

# Toward the true near-surface wind speed: Error modeling and calibration using triple collocation

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**Abstract.** Wind is a very important geophysical variable to accurately measure. However, a statistical phenomenon important for the validation or calibration of winds is the small dynamic range relative to the typical measurement uncertainty, i.e., the generally small signal-to-noise ratio. In such cases, pseudobiases may occur when standard validation or calibration methods are applied, such as regression or bin-average analyses. Moreover, nonlinear transformation of random error, for instance, between wind components and speed and direction, may give rise to substantial pseudobiases. In fact, validation or calibration can only be done properly when the full error characteristics of the data are known. In practice, the problem is that prior knowledge on the error characteristics is seldom available. In this paper we show that simultaneous error modeling and calibration can be achieved by using triple collocations. This is a fundamental finding that is generally relevant to all geophysical validation. To illustrate the statistical analysis using triple collocations, in situ, ERS scatterometer, and forecast model winds are used. Wind component error analysis is shown to be more convenient than wind speed and direction error analysis. The anemometer winds from the National Oceanic and Atmospheric Administration (NOAA) buoys are shown to have the largest error variance, followed by the scatterometer and the National Centers for Environmental Prediction (NCEP) forecast model winds proved the most accurate. When using the in situ winds as a reference, the scatterometer wind components are biased low by  $\sim 4\%$ . The NCEP forecast model winds are found to be biased high by  $\sim 6\%$ . After applying a higher-order calibration procedure an improved ERS scatterometer wind retrieval is proposed. The systematic and random error analysis is relevant for the use of near-surface winds to compute fluxes of momentum, humidity, or heat or to drive ocean wave or circulation models.

## 1. Introduction

Surface truth is very important for the computation of fluxes of momentum, humidity, or heat, as these are relevant for climate studies on the seasonal scale (El Niño Southern Oscillation) and the interannual scale. Ocean circulation models are driven by the near-surface wind. Surface-based anemometer winds cover the spatial and temporal domains poorly. On the other hand, meteorological analyses and scatterometers provide a wealth of information, but an absolute calibration of these is lacking. In this paper we attempt to solve this problem.

Wind errors are generally large, such that the signal-to-noise ratio (SNR) is not large with respect to 1. In such cases, standard regression or bin-average (BA) analyses could easily lead to pseudobias effects. It is shown in this paper that only by using triple collocations and a profound error analysis such effects may be avoided. We use a 1-month data set of triple collocations of anemometer winds from the

National Oceanic Atmospheric Administration (NOAA) buoys, ERS scatterometer winds, and National Centers for Environmental Prediction (NCEP) forecast model winds in a three-way comparison. Thus we readdress the wind calibration of CMOD4.

The current operational ERS scatterometer processing uses the transfer function CMOD4 to derive winds from the backscatter measurements. *Stoffelen* (1998) discusses the effect of backscatter calibration on the wind processing. Both backscatter and wind calibration may be performed over the ocean but in an almost independent way [*Stoffelen*, 1998]. This is not to say that the backscatter calibration has no effect in the wind domain. For instance, following an onboard hardware problem in mid-1996, the European Space Agency (ESA) switched to a redundant hardware module that slightly affected the radar backscatter calibration. A bias of  $-0.2 \text{ m s}^{-1}$  in the ESA “fast delivery” was the known consequence. In mid-1997 this bias was corrected. The results in this paper apply to ERS scatterometer winds processed from calibrated backscatter measurements using CMOD4 [*Stoffelen and Anderson*, 1997 a, b, c].

CMOD4 was derived with a maximum likelihood estimation (MLE) procedure using ERS measurements and

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European Centre for Medium-range Weather Forecasts (ECMWF) analysis winds (operational winds in November 1991) as input [Stoffelen and Anderson, 1997a, b, c]. Amongst some other proposals this transfer function was verified against winds from the ESA-led Haltenbanken field campaign and winds from the global forecast model of the United Kingdom Meteorological Office (UKMO) [Offiler, 1994] and selected as the preferable function. Winds from numerical weather prediction (NWP) models are only a good reference when they in turn are calibrated against in situ winds from conventional platforms. Also, in a calibration exercise it is important that a representative sample of the day-to-day weather events is present. With hindsight, the Haltenbanken campaign was perhaps too limited in extent to guarantee this.

We study the error characteristics of in situ, scatterometer, and forecast model winds in section 2. We discuss the selection of a measurement domain where the errors can be described simply by a systematic and random part. Pseudobias after nonlinear transformation of such errors are also discussed. The wind components rather than speed and direction are shown to be the most convenient to provide an accurate description of observation errors. Mean wind components of different measurement systems are generally close to each other. Therefore we first focus on the first-order calibration, which is a multiplication factor or scaling (a linear regression with zero bias term) that would for a particular true value  $t$  provide calibrated measurements  $x$  with expectation value  $\langle x \rangle = t$ . In section 3 it is stated that without prior knowledge it is in the case of intercomparison of two noisy systems not possible to resolve both the observation system error characteristics and the calibration. In section 4 it is shown that with three noisy systems it is possible to calibrate two of the systems with respect to the third and, at the same time, provide an error characterization for all three systems. We have used the in situ winds as a reference and scaled the scatterometer and forecast model winds to have the same average strength. In section 5 a higher-order, or more detailed, calibration is considered. Section 6 provides the error model parameters and calibration factors for the three collocation data sets. Section 7 discusses the implications of this study for scatterometer data processing and wind data interpretation and application.

## 2. Observation Errors and Error Domain

In order to calibrate an observing system we need to have a good notion of what parameter we want to measure, i.e., what variable, but also on what temporal and spatial scales. The variable that we deal with here is the vector wind at a height of 10 m above the ocean surface. We ignore temporal effects and assume that all observing systems involved represent the same temporal scale (10-min averages). We do not consider temporal averaging of the buoy winds, since in our analysis this would not affect the calibrations and would just reduce the random observation error of the buoys. In the spatial domain the in situ data represent a local estimate and therefore include the wind variability on all scales. On the

other hand, the scatterometer with a footprint of 50 km does not measure the variability on scales smaller than 50 km. The variability measured by an anemometer and not by the scatterometer is more generally indicated as representativeness error [see, e.g., Lorenc, 1986].

For a detailed calibration a good notion of the accuracy of the observation systems is necessary, that is, we need to know what may be called "the cloud of doubt" around the measurement. The nature and amount of system error has to be taken into account. Usually, errors are classified as systematic (bias) or random (by their standard error (SE)). For most observing systems one could distinguish detection errors and interpretation errors. The detection error includes measurement accuracy and digitizing effects, whereas the interpretation error is made when transforming the measurement(s) to the required variable(s).

For example, for buoys the detection error is determined by anemometer characteristics and buoy motion. The interpretation error for anemometer winds has only to do with the correction of the measurements to a height of 10 m and with the collocation time and space window (see, e.g., Wilkerson and Earle [1990] for a more detailed discussion).

For the scatterometer the detection error is fairly small and expressed in vector wind root-mean-square (rms roughly  $0.5 \text{ m s}^{-1}$  [Stoffelen and Anderson, 1997b, c]. On the other hand, the interpretation error is larger and depends mainly on the accuracy of CMOD4 since the inversion error is small. CMOD4 does contain effects for instance of stability, surface slicks, and waves but only as far as they are correlated with the area-averaged 10 m vector wind. However, backscatter effects that are not correlated with the 10 m wind will contribute to the random error of CMOD4.

Although a weather forecast model wind is not a measurement, it may be treated as if it was an observation, since it contains information from all tropospheric observations of mass and wind that were assimilated in the past. Its error will be largely independent from the errors of the current observations. The lowest model level is generally just below the top of the surface layer, which is roughly at 50 m. In a post-processing step, 10-m winds are derived from model variables. Errors here are caused by errors in the model state (dynamics) and by errors in the extrapolation module for the atmospheric boundary layer.

When trying to characterize measurement errors, it is practical to select a parameter domain where the cloud of doubt is simple to describe. When it is symmetric, then first- and second-order statistical moments may be sufficient to describe the errors. Although we need not limit ourselves to these, for wind the two physical choices are either wind components ( $u, v$ ) or wind speed and direction ( $f, \phi$ ). These sets are nonlinearly related, and random errors in the one domain may generate a serious pseudobias in the other domain, as will be shown later.

One way to approach error characterization is to look in detail at the above error sources. The anemometer characteristics for in situ winds will vary but will generally not be the dominant error source. Interpretation errors, including

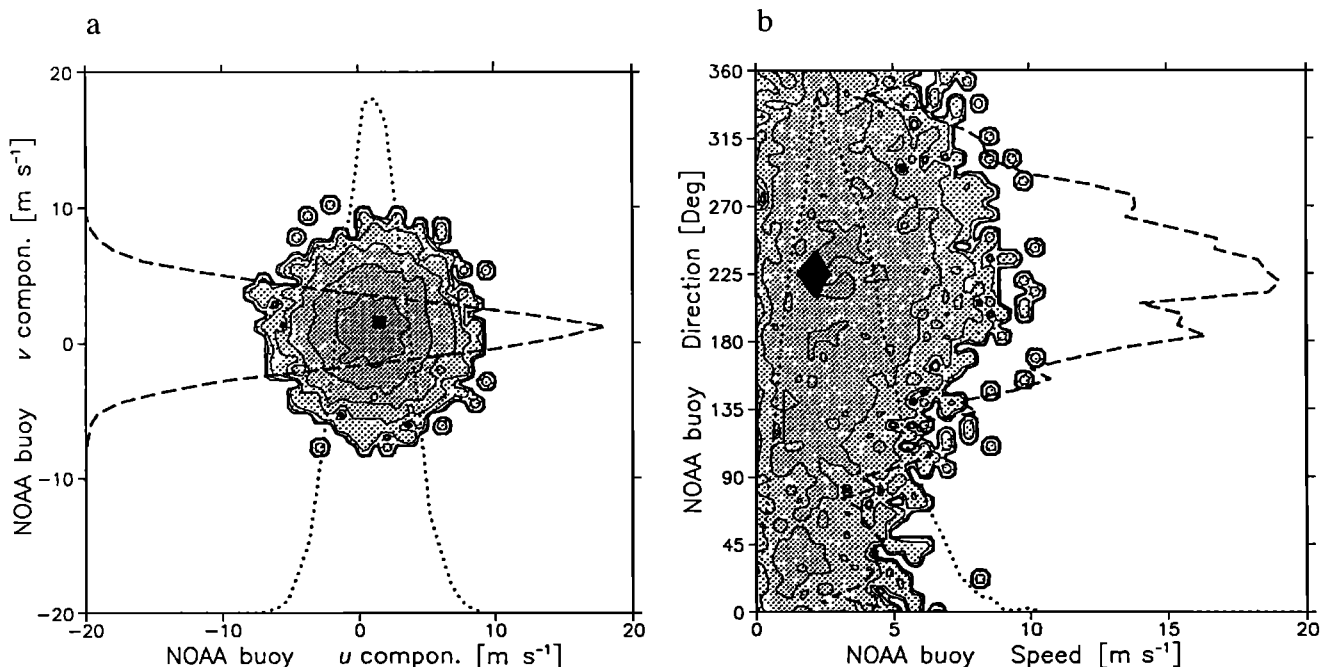
height correction to 10 m and platform motion correction errors, may be more substantial for the conventional winds. Some components of it may be well characterized in the  $(f, \phi)$  domain, while other components are better characterized in the  $(u, v)$  domain. A major contribution to the observation error for conventional winds when comparing to scatterometer data or forecast model winds will be the spatial representativeness error. This part of the total observation error is well characterized in the wind component domain. Scatterometer winds are empirically derived, and opinions will differ as to which geophysical elements (e.g., waves, stability, rain, or sea surface temperature) determine the interpretation error. The error sources in the forecast model that project onto the surface wind are even more difficult to elaborate on. It may be clear that a characterization of the total observation error from a quantification of all the error sources contributing to it will be undoable. Therefore an empirical approach is needed.

In Figure 1 the distribution of scatterometer winds for a fixed forecast model wind subdomain is shown in both physical spaces. Since the forecast model is not perfect, the subdomain of true winds will be larger than the subdomain of the model winds, and as such, it may be clear that the distribution shown is affected by errors in both the forecast model and the scatterometer. We can see that the combined component errors are well captured by a symmetric distribution, and one may assume that both scatterometer and forecast model error distributions are symmetric (Gaussian) as well. On the other hand, the wind direction random error

clearly depends on wind speed, i.e., the lighter the wind the larger the wind direction error. The wind speed error is not symmetrically distributed for light winds but skew; that is, large positive errors are more likely than large negative errors [Hinton and Wylie, 1985]. This is related to the fact that measured negative wind speeds cannot occur.

Moreover, the cloud of doubt in the  $(f, \phi)$  space is quite complicated and cannot be described by second-order statistics, whereas in  $(u, v)$  space the cloud of doubt seems much simpler to describe. Therefore, as is common practice in meteorological data assimilation, we define an error model in the wind components.

In practice, it is found that the random error on both the  $u$  and  $v$  components is similar, as one may expect (see, e.g., Figure 1a). By verifying the error distributions at higher speeds we found little evidence of a speed dependence of the component errors in the observation systems studied (see, e.g., Figure 2). As such an error model with constant and normal component errors appears appropriate. It implies for speed and direction that the expected rms wind speed difference  $\langle (f_X - f_Y)^2 \rangle$  of two noisy systems  $X$  and  $Y$  increases monotonically with wind speed, and the wind direction rms  $\langle (\phi_X - \phi_Y)^2 \rangle$  increases monotonically to a value of  $104^\circ$  for decreasing wind speed. Hinton and Wylie [1985] used a truncated Gaussian error distribution that did not allow negative speeds, to correct for the low-speed pseudobias. This procedure is rather unsatisfactory since it is not likely that the true error distribution contains discontinuities. By assuming Gaussian error distributions in the wind compo-



**Figure 1.** The distribution of scatterometer winds for forecast model winds with component values in between  $1.1$  and  $1.9 \text{ m s}^{-1}$  for 6,738 northern hemisphere high-latitude cases in March 1995. The distribution as a function of (a) the components and (b) as a function of speed and direction is shown. The forecast wind subdomain is indicated by a black box. The relative distribution of points (probability density function) along the horizontal and vertical parameter axes are represented by the dotted and dashed lines, respectively. Component errors are simpler to describe than speed and direction errors.

nents the cutoff speed effect is naturally simulated, thereby avoiding an ad hoc correction.

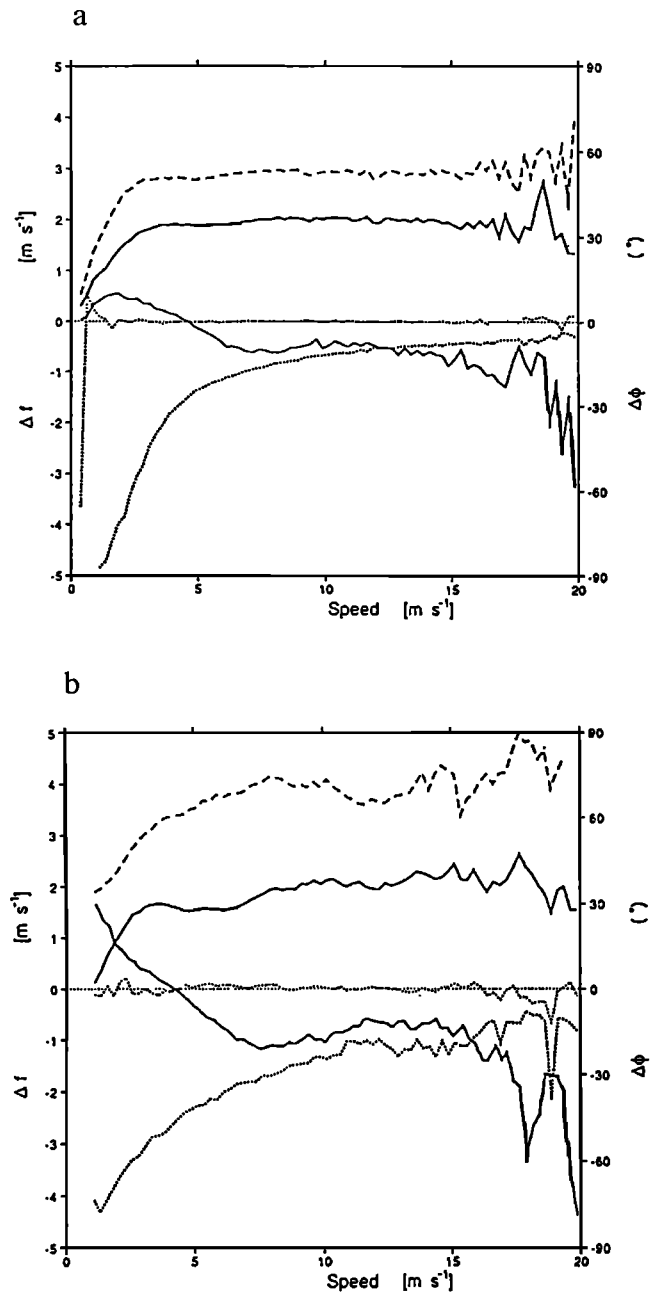
A good way to verify our approach is to simulate the wind speed and direction difference statistics with the error model we have obtained for the wind components. Figure 2 shows such a comparison (compare errors to Table 2). We can see that the average wind speed difference (pseudobias) indeed varies as a function of wind speed and that it can be as large as  $1 \text{ m s}^{-1}$  for realistic errors. The standard deviation of the wind speed difference and the vector rms difference go to a small value for low wind speed, as is observed for the real data as well. The wind direction standard deviation increases for decreasing wind speed and goes to a value of a hundred odd, as expected (random direction). Thus our error model set up to describe the observed difference statistics in the wind components also qualitatively describes the observed difference statistics in wind speed and direction very well, thereby confirming its adequacy. A quantitative validation of the error model can be made when the wind component errors are known.

### 3. Error Modeling and Calibration With Two Systems

Unfortunately, all observation systems contain error. This means that we cannot assume that one measurement represents the true state and calibrate the other against it, as is illustrated here. Assume we have a distribution of "true" states, indicated by the variable  $t$ , with expected variance  $\langle t^2 \rangle = \sigma^2$ , and two independent measurement systems  $X$  and  $Y$ , indicated by the variables  $x$  and  $y$  with error variances of  $\langle (t-x)^2 \rangle = \varepsilon_x^2$  and  $\langle (t-y)^2 \rangle = \varepsilon_y^2$  respectively. If the distribution of true values and the error distributions are normal, one can show that for fixed  $x$  the average of  $y$  does not lie at  $\langle y \rangle = x$  but at  $\langle y \rangle = \sigma^2 (\sigma^2 + \varepsilon_x^2)^{-1} x$  (see appendix A); that is for  $\sigma = 5 \text{ m s}^{-1}$  and a typical wind error of  $\varepsilon_x = 2 \text{ m s}^{-1}$  we find  $\langle y \rangle = 0.84 x$ , which implies a  $1.6 \text{ m s}^{-1}$  difference at  $10 \text{ m s}^{-1}$ . So, for unbiased Gaussian error distributions, computing the mean of  $y$  for a fixed subrange or bin of  $x$  (bin-average analysis) does, in general, reveal a pseudobias that depends on the error characteristics of system  $X$ .

Scatterometer data are often verified against buoy data, where the buoy data are assumed to be "surface truth" [see, e.g., Rufenach, 1995]. However, the representativeness error (see sections 1 and 4) for anemometer winds is substantial, and therefore this assumption does not hold. As such, in this work the observation error of in situ winds will be accounted for in the interpretation in order to be able to draw valid conclusions on the scatterometer and forecast model bias.

A better assumption often used either implicitly (e.g., in "geometric mean" linear regression) or explicitly is  $\varepsilon_Y = \varepsilon_X = \varepsilon$ , leading to the expectation  $\langle x^2 \rangle = \langle y^2 \rangle = \sigma^2 + \varepsilon^2$ . Again, for  $\sigma = 5 \text{ m s}^{-1}$  but now for the common wind errors of  $\varepsilon_X = 3 \text{ m s}^{-1}$  and  $\varepsilon_Y = 1 \text{ m s}^{-1}$ , we find a ratio of total variances of  $\langle x^2 \rangle / \langle y^2 \rangle = 1.32$ , which would lead after linear regression to the conclusion that system  $Y$  is biased low by 16% if system  $X$  is assumed to be bias free.



**Figure 2.** (a) Simulated and (b) true wind speed and direction difference statistics of ECMWF forecast model minus scatterometer as a function of average wind speed for all global collocations from February 13–16 1994. Speed bias (thin solid line), standard deviation (thick solid line), direction bias (thin dotted line), standard deviation (thick dotted line), and vector root-mean-square (dashed line) of differences are shown. The simulation (Figure 2a) is done with the scatterometer wind distribution as "truth" and wind component standard errors of  $1.0$  and  $1.8 \text{ m s}^{-1}$  for the forecast model and scatterometer, respectively (compare Table 2). Figure 2b is for the first node at the inner swath, which is the noisiest of all nodes. Although Figure 2b is noisier, the general speed and direction error characteristics are qualitatively well simulated in Figure 2a by the wind component error model.

Thus the assumption may imply a  $1.6 \text{ m s}^{-1}$  pseudobias at  $10 \text{ m s}^{-1}$  for, in reality, unbiased Gaussian error distributions. The examples illustrate that when a noisy system is used as a reference for calibration in a dual collocation, we will need to know the error characteristics of that system. Further proof of this is given in Appendix A.

Another possibility of generating pseudobias is by nonlinear transformation. An unbiased symmetric error distribution may then be transformed into a skew and biased error distribution. For example, Gaussian errors on the wind components  $u$  and  $v$  for system  $X$  or  $Y$  will not correspond to Gaussian error distributions on wind speed  $f$  and direction  $\phi$ . Using the same notation and assumptions common to the previous two examples, we show in Appendix B that  $\langle f_X \rangle = \sqrt{\pi/2} \sigma_X$ , where  $\sigma_X^2 = \sigma^2 + \varepsilon_X^2$ , with  $\sigma$  the standard deviation (SD) of the true wind component distributions,  $\varepsilon_X$  the SE of system  $X$ , and where the errors are assumed identical for the  $u$  and  $v$  components. A similar expression can be derived for system  $Y$ . The expected mean wind speed difference is approximated as  $\langle f_X - f_Y \rangle = \sqrt{\pi/2} (\sigma_X - \sigma_Y) \approx \sqrt{\pi/2} (\varepsilon_X^2 - \varepsilon_Y^2) \sigma^{-1}$ . For example, the typical values of  $(\sigma, \varepsilon_X, \varepsilon_Y) = (5, 3, 1) \text{ m s}^{-1}$  will lead to an average wind speed bias of  $0.4 \text{ m s}^{-1}$ . This is a pseudobias since the error in the wind components is unbiased. One can show that the pseudobias generally oscillates from positive to negative as a function of wind speed and is largest in a relative sense for low speeds (as in Figure 2).

It may be clear from the above that it is desirable that the error characteristics of measurement systems are well described, thereby avoiding pseudobias effects only caused by inaccurate assumptions on the errors. Moreover, in order to provide a calibration and error model of observing systems it is desirable that a domain is chosen where the errors are simple to describe, preferably avoiding statistical moments of order higher than 2 (see section 2). Also, in geophysical applications the use of data with complex error characteristics may lead to biased results when the error characteristics are not properly accounted for.

#### 4. Error Modeling and Calibration With Three Systems

In the previous section it was indicated that calibration of one noisy system against another is not possible without fundamental assumptions on the noise characteristics of at least one system. It was shown that these assumptions may lead to substantial pseudobias problems. This is further elaborated in appendix A. Here a method is introduced to perform calibration and error modeling using triple collocations. The method is quite general and is introduced as such. Later on, the method is applied on in situ, scatterometer, and forecast model wind components. Now suppose three measurement systems  $X$ ,  $Y$  and  $Z$  measuring a true variable  $t$ . Let us define

$$\begin{aligned} x &= t + \delta_X, & \varepsilon_X^2 &= \langle \delta_X^2 \rangle \\ y &= s_Y(t + \delta_Y), & \varepsilon_Y^2 &= \langle \delta_Y^2 \rangle \\ z &= s_Z(t + \delta_Z), & \varepsilon_Z^2 &= \langle \delta_Z^2 \rangle \end{aligned} \quad (1)$$

with as before,  $\sigma^2 = \langle t^2 \rangle$ , and now  $\delta_X$ ,  $\delta_Y$ , and  $\delta_Z$  are the random observation errors in the measurements  $x$ ,  $y$ , and  $z$  respectively. Here  $s_Y$  and  $s_Z$  are the calibration (scaling) constants. We have assumed no bias such that  $\langle \delta_X \rangle = \langle \delta_Y \rangle = \langle \delta_Z \rangle = 0$ . For marine winds this is valid to good approximation (see section 5), but otherwise, bias may be easily removed.

It is unlikely that the three systems represent the same spatial scales. Therefore we will arbitrarily assume that observation systems  $X$  and  $Y$  can resolve smaller scales than system  $Z$  by taking  $\langle \delta_X \delta_Y \rangle = r^2$ . Here  $r^2$  is the variance common to these smaller scales and taken as part of the observation errors  $\delta_X$  and  $\delta_Y$  and  $t$  only represents the spatial scales resolved by  $z$ . By definition  $r^2$  is the correlated part of the representativeness errors of  $X$  and  $Y$ . The choice for  $t$  to only resolve the coarsest scale measurement allows the approximation  $\langle \delta_X t \rangle = \langle \delta_Y t \rangle = \langle \delta_Z t \rangle = 0$ , that is, the observation errors are assumed uncorrelated with  $t$ . Furthermore, since  $z$  does not include the smaller scales, the observation error of system  $Z$  is independent of the errors of  $X$  and  $Y$ , that is,  $\langle \delta_X \delta_Z \rangle = \langle \delta_Y \delta_Z \rangle = 0$ . The assumption that the wind component errors of the different observation systems are uncorrelated, except for the representativeness error, is essential to determine the calibration. Now the calibration coefficients can be derived from the different covariances

$$\begin{aligned} s_Y &= \langle yz \rangle \langle zx \rangle^{-1} \\ s_Z &= \langle yz \rangle (\langle xy \rangle - r^2 s_Y)^{-1} \end{aligned} \quad (2)$$

These coefficients can be used to create

$$\begin{aligned} y^* &= s_Y^{-1} y \\ z^* &= s_Z^{-1} z \end{aligned} \quad (3)$$

which are the calibrated data. Subsequently, all random error parameters of the observation systems  $X$ ,  $Y$ , and  $Z$  can be resolved pairwise from the different covariances, as illustrated in Appendix A by (A5). Here we used observation system  $X$  as a reference system. This preference can be easily altered by scaling all parameters to one of the other systems.

So under the premise that we find an estimate for  $r^2$  we have found a way to perform a first-order calibration. In work by Stoffelen [1996] the spatial representativeness error of the scatterometer with respect to the ECMWF model is estimated to be  $r^2 = 0.75 \text{ m}^2 \text{ s}^{-2}$ . We use this as a baseline assumption here as well. The sensitivity of the results to this choice is discussed later on and shown to be small (section 6).

#### 5. Higher-Order Calibration

After the first-order calibration the three systems should be largely unbiased. However, in this section we consider a more detailed calibration of the systems by pairwise comparison. For the triple-collocated data the procedure is run comparing  $X$  and  $Y$ ,  $Y$  and  $Z$ , and  $Z$  and  $X$  so that consistency can be checked between the results.

Now first consider  $X$  and  $Y$ . After obtaining  $\varepsilon_X$  and  $\varepsilon_Y$  we decide which system is the least noisy; for example, suppose  $\varepsilon_X > \varepsilon_Y$ . Then system  $Y$  may be convoluted with a Gaussian distribution with width  $\sqrt{\varepsilon_X^2 - \varepsilon_Y^2}$  to obtain a distribution (and a system  $Y'$ ) that has the same error properties as that of system  $X$ , i.e.,  $\varepsilon_{Y'} = \varepsilon_X$ . In fact, since they represent the same true distribution, the resulting distributions of  $X$  and  $Y'$  should be identical in case of a large sample size. When dealing with winds, the errors of  $X$  and  $Y$  may be matched for both components, such that either components or speed and direction distributions should be identical. By comparing the cumulative distributions of these two systems,  $f(x)$  and  $g(y')$ , that are monotonically increasing functions, we can easily compute a mapping  $y'' = \mu(y')$  that results in identical distributions  $f(x)$  and  $g(y'')$ . The higher-order correction would then be  $\mu(y) - y$ , which may be plotted versus  $y$ .

The higher-order calibration is only reliable when the errors of system  $X$  and  $Y$  are well characterized by a normal distribution. However, if substantial errors of order higher than 2 would be present in either system  $X$  or  $Y$ , then the detailed bias computation method set out above may provide large pseudobiases. When more than two systems are involved, such as in our triple collocation data set, a consistency check between the different comparisons may reveal such problems. In the extreme parts of the domain, where the error distributions of either system are insufficiently sampled, further pseudobias effects may occur. To gain confidence, the computed corrections may be verified by Monte Carlo simulation to test such sampling problems.

## 6. Calibration and Error Model Results

In this section we describe the implementation of the method given earlier and show the results of the calibration of scatterometer and forecast winds relative to the anemometer winds. A 1-month data set kindly provided by NCEP from March 1995 with off-line anemometer winds from the NOAA buoys corrected to 10-m height [Wilkerson and Earle, 1990] was used collocated with the ESA-processed ERS-1 scatterometer and NCEP forecast model winds. The NCEP forecast wind is valid at the time and location of the buoy measurement. All scatterometer data within 200 km and 3 hours of a buoy were selected and as a result 40,091 triple collocations were available resulting from 1465 independent buoy measurements.

The average wind components of the in situ, scatterometer, and forecast winds are very close (within a few tenths of a  $\text{m s}^{-1}$ ). As such, the assumption just below (1) that the systems have no absolute bias, i.e.,  $\langle \delta_i \rangle = 0$  for  $i = (X, Y, Z)$  proves valid.

A quality control procedure is applied to exclude gross errors. An iterative scheme is followed, where in each trial a calibrated (equation (3)) collocation triplet is rejected when for any pair the following condition holds, illustrated here for pair  $(x, y^*)$

$$|x - y^*| > 3 \sqrt{\varepsilon_X^2 + \varepsilon_Y^2} \quad (4)$$

where the calibrations and the errors are taken from the previous trial. In the first trial we start with calibration factors equal to 1 and errors equal to  $2 \text{ m s}^{-1}$ . The calibration factors are within a percent of their final value after one iteration, and also, the rejection rates remain constant (at  $\sim 1\%$ ) after 1 or 2 trials; 6 trials were used. A wind direction bias correction is repeated after every trial, and the resulting corrections are  $4^\circ$ – $5^\circ$  for the scatterometer and  $1^\circ$ – $2^\circ$  for the forecast model, where the incremental correction in the sixth trial was very small ( $< 0.01^\circ$ ). Wind direction corrections of this size do not substantially impact the wind component statistics, but the scatterometer bias may need further attention. Stoffelen [1996] shows that the bias reverses in the southern hemisphere and is difficult to explain from existing theories on air-sea interaction.

### 6.1. First-Order Calibration

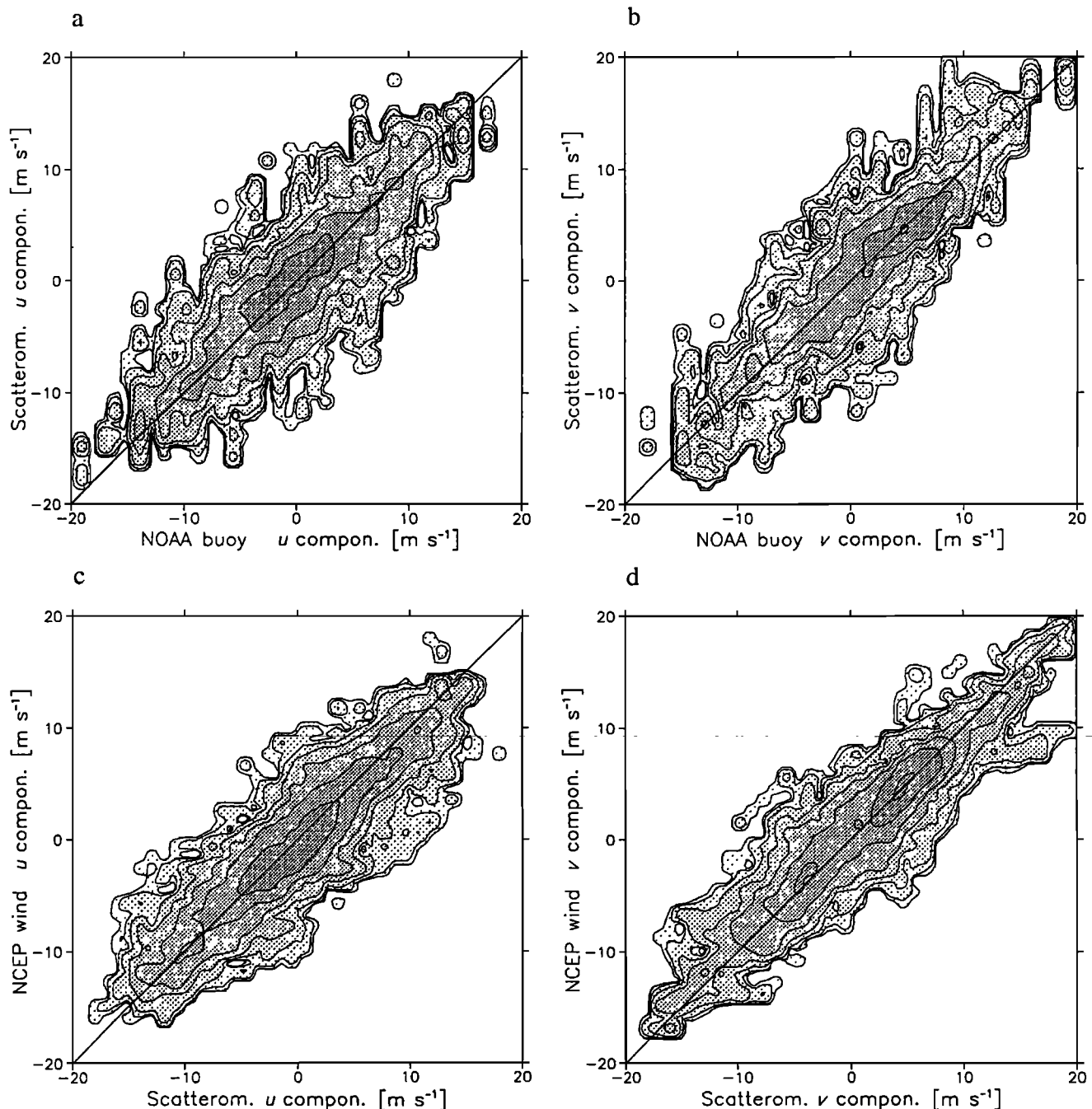
The calibration factors resulting from the above procedure are shown in Table 1. The NCEP forecast model appears biased high by roughly 6%. The representativeness error estimate modestly influences the calibration coefficient of the forecast model as we would expect from (2). In contrast, the scatterometer calibration enforces the winds. Remarkably, the scatterometer along-track component is biased less than the across-track component. This difference, however, may be explained by the relatively small number of independent collocations used.

Figure 3 shows the joint distributions of the wind components of in situ and scatterometer, scatterometer and NCEP, and NCEP and in situ data. It is evident that the scatter in the scatterometer and NCEP plot is smallest. This means that the in situ winds have the largest error. The in situ and scatterometer plot shows the largest scatter, which indicates that the NCEP winds are the most accurate. Table 2 shows the results of our random error estimates from (A5) in Appendix A, which confirm our subjective analysis. The error estimates for the  $u$  and  $v$  components are quite similar for NCEP and conventional winds, but for the scatterometer the along-track component seems slightly worse than the across-

**Table 1.** Calibration Scaling Factors Against Buoy Winds for Wind Components From the Scatterometer and Forecast Model for Different Representativeness Errors

	Component Scaling		
	$u$	$v$	$r^2, \text{m}^2 \text{s}^{-2}$
Scatterometer	0.97	0.95	all
NCEP model	1.06	1.06	0.50
NCEP model	1.06	1.07	0.75
NCEP model	1.07	1.08	1.00

Here  $u$  is the along-track, and  $v$  is the across-track wind component;  $r^2$  is the representativeness error (due to scatterometer and model spatial resolution difference).



**Figure 3.** Joint distributions for the along-track ( $u$ ) and across-track ( $v$ ) ERS-1 wind components, respectively, for the (a, b) NOAA buoy anemometer and ERS-1 scatterometer, (c, d) scatterometer and NCEP forecast model, and (e, f) forecast model and anemometer winds. These plots show the full characteristics of the triple collocation database in the wind domain.

track component. Given the fact that the wind direction was predominantly across-track in this data set, it may indicate some anisotropy in the scatterometer error distribution.

From a climatological wind spectrum one may estimate the representativeness error variance of the conventional winds with respect to NCEP winds to be  $2.1 \text{ m}^2 \text{ s}^{-2}$  [Stoffelen, 1996]. As such, the (local) error of the in situ winds may be estimated as  $1.41 \text{ m s}^{-1}$  for the  $u$  and  $1.21 \text{ m s}^{-1}$  for the  $v$  component. However, for many applications the local wind

is not as relevant as an area-averaged quantity such as provided by the scatterometer.

Since the scatterometer winds are not exactly collocated in space and time with the in situ and NCEP winds, a collocation error may be subtracted from the former. Wind measurements separated by in between 2 and 3 hours will have an additional error component of  $\sim 1.5 \text{ m}^2 \text{ s}^{-2}$  [Stoffelen and Anderson, 1997c]. When we assume that the collocations are randomly distributed in time (over 6 hours), the average er-

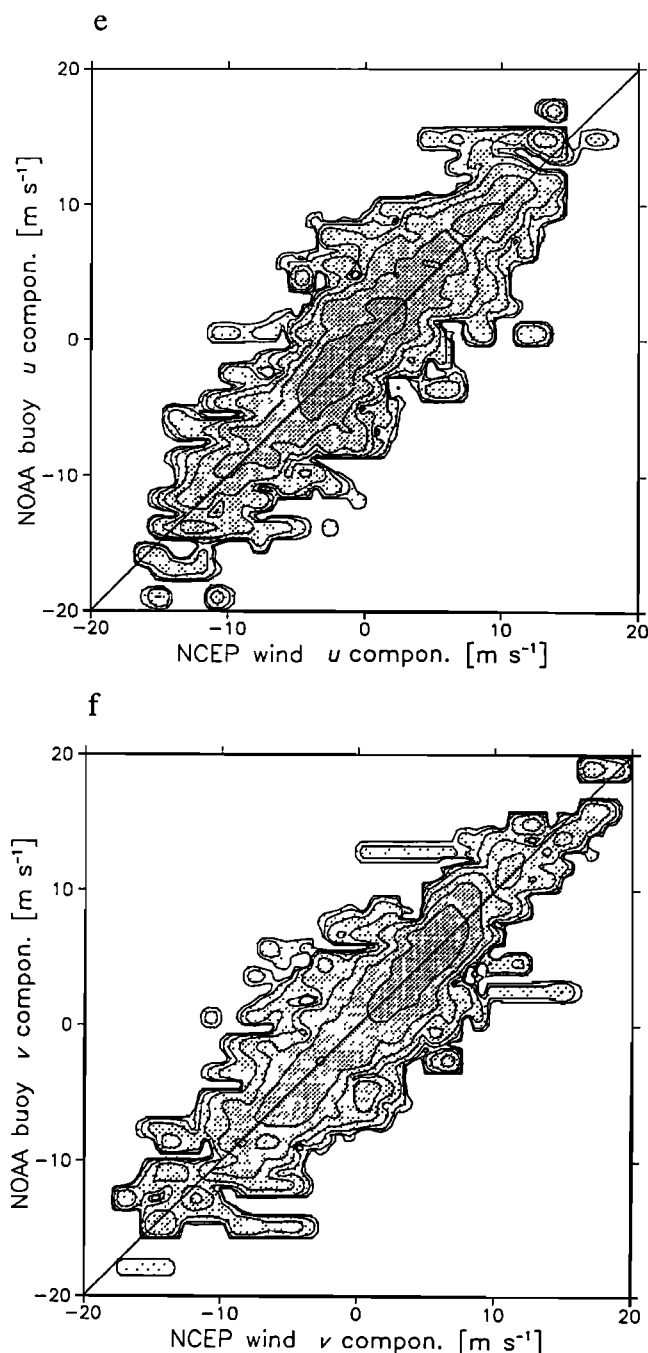


Figure 3. (continued)

error contribution would be  $\sim 0.75 \text{ m}^2 \text{ s}^{-2}$ . Such a collocation error would reduce the scatterometer error estimates by  $\sim 0.2 \text{ m s}^{-1}$ .

Stoffelen [1996] studied the spatial representation of the ECMWF forecast model and the ERS-1 scatterometer winds on scales between 50 and 250 km. On these scales the scatterometer contained substantially (20–40%) more variance. It was very likely that part of this additional variance verifies with the true wind and that part of it contributes to the scatterometer wind error. From the study it follows that the sum of the scatterometer error on scales between 50 and 250 km and the representativeness error would be  $1.4 \text{ m s}^{-1}$ , which

verifies reasonably well with the error estimates obtained in this work. The ECMWF and NCEP model errors would be comparable, since the ECMWF wind error on scales between 50 and 250 km was estimated to be  $1.1 \text{ m s}^{-1}$  in Stoffelen [1996].

## 6.2. Higher-Order Calibration

The higher-order calibration procedure of section 5 requires a convolution of the most accurate system with a Gaussian error distribution with a width determined by the difference in error variance of the two systems. Figure 4 shows the higher-order calibration by the cumulative distribution mapping method. The wind component biases appear to be rather random in nature. The smallest biases are generally present at small wind component values, and the highest are present at high component speeds. This is due to the fact that the largest number of data is present at low component speeds, and the lowest number is present at high speeds. In other words, the higher the speeds the less accurate the results are. In an attempt to fit the bias with a smooth function this would have to be taken into account, and changes at the tail of the distribution should be kept small.

Inconsistency of the wind component biases between the calibration pairs is most noticeable at the tail of the distributions; that is, for example, the bias of the in situ winds with respect to the scatterometer is not equal to the sum of the biases of the conventional winds with respect to NCEP and the bias of NCEP with respect to the scatterometer. Moreover, the plot suggests that the scatterometer has a generally negative bias with respect to the anemometer winds and NCEP for the along-track component. However, this effect is not confirmed by the differences in mean value of the scatterometer along-track component. Closer inspection reveals more (but smaller) inconsistencies. These indicate insufficient sample size or higher-order statistical moments in the error distributions than those accounted for.

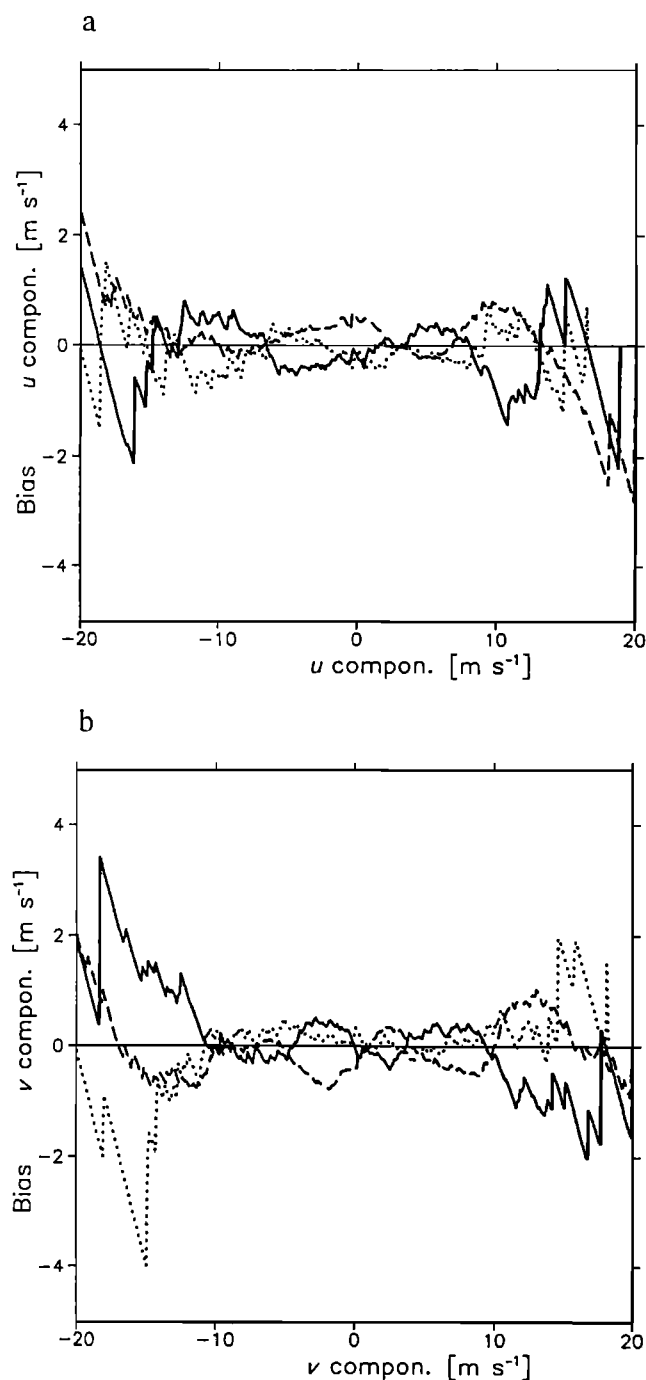
The cloud of doubt is assumed to be Gaussian with a fixed standard error. However, in reality, also higher-order moments may be relevant here. Furthermore, the standard error may depend on the geophysical condition, for instance on

**Table 2.** Estimates of the Wind Component Standard Deviation of the True Distribution and the Standard Errors of the Buoy, Scatterometer, and Forecast Error Distributions

	Component, $\text{ms}^{-1}$	
	$u$	$v$
True variance	4.68	5.24
In situ error	2.02	1.89
Scatterometer error	1.89	1.62
NCEP error	1.11	1.15

Here  $u$  is the along-track and  $v$  the across-track wind component. The values are computed at the spatial representativeness of the forecast winds with  $r^2 = 0.75 \text{ m s}^{-1}$  (see text).





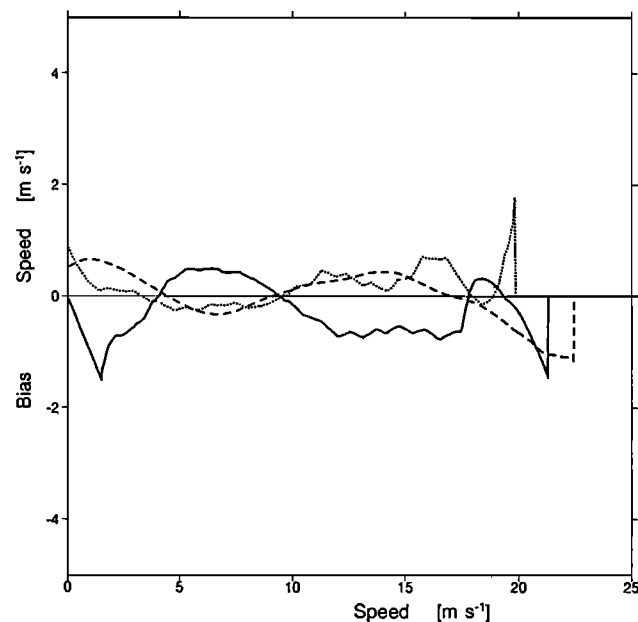
**Figure 4.** Higher-order calibration by cumulative distribution mapping (see text) for (a) the along-track and (b) the across-track ERS-1 wind components. The biases of scatterometer with respect to NOAA buoy anemometer (solid line), NCEP forecast model with respect to scatterometer (dotted line), and anemometer with respect to forecast model (dashed line) winds are shown. Although large biases are present, there is no consistent pattern apparent in the data.

stability, and we would need a representative sample of all these conditions to perform the higher-order calibration accurately. As such, the number of samples we need to determine the calibration and error model may be quite large.

Since there is no mechanism to remove the pseudobiases due to sampling and higher-order moments, we believe that the methodology has to be used with restraint.

Physically, one may expect systematic errors to scale with  $f$  and  $\phi$ , rather than with  $u$  and  $v$ . If the errors in  $u$  and  $v$  of systems  $X$  and  $Y$  are identical, then their  $f$  and  $\phi$  distributions should ideally also be identical. The wind direction cumulative mapping also does not result in substantial and consistent systematic effects, but for wind speed it does, as shown in Figure 5. The scatterometer is biased high for high and very low wind speed and biased low for moderate speeds with respect to the buoys. The NCEP model shows similar differences with respect to the buoys but roughly half in size. However, at the very low wind speeds, NCEP and scatterometer are more consistent. The comparison of NCEP and scatterometer winds generally confirms these results, except at the poorly sampled high speeds. After applying to the scatterometer and NCEP winds the first-order corrections and the second-order corrections up to  $17 \text{ m s}^{-1}$ , a repeated application of the calibration method does result in no further substantial corrections and in errors that are very similar to the ones of Table 2. As such, up to  $17 \text{ m s}^{-1}$  the higher-order correction of the scatterometer against the buoys appears sensible, and we suggest it, together with a 4% linear correction, as a modification to CMOD4.

It is worth noting at this point that by taking the buoys as a reference for the scatterometer calibration, we assume that the buoy generally provides an unbiased estimate of the scatterometer footprint area-averaged wind vector. Especially for the very low wind speeds, one may want to further investigate this.



**Figure 5.** As Figure 4, but for wind speed. A consistent speed correction for the NCEP model and scatterometer is present at wind speeds up to  $17 \text{ m s}^{-1}$ . For these speeds the solid line shows the suggested higher-order correction to CMOD4 (in addition to a 4% linear correction).

## 7. Conclusions

### 7.1. Résumé

In this paper, calibration and error modeling are discussed, and a methodology is provided to obtain the absolute calibration and accuracy of observing systems. In particular, the focus is put on ocean surface wind speed (or stress) biases that are detrimental for the computation of fluxes of momentum, humidity, and energy through the air-sea interface. An improved ERS scatterometer wind processing is proposed.

It was demonstrated that the selection of a simple measurement domain where second-order statistics are sufficient to describe the uncertainty of the measurements is preferred. More specifically, we have shown that wind error modeling using component error distributions that are Gaussian and constant represents a simple method to describe the more complex errors in speed and direction. We have shown that substantial pseudowind speed biases can occur through the nonlinear transformation of unbiased wind component errors to the wind speed and direction domain. In a direct wind speed calibration, where usually unjustly symmetric error distributions are assumed, the pseudobiases would be taken out, leading to biased wind components [see also *Hinton and Wylie*, 1985]. Wind component error modeling as proposed here elegantly solves this problem.

In order to calibrate one observing system with respect to the other, one may use, either explicitly or implicitly, a simplifying assumption on the errors of the two systems. For instance, it is common practice to assume that the errors of two systems that are compared are equal or to assume that one system is much more accurate (i.e., is "truth") than the other. Given our results in Table 2 and Figure 3, it is obvious that both of these choices would have been crude for any of the observation systems dealt with in this paper. We have shown that such assumptions may lead to substantial pseudobias effects. Furthermore, in Appendix A it is shown that it is impossible to calibrate one noisy system against another without such assumptions or other prior knowledge on the error characteristics of one or both systems.

For a proper calibration of an observing system a reference system is necessary and at least one other observation system. Using triple collocations, a method to calibrate noisy systems has been developed. Subsequently, in a pairwise comparison of the calibrated observation systems the covariances were used to estimate the true variance resolved by both systems and the error variance of the observations. To complement the linear calibration, a more refined bias estimation procedure was adopted.

We used the NOAA buoy anemometer winds as a reference, although they turned out to be the least accurate amongst the scatterometer and NCEP forecast model winds. The spatial representativeness error is the main reason for the low accuracy of the buoys in our triple comparison. One would expect this error to be of a random nature and not lead to biases in the results. We found that the CMOD4-derived scatterometer wind components are biased low by 4%. The

NCEP forecast model appears to be very accurate but biased high by 6% for the period we examined (March 1995). In another study, using triple collocations of the ECMWF forecast model, ERS scatterometer winds, and real-time available anemometer winds, similar results were obtained [Stoffelen, 1996]. The higher-order scatterometer calibration with respect to the buoys resulted in a correction additional to the 4% mentioned above. The total correction is recommended for operational implementation in the ESA fast delivery processing chain.

### 7.2. Application

Our statistical analysis on surface winds has direct implications in the area of data assimilation in numerical weather prediction (NWP) models and in ocean circulation and wave model forcing. However, the methodology may be applied for the interpretation of any geophysical variable with a high variability on the smaller scales or high signal-to-noise ratio. It provides a way to compare data with different amounts of noise or different spatial and/or temporal resolution.

It is essential that NWP models assimilate unbiased data. It has been observed by ECMWF that the scatterometer bias with respect to their forecast model (~10 %) had the tendency to slow down the forecast winds in the analysis and subsequently fill in low-pressure systems. This effect can be circumvented by a model wind correction to match the mean observed wind [Roquet and Gaffard, 1995]. The 6% bias we found between the buoys and the NCEP model may result from physical parameterizations that also control atmospheric boundary layer humidity, depth, and temperature and that require careful tuning. Such biases, when detected, are therefore not easily corrected, and a short-term solution such as adopted by Roquet and Gaffard will be beneficial. However, in the long term the forecast model bias correction should be replaced by forecast model improvements.

Roquet and Gaffard [1995] computed a bias correction in the wind speed domain, rather than in the wind components. The wind components, however, are used for data assimilation and should be unbiased. Figure 2 clearly shows that because of the nonlinear transformation, unbiased component errors will lead to biased speeds and vice versa. It is therefore essential to compute biases in the domain of the analysis variables, i.e., the wind components [see also *Le Meur et al.*, 1997]. For other analysis variables the same strategy may be applied; that is, observations and forecast data are compared in that domain where the errors are best described, and bias corrections are computed after the transformation of the random errors to the analysis variable domain. For noisy data a careful statistical error analysis as described in this work will be essential to arrive at an optimal bias correction and assimilation.

Wave models directly rely on NWP model winds. Here it was shown that NWP forecast model winds are very accurate in describing the synoptic scale flow but may be biased. However, since we quantified the bias, it is easily corrected for when the winds are used in wave models. We note that it is more problematic to take account of the error in the forc-

ing since this error is nonlinearly related to the random wind error. Also, it is relevant to be aware of the fact that a NWP model provides an area-averaged vector wind and that the additional forcing due to the wind on the unresolved scales needs be parameterized.

Tropical wind analysis is very important for ocean circulation models and as such for the study of the Earth's climate. In ocean circulation experiments, similar arguments apply as in wave forecasting concerning the forcing problem. Stoffelen [1996] and Bryan *et al.* [1995] noted a large directional inconsistency between scatterometer and ECMWF wind direction at the equator. The tropical array of (TAO) buoys may provide a relevant data set to enhance our knowledge on the utility of scatterometer and forecast winds in this area using the methodology described here.

## Appendix A: Necessity of Error Modeling Before Calibration or Validation

In this appendix the problem of calibration and validation of one noisy system with respect to another one will be discussed. Usually, scatterplots are used to compare the data followed by a regression analysis to compute a calibration coefficient or to validate the system(s). First, the interpretation of scatterplots and associated regression and bin average (BA) analyses are discussed, and it is illustrated that calibration or validation, without knowing the error characteristics of one or both systems, can easily lead to pseudobias. In the second part it is shown that calibration or validation of one noisy system against another, without knowing the error characteristics of the observing systems, is generally not possible.

### A1. Scatterplots and Regression

Usually, a scatterplot is used to determine the error characteristics of a measurement system (see, for example, Figure 4). In this section we quantify the properties of the scatterplot. If enough collocation data are available, then the density of points in the scatterplot is proportional to the joint probability density of  $x$  and  $y$  given by

$$p(x, y) = \int p(x|t) p(y|t) p(t) dt \quad (A1)$$

The integration is over the distribution of true states  $p(t)$  and over the distributions of error. Here  $p(x|t)$  is the conditional probability density of  $x$  given  $t$ , which includes all measurement and error characteristics of the measurements  $x$ . (It is closely related to what was introduced as the cloud of doubt around observation  $x$ , which formally reads  $p(t|x)$  and  $p(t|x) = p(x|t) p(t)$ .) We can see that the joint distribution of  $x$  and  $y$  is not only determined by the error characteristics of both systems but also by the distribution of true states. In the simple case of unbiased Gaussian errors with standard error (SE) equal to  $\epsilon_x$  or  $\epsilon_y$  and a Gaussian true distribution with zero mean and RMS  $\sigma$ , the joint probability of  $x$  and  $y$  can be written as

$$p(x, y) \propto \exp\left[-\frac{(\sigma^2 + \epsilon_x^2)x^2 + (\sigma^2 + \epsilon_y^2)y^2 - \sigma^2 xy}{2(\sigma^2 \epsilon_x^2 + \sigma^2 \epsilon_y^2 + \epsilon_x^2 \epsilon_y^2)}\right] \quad (A2)$$

For given  $x$  the mean  $y$  value of this distribution does not lie at  $y = x$  but at  $y = \sigma^2 (\sigma^2 + \epsilon_x^2)^{-1} x$ . So, even for unbiased Gaussian error distributions, computing the mean of  $y$  for a fixed subrange or bin of  $x$  (bin average) does, in general, reveal a pseudobias that depends on the error characteristics of  $x$ . This needs to be accounted for in the interpretation, and therefore, when correcting for bin-average biases with respect to a reference system, the error characteristics of that system, in this case  $\epsilon_x$ , need to be known well.

For calibration or validation, often linear regression is used as a tool. For a well-calibrated system and in the case of  $\epsilon_x = \epsilon_y$  a geometric mean linear regression on the joint distribution would indeed result in the line  $y = x$ , but in the more general case of  $\epsilon_x \neq \epsilon_y$  it would result in  $y = (\sigma^2 + \epsilon_y^2)(\sigma^2 + \epsilon_x^2)^{-1} x$ , where it would again result in a pseudobias. When the error characteristics of  $x$  and  $y$  are known, a weighted fit may result in a proper calibration. However, most often the errors are unknown.

### A2. Necessity of Error Modeling Before Calibration

Then the question emerges; Is it possible to perform a calibration or validation of one noisy system against the other without prior information on the error characteristics of one or both of the systems? Below we illustrate that this is generally not possible.

Suppose we have a set of true states, indicated by variable  $t$ , measured by systems  $X$  and  $Y$  resulting in measurements  $x$  and  $y$ . We define  $\sigma^2 = \langle t^2 \rangle$ , where  $\langle \rangle$  denotes the expected mean, and introduce the error model

$$\begin{aligned} x &= t + \delta_x & \epsilon_x^2 &= \langle \delta_x^2 \rangle \\ y &= t + \delta_y & \epsilon_y^2 &= \langle \delta_y^2 \rangle \end{aligned} \quad (A3)$$

where  $x$ ,  $y$ , and  $t$  are as defined before and  $\delta_x$  and  $\delta_y$  are the independent observation errors on  $x$  and  $y$  respectively, i.e.,  $\langle \delta_x \delta_y \rangle \approx 0$ . The observation errors are random and uncorrelated with  $t$ , i.e.,  $\langle \delta_x t \rangle \approx 0$  and  $\langle \delta_y t \rangle \approx 0$ . For simplicity we have removed the true distribution's mean and the systematic errors, i.e.,  $\langle t \rangle = 0$ ,  $\langle \delta_x \rangle = 0$ , and  $\langle \delta_y \rangle = 0$ . We now find

$$\begin{aligned} \langle x^2 \rangle &= \sigma^2 + \epsilon_x^2 \\ \langle y^2 \rangle &= \sigma^2 + \epsilon_y^2 \\ \langle xy \rangle &= \sigma^2 \end{aligned} \quad (A4)$$

which are three equations with three unknowns that are easily resolved

$$\begin{aligned} \epsilon_x^2 &= \langle x^2 \rangle - \langle xy \rangle \\ \epsilon_y^2 &= \langle y^2 \rangle - \langle xy \rangle \\ \sigma^2 &= \langle xy \rangle \end{aligned} \quad (A5)$$

Thus from the covariances we can resolve the true variance and the standard errors of systems  $X$  and  $Y$ .

Now suppose that one system is not calibrated, for example, we change (A3) to

$$\begin{aligned} x &= t + \delta_x & \varepsilon_x^2 &= \langle \delta_x^2 \rangle \\ y &= s_Y(t + \delta_Y) & \varepsilon_Y^2 &= \langle \delta_Y^2 \rangle \end{aligned} \quad (\text{A6})$$

where  $s_Y$  is the calibration (scaling) constant. We now find

$$\begin{aligned} \varepsilon_x^{*2} &= \langle x^2 \rangle - \langle xy \rangle = \varepsilon_x^2 + (1 - s_Y) \sigma^2 \\ \varepsilon_Y^{*2} &= \langle y^2 \rangle - \langle xy \rangle = s_Y^2 \varepsilon_Y^2 + s_Y(s_Y - 1) \sigma^2 \\ \sigma^{*2} &= \langle xy \rangle = s_Y \sigma^2 \end{aligned} \quad (\text{A7})$$

such that for  $\varepsilon_x^{*2} \geq 0$  and  $\varepsilon_Y^{*2} \geq 0$  the transformed distribution of  $t^* = \sqrt{s_Y} t$  in combination with error model

$$\begin{aligned} x^* &= t^* + \delta_x^* & \langle \delta_x^{*2} \rangle &= \varepsilon_x^{*2} \\ y^* &= t^* + \delta_Y^* & \langle \delta_Y^{*2} \rangle &= \varepsilon_Y^{*2} \end{aligned} \quad (\text{A8})$$

is statistically identical to the system defined in (A3). Consequently, one can show that substituting the transformed quantities defined in (A7-8) into (A2) rather than the real quantities of (A3) leads to an identical joint distribution. As such, the calibration coefficient cannot be resolved unambiguously without further information on the errors in this general case.

This is due to the fact that we have three independent statistical variables, i.e.,  $\langle x^2 \rangle$ ,  $\langle y^2 \rangle$ , and  $\langle xy \rangle$ , and four unknowns that are  $s_Y$ ,  $\sigma$ ,  $\varepsilon_x$ , and  $\varepsilon_Y$ , which leaves one degree of freedom. The constraint that the error variances need to be larger than zero allows the following values for the scaling constant  $s_Y$  in the case of  $s_Y = 1$ :  $-\varepsilon_Y^2 (\sigma^2 + \varepsilon_Y^2)^{-1} \leq s_Y - 1 \leq \varepsilon_X^2 \sigma^{-2}$ . Only the addition of an independent third system can help determine the unique and correct value of  $s_Y$ .

## Appendix B: Pseudobias Through Nonlinear Transformation

A statistical problem that is relevant for considering the optimal error domain may occur through nonlinear transformation. This is easily shown for wind speed  $f$  that depends in a nonlinear manner on the wind components ( $u$ ,  $v$ ). As an alternative to Hinton and Wylie [1985], we assume normal distributed errors on the wind components  $u$  and  $v$  for measurement systems  $X$  and  $Y$ , i.e.,  $u_X = N(u, \varepsilon_X)$ ,  $v_X = N(v, \varepsilon_X)$ ,  $u_Y = N(u, \varepsilon_Y)$ , and  $v_Y = N(v, \varepsilon_Y)$  and, in addition, normal distributed true components,  $u_t = N(0, \sigma)$  and  $v_t = N(0, \sigma)$ , where  $N(0, \sigma)$  indicates the normal distribution with zero mean and standard deviation  $\sigma$ . The wind speed distribution of system  $X$ ,  $p(f_X) df_X$ , then becomes

$$p(f_X) df_X = \frac{f_X}{\sigma_X^2} \exp\left[-\frac{f_X^2}{2\sigma_X^2}\right] df_X \quad (\text{B1})$$

where  $\sigma_X^2 = \sigma^2 + \varepsilon_X^2$ . A similar expression can be derived for system  $Y$ . The expected mean value of  $f_X$  will be  $\langle f_X \rangle = \sqrt{\pi/2} \sigma_X$ , and  $\langle f_X - f_Y \rangle = \sqrt{\pi/2} (\sigma_X - \sigma_Y) \approx \sqrt{\pi/2} (\varepsilon_X^2 - \varepsilon_Y^2) \sigma^{-1}$ . Thus the difference in mean wind speed is generally nonzero, and a pseudobias occurs, since the component error distributions were not biased. More detailed analysis shows that the pseudobias results from the fact that the wind speed error distribution is asymmetric in the case of symmetric wind component error distributions, especially for low wind speeds. The magnitude of the pseudobias depends on wind speed (see, e.g., Figure 2).

Thus the difference in mean wind speed is generally nonzero, and a pseudobias occurs, since the component error distributions were not biased. More detailed analysis shows that the pseudobias results from the fact that the wind speed error distribution is asymmetric in the case of symmetric wind component error distributions, especially for low wind speeds. The magnitude of the pseudobias depends on wind speed (see, e.g., Figure 2).

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