantly from the 30-min average in terms of estimated energy density. The largest effect, neglecting the sparse data series analysis, is the bias introduced by truncation of the dataset to replicate the operational range of the SAR algorithms. The energy density calculated using the distribution parameters calculated for

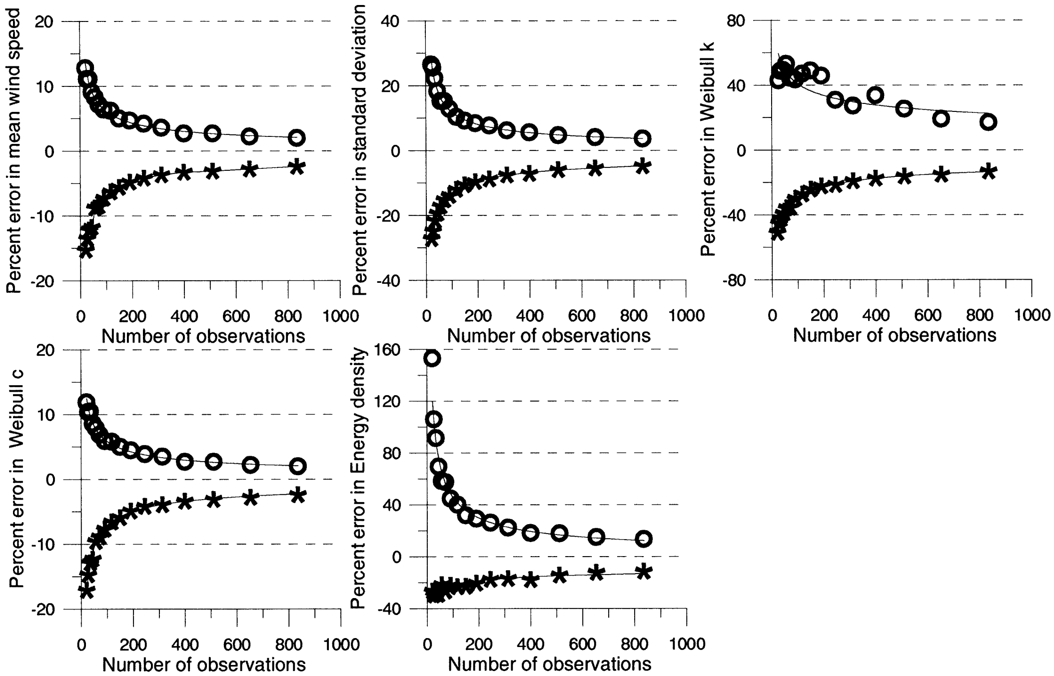

FIG. 7. The 90% confidence interval for percent errors in the wind speed probability distribution parameters and energy density for measurements from 10 m taken at Vindeby SMW. The fits are given in Table 3.

$2 < U < 24$ m s^{-1} is over 10% higher than that calculated using the entire data series, as is the energy density computed for the dataset conditionally sampled for all of the SAR data stratification parameters.

c. Concluding remarks

Wind speeds over the oceans are required for a range of applications but are difficult to obtain through in situ methods. Hence, remote sensing tools, which also offer the possibility of describing spatial variability, represent an attractive proposition. However, previous work has demonstrated significant uncertainties regarding the absolute accuracy and precision of wind speeds derived from SAR and scatterometer images. These issues are largely the result of low signal-to-noise ratios and will no doubt be remedied at least in part in the future by improvements to the technology and algorithms (Korsbakken et al. 1998; Stoffelen 1998). In this regard, it is important to note that SAR provides the highest spatial resolution among existing remote sensing instruments, but there have been recent improvements to scatterometers in terms of coverage, resolution, and accuracy (Lui 2002). However, as demonstrated herein, there are a number of biases inherent in satellite retrieval of wind speeds that are of sufficient magnitude to render current use of remote sensing for generating power estimations for prospective offshore wind farms highly speculative. These merit further consideration.

In response to the question posed in the title of this paper the answer is an equivocal "yes" or "no" dependent on the specific application. It should be acknowledged that this study has focused on a relatively high-speed regime, and that the results may differ in other locations and environments. Based on the data analyzed herein, assuming an uncertainty of ±10% at a confidence level of 90% is acceptable, then, according to the results provided in Table 2, approximately 60–70 randomly selected images are required to characterize the mean wind speed and Weibull *c* parameter, about

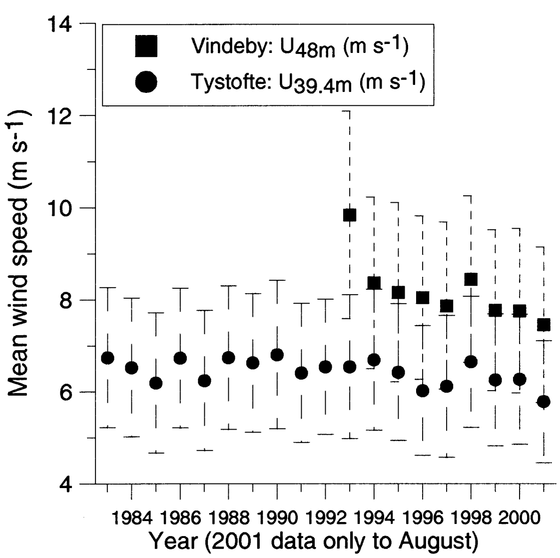

FIG. 8. Interannual variability of mean wind speed (shown ± 0.5 std dev) at Tystofte (measurement height = 39.4 m AGL) and Vindeby SMW (measurement height = 48 m MSL).

TABLE 4. Wind speed distribution parameters for data from Tystofte (39.4 m) for the entire dataset (1983–2001) and for the period of the Vindeby dataset (1996–2001).

Period	Mean (m s^{-1})	Std dev (m s^{-1})	Skewness	Kurtosis	Weibull k	Weibull c (m s^{-1})	Energy density (W m^{-2})
1983–2001	6.40	2.97	0.651	0.730	2.10	7.23	286
1996–2001	6.24	2.85	0.682	1.00	2.11	7.04	265

150 images are required to obtain a variance estimate, and nearly 2000 are needed to obtain an energy density (or Weibull k) estimate. As described herein, these estimates are conservative of actual needs since they assume perfect accuracy of the wind speed retrievals and that the remotely sensed data do not exhibit range or temporal biases, such as those that characterize the current applications of SAR. It should further be noted that discussion of the inaccuracies in vertical extrapolation of resolved wind speeds from the nominal height of 10 m associated with SAR to the desired level above the sea surface is beyond the scope of this paper but significantly adds to uncertainties in remotely derived wind speeds.

Neglecting biases associated primarily with nonrandom temporal sampling (especially on seasonal timescales) as an interim measure, we also propose error bounds that may be applied to sparse datasets such as those likely to be obtained from satellite-borne instrumentation. These uncertainty bounds, calculated from in situ observations, are not intended as definitive but rather are presented as an operational tool, which may be refined by further analysis.

Acknowledgments. Financial support for this research was given in part by the European Commission's Fifth Framework Programme under the Energy, Environment and Sustainable Development Programme. Project References: ERK6-CT99-00017 WEMSAR and ERK6-CT1999-00001 ENDOW. The authors gratefully acknowledge useful discussions with Charlotte Bay Hassager and Morten Nielsen and the comments of three anonymous reviewers. Data collection at Vindeby is supported by SEAS, Techwise conducts data collection at Horns Rev, and data collection at Tystofte is supported by Risø National Laboratory. This research was conducted while the second author was on sabbatical at Risø from Indiana University.

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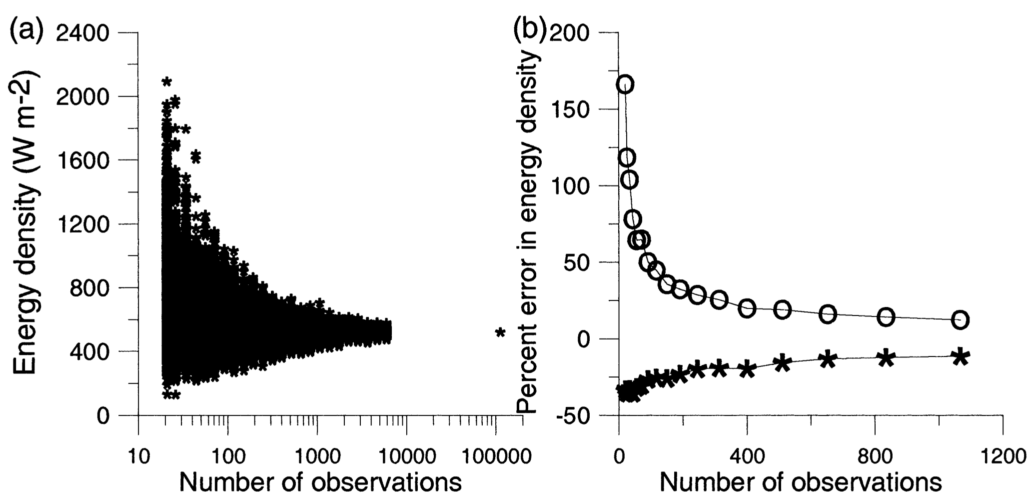

FIG. 9. (a) The energy density calculated for the data from Vindeby SMW shown for the each of the 1000 iterations of randomly sampling the wind speed probability distribution for differing sample numbers. (b) The 90% confidence interval for percent errors in energy density for 48 m based on varying number of observations randomly selected from the Vindeby SMW data series. The fits are given in Table 3.

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