Wind resource assessment from C-band SAR

Merete Bruun Christiansen a,⁎, Wolfgang Koch b, Jochen Horstmann b, Charlotte Bay Hasager a, Morten Nielsen a

a Risø National Laboratory, Wind Energy Department, Frederikborgvej 399, DK-4000 Roskilde, Denmark
b GKSS Research Center, Institute for Coastal Research, Max-Planck-Str. 1, D-21502 Geesthacht, Germany

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Abstract

Using accurate inputs of wind speed is crucial in wind resource assessment, as predicted power is proportional to the wind speed cubed. First, wind speeds retrieved from a series of 91 ERS-2 SAR and Envisat ASAR images, at moderate wind speeds (2–15 m s−1), were validated against in situ measurements from an offshore mast in the North Sea. The wind direction input, necessary for SAR wind speed retrievals, was obtained from the meteorological mast and from a local gradient analysis of wind streaks in the SAR images. A wind speed standard deviation of ∼1.1 m s−1 was found when in situ wind directions were used. The use of local gradient wind directions yielded a standard deviation of ∼1.3 m s−1. Wind speeds retrieved from three geophysical model functions (CMOD-IFR2, CMOD4, and CMOD5) were compared. The best approximation to the in situ measurements of wind speed was found for CMOD-IFR2, despite a bias on the order of −0.3 m s−1. CMOD4 retrievals also underestimated the wind speed, whereas the bias on CMOD5 retrievals was negligible. Then, wind resource assessments were made from the SAR-based wind observations to show how errors in wind speed from the different SAR wind retrievals were reflected in the wind statistics. The mean wind speed, obtained for all of the 91 SAR scenes, was linked closely to the bias of SAR wind retrievals. Agreement to ±15% of the in situ measurements was found for all the wind retrieval methods tested. The accuracy of power density estimates for the entire data set was evaluated by the standard deviation of SAR wind retrievals relative to the in situ measurements. SAR wind fields retrieved with CMOD-IFR2, using in situ wind direction inputs, exactly yielded the power density predicted from in situ measurements alone. The SAR-based wind resource assessment also corresponded well to predictions from longer time series of in situ measurements. This indicates that a reliable wind resource assessment may be achieved from a series of randomly selected SAR images. The findings presented here could be useful in future wind resource assessment based on SAR images.

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1. Introduction

Development of offshore wind power has caused a demand for wind resource mapping over the sea. Wind resource is commonly assessed through the fitting of a Weibull function to time series observations of wind speed and direction obtained over at least 1 year. The fitted probability density function is characterized by a scale parameter (A) and a shape parameter (k), which may be used to determine the mean wind speed and the wind power density (Troen & Petersen, 1989). In screening for potential offshore wind farm sites, year-long time series of meteorological data are generally unavailable. Wind maps retrieved from satellite synthetic aperture radar (SAR) data are useful for this task as they provide high-resolution spatial information. Further advantages include, from a wind farm developers point of view, the low cost of SAR images compared to the cost of installing a meteorological mast, and the opportunity to obtain archived data for any given site. The variability of the mean wind speed within single, or multiple, SAR image frames has been addressed in several publications (Choisnard et al., 2004; Hasager et al., 2005; Schneiderhan et al., 2005). As SAR data archives continue to grow, assessment of the wind resource in absolute terms, from a series of SAR images, is becoming a realistic supplement to traditional assessments from in situ data. In this paper, we focus on the absolute accuracy of SAR-based wind resource assessment.

⁎ Corresponding author. Tel.: +45 4677 5002; fax: +45 4677 5970.
E-mail address: merete.bruun.christiansen@risoe.dk (M. Bruun Christiansen).

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Two types of uncertainty are introduced as wind power prediction is based on SAR data instead of in situ measurements. Firstly, biases may be associated with the data sampling in that i) the sampling density is low for satellite data compared to time series measurements, ii) the sampling occurs at fixed times of the day neglecting diurnal variation in the wind climate, and iii) the valid range of SAR wind retrieval is 2–24 m s\(^{-1}\) leading to a truncation of the actual wind speed distribution (see also Section 2). These biases would remain even if the SAR observations were perfectly accurate with respect to in situ measurements. Sampling biases have previously been quantified through statistical analyses of a large number of in situ observations selected specifically to match the sampling criteria of satellite scenes (Barthelmie & Pryor, 2003; Pryor et al., 2004). Based on these analyses, a total of 60–70 randomly selected and perfectly accurate SAR scenes are required to characterize the mean wind speed and the Weibull parameter \(A\) whereas \(\sim 2000\) samples are necessary to estimate the power density or the Weibull parameter \(k\) to \(\pm 10\%\) at the 90\% confidence interval. The second source of uncertainty is related to the accuracy of SAR wind retrievals. Accurate estimates of the mean wind speed are vital for a reliable wind power prediction as the mean power density, \(E\) [W m\(^{-2}\)] is proportional to the wind speed cubed:

\[
E = \frac{1}{2} \rho U^3
\]

where \(\rho\) [kg m\(^{-2}\)] is the air density and \(U\) [m s\(^{-1}\)] is the mean wind speed.

The aim of this paper is to quantify the total accuracy related to the application of SAR data in wind resource assessment. We first evaluate wind retrievals from a total of 91 images of C-band satellite SAR against in situ measurements obtained from an offshore meteorological mast at Horns Rev in the North Sea. The analysis is more comprehensive than previous wind speed validation studies because the number of SAR scenes is sufficient to give relatively robust statistics. An operational tool is used for the SAR wind retrievals to meet the prospect of including thousands of SAR images in future wind resource assessment studies. Different methods are considered for the comparison of satellite snapshots to in situ measurements averaged over time and the consequence of automating the wind vector retrieval is evaluated. Our evaluation encompasses three different algorithms for SAR wind retrieval. Next, the influence of atmospheric parameters is quantified. The study site is located 14–21 km offshore and 2 km from a large offshore wind farm. SAR and in situ observations may thus be affected by internal boundary layers from the land (Garrat, 1990), interplaying with atmospheric stability effects (Stull, 1988) and wind farm wake effects (Christiansen & Hasager, 2005, in press). We briefly address the effect of spatial resolution in the radar backscatter cross section (NRCS) for open oceans with a neutrally stable atmosphere. The backscattered power depends on surface waves comparable in size to the radar wavelength. As wind speed increases, the sea surface roughness also increases, increasing the normalized radar cross section (NRCS). Here we are concerned with the C-band (5.3 GHz) SAR sensors on board the polar-orbiting ERS-2 and Envisat satellites.

Empirical geophysical model functions (GMFs) have been developed to identify the relationship of wind speed at 10 m to NRCS for open seas with a neutrally stable atmosphere. The functions also depend on the wind direction relative to the radar look direction and on the radar incidence angle. A series of C-band GMFs known as the CMOD functions were originally developed for global coverage scatterometry wind retrievals (Hersbach, 2003; Quilfen et al., 1998; Stoffelen & Anderson, 1997). Later, the CMOD functions were successfully applied to wind retrievals from higher-resolution SAR images. Monaldo and Kerbaol (2003) provide a comprehensive overview of previous work in the field of SAR wind retrieval and a brief summary is given in the following.

For a given wind speed and direction, a GMF will predict a unique NRCS. However, the inverse is not true as a given NRCS may be associated with a large number of wind speed and direction pairs. Scatterometers deal with this problem by acquiring multiple NRCS at the same spot on the ocean surface from different aspect angles and at different polarizations. This allows the determination of both wind speed and direction. SAR images, in contrast, are acquired with a single look angle. It is therefore necessary to know the wind direction a priori in order to determine the wind speed.

Wind directions may be obtained from atmospheric models (Monaldo, 2000; Monaldo et al., 2001), scatterometry (He et al., 2005; Monaldo et al., 2004), or in situ measurements (Hasager et al., 2004). In addition, it is possible to extract the wind direction from streaks in the SAR images. The wind streaks originate from roll vortices aligned approximately with the wind direction. Methods to determine the wind streak direction include FFT (Furevik et al., 2002; Gerling, 1986; Lehner et al., 1998), wavelet analysis (Du et al., 2002; Fichaux & Ranchin, 2002) and local gradients (Horstmann et al., 2002a; Koch, 2004). The 180° ambiguity associated with these methods may be removed through comparison with other data sources or through a study of wind shadows in the images. There is usually a trade-off between the accuracy of wind direction estimates and the degree of automation in the process of determining the directions. In situ measurements and image streaks have the advantage of being correlated in time with satellite overpasses, and are therefore particularly attractive data sources for deriving wind directions.

Wind speeds of 2–24 m s\(^{-1}\) can be retrieved with the nominal accuracy \(\pm 2\) m s\(^{-1}\) for radar incidence angles of 20–60° using the scatterometer approach (Stoffelen & Anderson, 1997). The approach applies to SAR data acquired with vertical polarization. It is possible to account for the lower NRCS of horizontally-polarized SAR data through multiplication with a polarization factor.
Fig. 1. Normalized radar cross section (NRCS) as a function of wind speed for the fixed radar incidence angle 40°. The relationship is plotted for three geophysical model functions (CMOD-IFR2, CMOD4, and CMOD5) with the SAR looking upwind and crosswind, respectively.

Validation studies have shown that winds retrieved from SAR correspond well to scatterometer measurements over open oceans (Horstmans et al., 2003; Monaldo et al., 2004). However, validation of SAR-retrieved winds against scatterometer measurements cannot distinguish between the accuracies of different GMFs, as the scatterometer winds are retrieved from similar GMFs. SAR wind retrievals have also been validated for near-shore areas. Monaldo et al. (2001) found a standard deviation of 1.8 m s\(^{-1}\) for comparisons of horizontally polarized RADARSAT wind retrievals to buoy measurements along the US east coast using CMOD4. Furevik et al. (2002) compared ERS-2 SAR wind retrievals along the marginal ice zone of Svalbard to measurements from ships. They found an rms error of 1.6 m s\(^{-1}\) using CMOD-IFR2 and a larger rms error for CMOD4. In situ measurements from buoys and ships may be distorted due to blockage or motion of the sensor (Brown, 2000b) and measurements are typically obtained at low levels above the sea surface. Using buoy and ship measurements as the basis for validation of SAR winds is therefore problematic.

Ideally, SAR-retrieved winds should be validated against in situ measurements from meteorological masts with minimum
flow distortion. High-quality meteorological measurements are obtained at most offshore wind farm sites but are usually confidential. Validation studies based on such measurements are thus rare. One exception is the work of Hasager et al. (2004) who validated CMOD4 and CMOD-IFR2 wind retrievals from ERS-2 SAR data against measurements from a meteorological mast at Horns Rev in the North Sea. A standard error of 0.9 m s$^{-1}$ was found for CMOD4 wind retrievals using in situ wind direction inputs. For CMOD-IFR2 the standard error was 1.2 m s$^{-1}$. The same GMFs used with FFT-derived wind directions resulted in standard errors of 1.5 m s$^{-1}$ and 1.6 m s$^{-1}$ for CMOD4 and CMOD-IFR2 respectively.

The most recent GMF is CMOD5, which was developed to improve scatterometer wind retrievals at very high winds (Hersbach, 2003). Horstmann et al. (2005) tested the performance of this GMF at hurricane wind speeds retrieved from SAR and found it more suitable than CMOD4, as it copes better with saturation of NRCS at high winds. We are not aware of previous validations of CMOD5 wind retrievals at low to moderate wind speeds (<15 m s$^{-1}$).

3. Data analysis

The offshore site Horns Rev in the North Sea (Fig. 2) has been subject to intensive studies since 1998 when it was decided to build the world’s first large scale offshore wind farm there. An offshore meteorological mast was erected in 1999. The wind farm, consisting of 80 turbines, has been operated since December 2002. We have collected ERS-2 and Envisat SAR images acquired at Horns Rev over the period 1999–2005. SAR data and in situ measurements of wind speed and direction were obtained simultaneously for a total of 91 incidents with wind speeds within the range 2–24 m s$^{-1}$ (i.e. the valid range for SAR wind speed retrieval). This data set provides the basis for our analysis. Of the 91 available SAR scenes, a total of 69 were acquired from ERS-2 and the remaining 22 scenes were from Envisat. Some of the Envisat scenes (15 in total) were acquired in wide swath mode covering 400 km × 400 km with a spatial resolution of ∼100 m. All other scenes (76 in total) were acquired in image mode by ERS-2 or Envisat and covered approximately 100 km × 100 km with a spatial resolution of ∼30 m (Attema et al., 2000).

3.1. SAR wind retrieval

Winds were retrieved from the SAR images with the operational tool WiSAR developed at GKSS Research Center, Germany (Horstmann et al., 2002a; Koch, 2004). The tool handles calibration to NRCS, wind direction retrieval using the local gradient (LG) method, and wind speed retrieval with CMOD-IFR2, CMOD4, and CMOD5. To retrieve wind directions, the 91 SAR images were divided into 10-km grid cells. Within each grid cell, local gradients of NRCS were computed at the scales 100 m, 200 m, and 400 m. Wind directions were assumed to be perpendicular to the local gradient of NRCS, especially at the smaller scales. Land was masked out of the images, as were other image features causing local gradients too steep to be associated with the wind. Examples of such features included wind turbines and ships, causing direct scattering (i.e. very bright pixels). Steep gradients were also caused by surfactants (Alpers & Hühnerfuss, 1989; Gade et al., 1998) and bathymetry (Alpers & Hennings, 1984; Römeiser & Alpers, 1997), interacting with sea currents to alter the surface roughness and NRCS.

Several wind directions were typically suggested by the WiSAR program for each grid cell. This is because each solution had a 180° ambiguity and because a solution was given for each scale. The appropriate wind direction was selected manually according to streaks and wind shadows visible in the images. A second selection of wind directions was made automatically through comparison with model data. For the period 1999–2003, re-analysis data (REMO) with the spatial resolution 55 km × 55 km were available from GKSS for the comparison. For 2004–2005, atmospheric model data provided by the German Weather Service (DWD) with the spatial resolution 0.75°×0.75° were used. Both types of model data had a 6-hour temporal resolution.

For wind speed retrievals, the original NRCS images were reduced to eliminate the effects of speckle noise and longer period waves on the wind retrievals. We averaged to a pixel size of 500 m as recommended by Horstmann et al. (2000). The LG wind directions, found through supervised and automatic image analysis, were also re-sampled to a 500-m grid. The model functions CMOD-IFR2, CMOD4, and CMOD5 were all separately used for wind speed retrieval for each image initiated with the two types of wind direction input. In addition, the model functions were run using wind directions from the meteorological mast at Horns Rev as input (see Section 3.2 for details). This resulted in nine different estimates of wind speed per pixel in the SAR images.

3.2. In situ measurements

The meteorological mast at Horns Rev is 62 m tall and operated by Elsam. Wind speed (15, 30, 45, and 60 m), wind direction (62 m), and air temperature (13 and 55 m) are sampled at 1 Hz and stored as 10-minute mean values. The error in measured wind speeds is <0.1 m s$^{-1}$. Wind speed at the three lower levels is measured simultaneously at both ends of a boom with the alignment 45°/225° from the north. Wind shadowing from the mast was avoided by consequently selecting the upwind anemometer. No correction for atmospheric stability or tidal sea level variations was made. The effect of such corrections has previously been found negligible for the site (Hasager et al., 2004). In situ measurements were averaged over 1 h centred at the time of each satellite overpass to eliminate short-term fluctuations. The relatively long averaging period was chosen to ensure a representative number of large turbulent eddies (Stull, 1988). Differences in wind statistics generated from 10-minute to hourly averages are usually considered small (Barthelmie & Pryor, 2003; Petersen et al., 1981). Measured wind speeds were extrapolated to the height 10 m corresponding to the SAR-retrieved winds. Practically, the logarithmic measurement heights were plotted as a function of wind speed and a linear fit was made. The 10-m wind speeds were then extracted.

To determine the atmospheric stability at the acquisition time of each SAR scene, we computed the bulk Richardson number,
\[ Ri_B = \frac{g}{T} \left( \frac{(\theta(z_1)-\theta(z_2))}{(z_1-z_2)} \right) \]

where \( g \) [m s\(^{-2}\)] is the acceleration due to gravity, \( T \) [K] is the absolute temperature at a given height (\( z_1 \) in our case) and \( \theta \) [K] is the potential temperature, which is derived from \( T \) using the adiabatic lapse rate (\(-0.01\) K m\(^{-1}\)). The measurement heights were \( z_1 = 55 \) m, \( z_2 = 13 \) m, \( z_3 = 62 \) m, and \( z_4 = 15 \) m. Estimates of atmospheric stability were valid at 55 m. The following intervals were defined: \( Ri_B < -0.4 \) for unstable atmospheres, \(-0.4 \leq Ri_B \leq 0.1 \) for near-neutral atmospheres, and \( Ri_B > 0.1 \) for stable atmospheres.

3.3. Comparison of SAR and in situ wind fields

SAR winds were retrieved as spatial means whereas in situ measurements were temporal means obtained at one point. The comparison of SAR and in situ wind speeds relied on the Taylor’s hypothesis of frozen turbulence, assuming that wind speed can be used to translate turbulence measurements as a function of time to their corresponding measurements in space (Stull, 1988). Here SAR-retrieved wind fields were compared to measurements from the meteorological mast at Horns Rev using a scalar footprint approach (e.g. Hasager et al., 2004) and a simple box averaging method. The former has the advantage of preserving spatial variability, which is desirable in wind engineering. The latter is much simpler but involves averaging over large areas and a loss of spatial detail.

A scalar footprint is a response function based on dispersion theory, which quantifies the relative significance of distributed surface conditions at an elevated point in the atmospheric boundary layer. The weighted footprint of Gash (1986) was used to define the effective fetch, \( X_F \) [m] upstream of the meteorological mast:

\[
X_F = -\frac{z}{\kappa^2 \ln \left( \frac{F}{100} \right)} \left( \ln \left( \frac{z}{z_0} \right) - 1 + \frac{z_0}{z} \right)
\]

where \( F \) [%] is the percentage of effective fetch, \( z_0 \) [m] is the roughness length, \( z \) [m] is the measurement height, and \( \kappa \) is the von Karman’s constant. The footprint of Gash (1986) applies to neutral atmospheric conditions and is the preferred footprint when stability information is unavailable (Nielsen et al., 2004). The footprint theories by Hsieh et al. (2000) and Horst and Weil (1994) take atmospheric stability into account, but they require vertical
temperature structures, which generally are unavailable for remote sensing applications.

Eq. (3) defines the upwind variation of a crosswind integrated footprint. According to the theory, the crosswind variation is equal to that of a spreading plume, i.e. with a Gaussian profile (Horst & Weil, 1994). The upwind development of the length scale of the crosswind profile was predicted by the model of Gryning et al. (1987). For each SAR image, a response function was evaluated by the observed wind speed and direction and used to calculate a weighted average of pixel values upstream the mast. For the measurement height of 10 m, the 90% effective fetch was 2.3 km for \( z_0 = 0.2 \) mm. This roughness length is typically used for water areas comprising the sea, fjords, and lakes (Troen & Petersen, 1989).

In addition to footprint averaging, we used simple box averaging to obtain the mean winds for the area surrounding the meteorological mast at Horns Rev. Pixels were averaged within a 5 km square box centered at the meteorological mast. To avoid any contribution from wind turbine backscattering, a polygon mask was defined over the wind turbine array. Pixels located within the polygon were eliminated, both from the scalar footprint and the box averaging. The wind farm polygon and the box used for pixel averaging are seen in Fig. 3. Very bright or dark pixels, resulting from the interaction of bathymetry with sea currents, were found within the box for some SAR scenes. To eliminate these effects, box averaging was repeated using the mask that was defined during the computation of local gradients. The mask covered areas with very large gradients of NRCS.

3.4. Wind resource assessment

The Risø Wemsar Tool (RWT) has been developed for wind resource assessment based on SAR-retrieved wind maps. The principle is to combine multiple SAR wind maps for the computation of wind statistics over an area of interest defined by the user. The computation follows state-of-the-art procedures of wind power prediction from the Wind Atlas Analysis and Application Program (WAsP, see www.wasp.dk or (Mortensen et al., 2005)). A Weibull fit is made to frequency observations of wind speed:

\[
f(u) = \frac{k}{A} \left( \frac{u}{A} \right)^{k-1} \exp \left( - \frac{u}{A} \right)
\]

where \( f \) is a probability density function, \( u \) [m s\(^{-1}\)] is wind speed, \( A \) [m s\(^{-1}\)] is a scale parameter, and \( k \) is a shape parameter. A further description of the Weibull distribution applied to wind resource assessment is given by Troen and Petersen (1989).

SAR wind retrievals are valid at 2–24 m s\(^{-1}\). However, to make a correct Weibull fit all wind speeds that are likely to occur at a site must be represented. To overcome this problem, RWT...
features an opportunity to type in the number of samples deselected due to high or low wind speeds (six in our case). These samples are then taken into account in the fitting. Users of RWT have the opportunity to implement ground truth data for comparison studies using various footprint methods e.g. Gash (1986).

RWT requires input arrays of wind speed and direction and a header file containing geo-information. For our analysis, the nine different wind fields computed with WiSAR were analyzed for the parameters \( U \), \( A \), \( k \), and for \( E \) assuming a constant air density of 1.23 kg m\(^{-3}\) (Eq. (1)).

\[
\begin{align*}
U & \quad \text{[m s}^{-1}\text{]} \\
A & \quad \text{[m s}^{-1}\text{]} \\
k & \quad \text{[W m}^{-2}\text{]} \\
E & \quad \text{[W m}^{-2}\text{]} \\
\end{align*}
\]

### 4. Results

#### 4.1. Wind direction retrievals

Fig. 3 shows a typical example of a SAR wind speed map. Streaks are visible in the image, indicating the wind direction. In addition, orthogonal internal waves are seen at the top left image corner. Arrows show the wind direction measured at the meteorological mast (white) and wind directions retrieved with the LG method for the automatic runs (black). The local gradients deviate by \( \sim 10^\circ \) from the in situ measurements and the orientation of visible wind streaks in the example. However, they still give a good approximation of the wind direction. The internal waves did not impact the LG retrievals.

Wind directions estimated from LG analyses are plotted in Fig. 4 against in situ wind directions for scenes with wind speeds above \( 5 \text{ m s}^{-1} \). At lower wind speeds, in situ measurements of the wind direction may not be accurate. It is therefore common practice to eliminate low wind samples in wind direction validations. The plots show that wind directions were distributed over the full range of 0–360°. For the supervised runs, a standard deviation (SD) of 21° and a correlation coefficient \( (R^2) \) of 0.95 was found between the LG and in situ wind directions. For the fully automatic runs, SD was 33° and \( R^2 \) was 0.87. Manual supervision of the LG retrievals thus led to a gain of accuracy on the wind direction estimates. Two outliers, showing deviations larger than 90°, are seen for the automatic LG retrieval (Fig. 4b). Both of these incidents were associated with a weather front in the SAR images, confusing the automatic wind vector retrieval. Eliminating the two samples resulted in an improvement of SD to \( \sim 18^\circ \) for both types of LG retrieval.

Fig. 5 shows a wind rose based on in situ measurements and the two different LG wind direction retrievals. All three

<table>
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<th>Wind direction from mast</th>
<th>SD [m s(^{-1})]</th>
<th>Bias [m s(^{-1})]</th>
<th>( R^2 )</th>
<th>( U ) [m s(^{-1})]</th>
<th>( A ) [m s(^{-1})]</th>
<th>( k )</th>
<th>( E ) [W m(^{-2})]</th>
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<th>( U ) [m s(^{-1})]</th>
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<th>( U ) [m s(^{-1})]</th>
<th>( A ) [m s(^{-1})]</th>
<th>( k )</th>
<th>( E ) [W m(^{-2})]</th>
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<th>( A ) [m s(^{-1})]</th>
<th>( k )</th>
<th>( E ) [W m(^{-2})]</th>
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<td>8.5</td>
<td>2.5</td>
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Also listed are the mean wind speeds \( (U) \), the Weibull \( A \) and \( k \) parameters, and the mean power density \( (E) \) computed from Eq. (1) with an air density of 1.23 kg m\(^{-3}\). The number of samples is 91.
directional retrievals were based on 91 samples and suggest that winds from the south-easterly sector (120±15°) were prevailing with contributions of 15–18%. Contributions exceeding 10% were also found from the south-westerly and north-westerly sectors. The in situ wind directions deviated from the LG retrievals in showing a large contribution around 300° (13%), whereas both LG retrievals yielded larger contributions around 330° (9–13%). Observations of the wind climate at the
meteorological mast for the period April 1999 to November 2002 have been published by Sommer (2003). For the 3.5 years of measurements, winds from 210–300° show almost equal prevalence (≈12%). The frequency of winds from the west (270±15°) was thus remarkably low for our data set, compared to the longer time series of data. A significant contribution (9%) is reported for the sector centred at 120°, which is in agreement with our findings. Low frequencies of winds from the north and north–east occur in our data set as well as in the 3.5-year data series. The low frequencies of winds from these sectors are associated with the synoptic wind climate of Denmark, as it is observed at most Danish measurement stations.

4.2. Wind speed retrievals

Table 1 shows the results of the correlation analyses between SAR-retrieved and in situ wind speeds. The matrix contains the results for the three different wind direction inputs, the three geophysical model functions, and the three comparison methods used. Also contained is the estimated mean wind speed, the Weibull A and k parameters, and the power density (see Section 4.3 for description).

Wind speeds retrieved from SAR with in situ wind direction inputs yielded the best correlation with in situ wind speeds. A SD of 1.11 m s−1 with $R^2=0.89$ was found for CMOD-IFR2 using the box averaging method. Only a slight improvement of SD was found when a mask was implemented during the box averaging. However, the bias changed from $-0.27$ to $-0.36$ m s−1, indicating that bright pixels were removed by the mask. The scalar footprint averaging method led to a SD of 1.44 m s−1 with $R^2=0.83$. The reason for the lower accuracies found from footprint averaging may be that fewer samples were obtained within the footprint compared to the 5-km square box. Moreover, the relatively small number of pixels located within the 10% effective fetch of the meteorological mast was weighed very high in our footprint analysis. To increase the size of the scalar footprints, the analysis was repeated, changing the height ($z$) in Eq. (3) to 30 m with all other parameters constant. This resulted in an effective fetch of 21 km (90%). Our results did not improve significantly with the increased fetch, presumably because the fetch was limited by the coastline or the image border in several cases.

Wind speeds retrieved from the model functions CMOD-IFR2, CMOD4, and CMOD5 with in situ wind direction inputs are plotted against in situ wind speeds in Fig. 6. The results were obtained from the box averaging method but trends were similar for box averaging using a mask, and for the footprint averaging (Table 1). CMOD-IFR2 wind retrievals yielded the minimum SD (1.11 m s−1) and the maximum $R^2$ (0.89). SD was higher for CMOD5 (1.34 m s−1) than for CMOD4 (1.21 m s−1) but CMOD4 wind retrievals were better correlated with the in situ measurements than CMOD5 retrievals. CMOD-IFR2 and CMOD4 wind

![Fig. 7. In situ wind speed (15 m) as a function of atmospheric stability, expressed by the bulk Richardson number, $Ri_B$. Intervals are defined as $Ri_B < -0.4$ for unstable atmospheres, $-0.4 \leq Ri_B \leq 0.1$ for near-neutral atmospheres, and $Ri_B > 0.1$ for stable atmospheres. Offshore winds (0–180°) and onshore winds (180–360°) are plotted separately. The number of samples is 91.](image)
retrievals were negatively biased, whereas the bias was negligible for the CMOD5 retrievals.

A noticeable difference in SAR-retrieved wind speeds from the three model functions occurred for two incidents with in situ wind speeds of \( \sim 15 \text{ m s}^{-1} \). One of these incidents showed SAR wind speeds of \( \sim 16, \sim 15, \) and \( \sim 22 \text{ m s}^{-1} \) retrieved from CMOD-IFR2 (Fig. 6a), CMOD4 (Fig. 6b), and CMOD5 (Fig. 6c), respectively. This particular satellite scene was acquired with the SAR looking almost directly into the wind. As seen from Fig. 1, CMOD5 wind speed retrievals deviate from those of CMOD-IFR2 and CMOD4 for wind speeds above \( 15 \text{ m s}^{-1} \), looking upwind. A small increase of NRCS may thus lead to a very large increase of the predicted wind speed from CMOD5. In our correlation analysis, the wind speed retrieved with CMOD5 for one satellite scene contributed largely to the standard deviation found for this model function. Eliminating the outlier improved the SD of CMOD5 to \( 1.13 \text{ m s}^{-1} \) (i.e. nearly equal to CMOD-IFR2 retrievals but without a bias).

The standard deviation of SAR-retrieved wind speeds increased when wind directions were obtained from LG image analysis instead of in situ measurements. The minimum SD on wind speed, found using wind direction inputs from the supervised LG method, was \( 1.26 \text{ m s}^{-1} \) with \( R^2 = 0.83 \). The corresponding SD found using wind direction inputs retrieved automatically was \( 1.51 \text{ m s}^{-1} \) with \( R^2 = 0.77 \). In the following, we investigate the effect of internal boundary layers, atmospheric stability and wind farm wakes for the 91 SAR scenes. We also compare wind retrievals for SAR scenes with the spatial resolution \( \sim 30 \text{ m} \) and \( \sim 100 \text{ m} \) to determine how the choice of raw data impacts SAR wind retrievals.

4.2.1. Internal boundary layer effects

Internal boundary layers develop as wind flow gradually adjusts to an aerodynamic roughness change or a change of air temperature. This typically occurs at the land–sea interface. As a consequence, the logarithmic velocity profile, which is assumed in SAR wind retrievals, may fail to predict the wind speed at a given height.

To quantify possible effects of internal boundary layers from the land, SAR scenes acquired with offshore winds were separated from scenes acquired with onshore winds. The Danish coastline facing the North Sea is aligned approximately from north to south. Wind directions ranging \( 0–180^\circ \) from the north were considered offshore and directions ranging \( 180–360^\circ \) from the north were considered onshore. A total of 49 SAR scenes appeared in the onshore bin, whereas 42 scenes appeared in the offshore bin. Computation of wind statistics was performed separately on the offshore and onshore data bins. As seen from Table 2, SD and \( R^2 \) were almost equal for the two bins, which suggests that scenes acquired with onshore and offshore winds were equally valid for the wind resource assessment study at Horns Rev. The bias, in contrast, was \( -0.52 \text{ m s}^{-1} \) for offshore winds and only \( -0.06 \text{ m s}^{-1} \) for onshore winds. This indicates that the biases associated with our SAR wind retrievals may originate partly from internal boundary layers due to the proximity of land.

4.2.2. Atmospheric stability effects

According to the bulk Richardson number \( (R_{Bi}) \), unstable atmospheric conditions occurred for 57% of the cases studied, whereas near-neutral and stable cases represented 24% and 19%, respectively. The SAR scenes were binned according to these intervals and comparisons of the SAR-derived and in situ wind speeds were made for each bin.

Table 2 shows that the SD found for near-neutral stability \( (0.95 \text{ m s}^{-1}) \) was lower than SD found for unstable \( (1.06 \text{ m s}^{-1}) \) and stable \( (1.47 \text{ m s}^{-1}) \) conditions. \( R^2 \) was 0.93 for near-neutral stability, which was higher than for any other selection of SAR scenes.

Scenes with stable conditions showed a relatively large negative bias \( (0.86 \text{ m s}^{-1}) \). The bias may result from a low wind stress at the sea surface, which is characteristic for highly stratified atmospheric boundary layers. Wind speeds from SAR were thus underestimated relative to the 10-meter wind speeds measured at the mast. Similar results have been found from real aperture radar measurements by Dankert et al. (2003). Unstable conditions showed a smaller negative bias \( (0.26 \text{ m s}^{-1}) \). Normally, a high degree of atmospheric mixing compared to neutral conditions would lead to an overestimation of the wind speed at a given height according to the logarithmic profile law. In our case, unstable atmospheric conditions may have affected both the extrapolation of in situ measurements down to 10 m and the SAR wind retrievals. The small negative bias found here may also result from parameters other than atmospheric stability.

Fig. 7 illustrates the coupling between atmospheric stability, wind speed, and offshore/onshore winds, as obtained from our dataset. According to the intervals of \( R_{Bi} \) defined in Section 3.2, positive values in the diagram indicate stable conditions and negative values indicate unstable conditions. Very stable and unstable conditions occurred at relatively low wind speeds in line with the measurements from other meteorological stations in Denmark (Motta et al., 2005). The most extreme values of \( R_{Bi} \), both for stable and unstable conditions, were found for offshore

![Fig. 8. Frequency distribution of wind speeds at 10 m and Weibull fits for SAR winds retrieved with CMOD-IFR2 and in situ wind directions. The lack of SAR winds <2 m s$^{-1}$ was accounted for in the Weibull fitting. The number of samples is 91.](Image)
winds. Of the samples acquired with onshore winds, 66% showed near-neutral atmospheric conditions.

4.2.3. Wind farm wake effects

The meteorological mast is located 2 km away from the wind farm at Horns Rev. It is thus possible that both SAR and in situ measurements experienced some influence of the wind farm. A total of 46 SAR scenes were acquired before the wind farm at Horns Rev became operational in December 2002. This group of scenes was validated against in situ measurements, as was the group of 45 scenes acquired with turbines in operation. Table 2 shows an increase of SD from 0.93 to 1.20 m s$^{-1}$ was the group of 45 scenes acquired with turbines in operation. The meteorological mast was located downwind of the wind farm. It is thus possible that both SAR and in situ measurements experienced some influence of the wind farm. Wake effects may be reflected in the change of bias from −0.57 to 0.06 m s$^{-1}$ after the wind farm installation. Direct scattering from the wind farm could not impact our results, as the wind farm area was eliminated in the SAR images through masking.

4.2.4. Effects of spatial resolution

To test the importance of spatial resolution in the SAR images for accurate wind retrievals, correlation analyses were carried out for the SAR images with a ∼30 m and a ∼100 m spatial resolution, separately. The resolutions apply to the raw SAR data (see Section 3). Table 2 shows a small improvement of SD and $R^2$ for the scenes with about 30-m resolution alone. Note that only 15 scenes were acquired with the ∼100 m resolution, thus the two data types were not equally represented.

4.3. The wind resource

Fig. 8 shows the frequency distribution of SAR wind speeds found from our 91 samples. Also shown is the Weibull fit to the data. In the following, we compare wind statistics based on Weibull fitting to the SAR data to corresponding statistics based on in situ measurements. The mean wind speed ($U$) computed from in situ measurements at Horns Rev was 7.6 m s$^{-1}$, leading to a mean power density ($E$) of 422 W m$^{-2}$ for our 91 samples (Table 1). A Weibull scale parameter of $A=8.5$ m s$^{-1}$ and a shape parameter of $k=2.5$ was found.

Mean wind speeds were most accurately determined from SAR when the bias between in situ and SAR measurements was numerically small. Using in situ wind directions in combination with CMOD5 led to a mean wind speed identical to the in situ measurement. Results based on CMOD-IFR2 and CMOD4 showed under-predictions of $U$ to −6% and −14%, respectively. Estimated power densities from SAR were generally most accurate where the SD was small. Wind directions from the meteorological mast in combination with CMOD-IFR2 yielded a very good agreement on $E$ with the in situ measurements. An $E$ of 421 W/m$^2$ was found from box averaging. $E$ was under-estimated by −29% for the CMOD4 retrievals and over-estimated up to 27% for the CMOD5 retrievals. Estimates of $E$ based on LG wind directions were possible to an accuracy of 17% for the supervised run and 21% for the automatic run, using CMOD-IFR2 and box averaging. The Weibull $A$ parameter is roughly proportional to $U$, therefore the best approximations to in situ data occurred with the best estimates of $U$ from the SAR data. The Weibull $k$ parameter found from the SAR wind fields was always lower than $k$ from the in situ measurements, as $k$ varied within the range 1.9–2.3.

5. Discussion

The aim of our study was to quantify the total accuracy of wind resource assessment from SAR. This accuracy depends, to a large degree, on the accuracy of SAR wind retrievals. The best approximation of SAR wind fields to in situ measurements was achieved using in situ wind direction inputs to feed the GMFs. Of the three GMFs validated at moderate wind speeds (2−15 m s$^{-1}$), CMOD-IFR2 yielded the lowest SD and the best correlation. However, a negative bias was found for this GMF in line with previous studies of a single SAR scene by Horstmann et al. (2002b), who concluded that CMOD-IFR2 is not completely suited to fetch-limited conditions. CMOD4 retrievals showed a larger negative bias in our study, whereas the wind speed bias on CMOD5 retrievals was negligible.

In situ measurements of the wind direction are usually not available during the initial phase of planning an offshore wind farm, therefore the opportunity to estimate the wind direction from streaks in the SAR images is attractive. Detection of the wind direction from local gradients was possible with an accuracy of 21° when wind directions were selected manually amongst suggestions provided by the WiSAR program. Fully automatic retrievals, using model data to select the appropriate direction, yielded an accuracy of 33°. Wind speed retrievals based on the SAR wind directions were accurate to a SD of ∼1.3 m s$^{-1}$, using manual supervision and to ∼1.5 m s$^{-1}$ for the fully automatic retrievals. As the accuracy on wind speed retrievals improved significantly when LG wind direction retrievals were manually assisted we recommend this method to the fully automatic directional retrievals. The main reason for deviations of the automatic LG retrievals from the manually assisted retrievals was that interpolation was necessary between 6-hourly model runs used to resolve LG ambiguities. The model wind directions failed to give accurate directions in situations when a rapid change of the wind field occurred (e.g. during a front passage). Further, the model resolution in space was coarser than the SAR resolution. In contrast to the in situ measurements, LG wind vectors had the advantage of showing spatial variability of the wind direction. At Horns Rev, this variability was limited. For other sites, variations may occur, as the wind is directed around topographical features such as mountains or islands. Examples of such variations in the form of gap flows and barrier jets have been given by Young and Winstead (2005).
Our analysis reveals that the method used to compare spatial means of SAR winds to temporal means of in situ measurements impacts correlation analyses. Simple averaging of pixels in the SAR images led to a better agreement between SAR and in situ measurements of wind speed than the scalar footprint approach. The same conclusion was previously drawn by Hasager et al. (2004). Scalar footprint averaging is based on atmospheric physics and preserves the spatial resolution of SAR wind fields better than simple box averaging. A shortcoming of the method may be that too few pixels were averaged within the scalar footprint, leading to a higher noise level than for simple pixel averaging. Work is ongoing to adjust the width of scalar footprints used in RWT, in agreement with laws of atmospheric physics, to ensure that a sufficient number of SAR samples are included.

Winds from onshore directions showed the best agreement on wind speed between SAR and in situ measurements, due to a long fetch. An improvement of SD was also found for cases with near-neutral atmospheric stability. This was expected, as the GMFs used for SAR wind retrievals are developed for open seas with a neutral atmosphere. Note that the empirical GMFs used for SAR wind retrievals are based on comparisons of NRCS to wind speed measurement from buoys and ships, usually without any correction for atmospheric stability (Brown, 2000a). Uncertainties related to offshore in situ measurements and stability effects are thus inherent.

Meteorological time series from different offshore masts in Denmark show that unstable conditions occur over 50% of the time at some locations (Motta et al., 2005). The frequent occurrence of unstable conditions found here (57%) is therefore realistic, especially because the prevailing wind direction in our dataset was southeast (i.e. from the land). Unstable conditions are normally associated with buoyancy effects generated through heating of air parcels over land. We have investigated SAR scenes acquired at moderate wind speeds (<15 m s\(^{-1}\)). Stable and unstable atmospheric conditions occurred mainly at low wind speeds; therefore a relatively large impact of atmospheric stability effects was to be expected. Stability correction offshore is a notorious problem (e.g. Lange et al. (2004)).

Satellite images, which were acquired before the wind farm at Horns Rev became operational, showed an improved accuracy on wind speed retrievals compared to the entire dataset. However, a further analysis of scenes obtained when the meteorological mast at Horns Rev was located in the wind farm wake revealed very similar accuracies in terms of SD and \(R^2\) for the wake and non-wake samples. Christiansen & Hasager (2005, in press) have shown that reductions of the mean wind speed are detectable in SAR images up to 20 km downstream of large offshore wind farms. In the present study, it is likely that nearly identical wake impacts were observed from the SAR and in situ measurements.

None of the data bins investigated here showed errors large enough to justify elimination from our wind resource assessment. Instead, we recommend that the number of randomly selected samples is kept as high as possible in this type of study to meet the sampling criteria of 60–70 scenes for estimates of the mean wind speed, \(U\) and the Weibull \(A\) parameter and \(\sim 2000\) scenes for the prediction of the power density, \(E\) and the Weibull \(k\) parameter (Barthelmie & Pryor, 2003; Pryor et al., 2004). Satellite scenes are not acquired randomly in time. However, diurnal variation of the wind appears to be limited offshore (Pryor & Barthelmie, 2001) and seasonal variability may be accounted for by the selection of SAR scenes throughout the year.

The wind resource assessment presented here was based on 91 SAR scenes. We can thus consider our estimates of \(U\) and \(A\) robust. Wind statistics based on 3.5 years of data from the meteorological mast at Horns Rev have been reported by Sommer (2003). Extrapolation of the mean velocity profile down to 10 m leads to a \(U\) of \(\sim 7.6\) m s\(^{-1}\), which corresponds exactly to our prediction. A longer time series of data is available from a light ship, which was operating at Horns Rev in the period 1962–80 (Troen & Petersen, 1989). From this data series, \(U\) at 10 m is 7.3 m s\(^{-1}\), \(E\) is 456 W/m\(^2\), and the Weibull parameters are \(A=8.3\) m s\(^{-1}\), and \(k=2.0\) for roughness class 0, corresponding to oceans with \(z_0=0.2\) mm. The data are in very good agreement with our findings (Table 1), even though our dataset is too small for robust estimates of Weibull \(k\) and \(E\). Obtaining a total of ~2000 SAR scenes for more robust wind power predictions is realistic as the cost of purchasing satellite data is currently decreasing as the SAR data archives grow. On the other hand, a lot of information about the wind resource may be gained from relatively few well-distributed SAR samples, simply by studying the spatial variability of the mean wind speed (Hasager et al., 2005, 2006; Schneiderhan et al., 2005). Weighting of the wind energy contribution from different wind sectors may be useful in situations when the prevailing wind direction found from the SAR samples and meteorological time series measurements differ (Choisnard et al., 2004). Further investigation of this approach is needed.

The results presented here are based on wind speeds at 10 m above the surface. Projecting the power predictions to a higher level (i.e. turbine hub height, typically at 70 m) is attractive for wind farm developers. Such projections are feasible as RWT is compatible with WASP (see Section 3.4). Wind speed and distribution tables, generated from satellite samples, may thus be opened in WASP for further analysis. For example, one can position a wind farm and estimate its power output for different turbines types and layouts. Additional error may be introduced due to necessary assumptions about vertical and horizontal wind speed variations (Barthelmie & Giebel, 2006). The vertical extrapolation of SAR-based wind resource assessments is beyond the scope of this paper but further analysis of the task is planned.

### 6. Conclusion

Our systematic analysis shows that it is possible to estimate wind resources accurately from a series of SAR images. The accuracy of mean wind speeds was determined by the bias on SAR wind retrievals. The accuracy on power prediction, in contrast, was determined by the standard deviation of SAR winds relative to ground truth data. The best approximation of SAR winds to offshore in situ measurements at Horns Rev was obtained from the model function CMOD-IFR2, using in situ wind directions as input (SD ~1.1 m s\(^{-1}\), \(R^2=0.89\)). Satisfactory results were also achieved using wind directions obtained from local gradients in the SAR images, independently of in situ measurements (SD ~1.3 m s\(^{-1}\), \(R^2=0.83\)). A negative bias was found with SAR data significant.
for wind retrievals with CMOD-IFR2 and CMOD4, whereas CMOD5 retrievals were bias-free.

The mean wind speed and power density found for a series of 91 randomly selected SAR scenes compared well to results obtained from in situ measurements, both for the SAR data acquisition times and for longer time series of in situ data. We therefore conclude that SAR images are valuable in offshore wind resource assessment, as they provide spatial information at an absolute accuracy sufficient in the early stage of wind farm planning. The absolute accuracy on SAR-based wind power prediction may improve in the future, as more SAR scenes are made available at a lower cost.

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References


