WIND BIAS CORRECTION GUIDE

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KNMI

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General

This document is written for all users of Numerical Weather Prediction Satellite Application Facility (NWP SAF) scatterometer wind processors or Ocean and Sea Ice (OSI) SAF wind products. It gives the state of the art concerning scatterometer wind error characteristics in terms of resolution, bias, and accuracy, and contains recommendations how to correct for biases. The authors hope that this will help the user community to exploit the potential of scatterometer wind data as much as possible. They much appreciate feedback.

Within the NWP SAF software is made for processing scatterometer data over the open ocean to ocean vector winds. This software is freely available upon registration, and is also used in the OSI SAF to produce near-real-time ocean vector wind products.

It has been demonstrated that the SAF scatterometer winds are accurate and reliable. Yet, as every measured quantity, these products have their particular error characteristics. Long term monitoring is needed to reveal these characteristics, and this is part of the tasks of the NWP SAF and OSI SAF project teams. Correction for biases in scatterometer winds is considered to be the responsibility of the OSI SAF and performed according to requirements from the broad user community, extending beyond NWP users. For example, requirements are expressed within EUMETSAT user meetings or the International Ocean Vector Winds Science Team (IOVWST).

Several reasons may exist why users wish to perform further bias correction:

- The SAF product specifications for product quality are inadequate, for example, a user may wish to use a different spatial sampling, corresponding to a different accuracy and bias (wind biases are resolution dependent);
- The SAF winds are biased with respect to a particular NWP model wind climate, which the scatterometer winds are blended with or assimilated in for a particular user application or service.

Introduction

This guidance document addresses how systematic differences between NWP models and scatterometer wind observations, further referred to as biases, may be estimated and corrected. These biases are relevant for NWP data assimilation. The purpose of data assimilation is to find a model state that gives the best match between the most recent model prediction and the observations that became available since the forecast was produced. This state is called the analysis. Modern assimilation techniques as Kalman filtering, 3DVar, and 4DVar require as good as possible estimates for the random error characteristics of both model and observations, since the error variances determine the relative weight of each of the information sources in the analysis. These techniques are based on BLUE, Best Linear Unbiased Estimates, and therefore do not deal with biases, either constant or variable.

Biases can be detrimental for NWP impact, e.g., it is well known that biases in wind climate and the particular sampling of a scatterometer in space and time may cause artificial and unwanted interference patterns (waves) in the wind field. Also, negative impacts may occur by decelerating or accelerating flows and thereby filling in or intensifying atmospheric disturbances or lows. It is therefore important to correct for biases with respect to the NWP model wind climate. Note that bias correction schemes for satellite radiances are common in data assimilation to facilitate BLUE by providing consistent satellite and NWP model data; see *Dee* (2005) and references therein or *Dee and Uppala* (2008). In practice best results are obtained when the observations are corrected to fit the model wind climate, even when the biases are caused by model imperfections: consistency appears to be generally more important than absolute calibration in NWP dynamics.

Biases in scatterometer observations are studied in detail (e.g., *Stoffelen*, 1998b; *Vogelzang et al*., 2011). Moored buoys are generally taken as calibration target to establish “surface truth”. This does not mean that biases of scatterometer winds against all NWP models will be minimized in this way. In the next sections we discuss what scatterometer winds and NWP winds represent and how these different representations may lead to biases w.r.t. the buoys. We specifically address so-called pseudo biases due to differences in spatial representation of NWP model, scatterometer and buoy winds. Moreover, biases may change with wind speed, time, atmospheric stratification, etc.

What does a Scatterometer wind represent?

A scatterometer is a radar instrument that measures the radar cross section of a portion of the Earth’s surface (for spaceborne scatterometers typically of size 25 km × 25 km) from a number of incidence and/or azimuth angles and/or polarizations. The radar cross section, σ_0, is a surface property and a measure for the fraction of incident radar radiation scattered back under given azimuth and incidence angle. It is measured by a scatterometer antenna with known antenna gain pattern and distance between radar and scattering surface.

There are two ways of modeling σ_0 as a function of the other parameters: empirical and fundamental. In the fundamental approach wave generation by wind and radar backscatter from the ocean surface are modeled to yield σ_0. The empirical approach assumes some form of σ_0 as a function of the other parameters with a number of coefficients that are fitted to the observations. The outcome of the two approaches is the same: a prescription of how to calculate σ_0 as a function of wind speed and direction, measurement geometry, radar properties, etc. This function is called the Geophysical Model Function (GMF). The empirical approach has two main advantages over the more fundamental approaches (given the present state of the fundamental algorithms): the radar cross section is calculated faster and it is calculated more accurate. This makes the empirical approach better suited for applications.

The radar cross section Geophysical Model Function is defined as

$$\sigma_0 = GMF\left(U_{10N}, \phi, \theta, p, \lambda\right) \tag{1}$$

with U_{10N} the equivalent neutral wind speed, ϕ the wind direction w.r.t. beam pointing azimuth φ, θ the beam incidence angle, p the radar beam polarization and λ the microwave wavelength. An example is shown in figure 1.

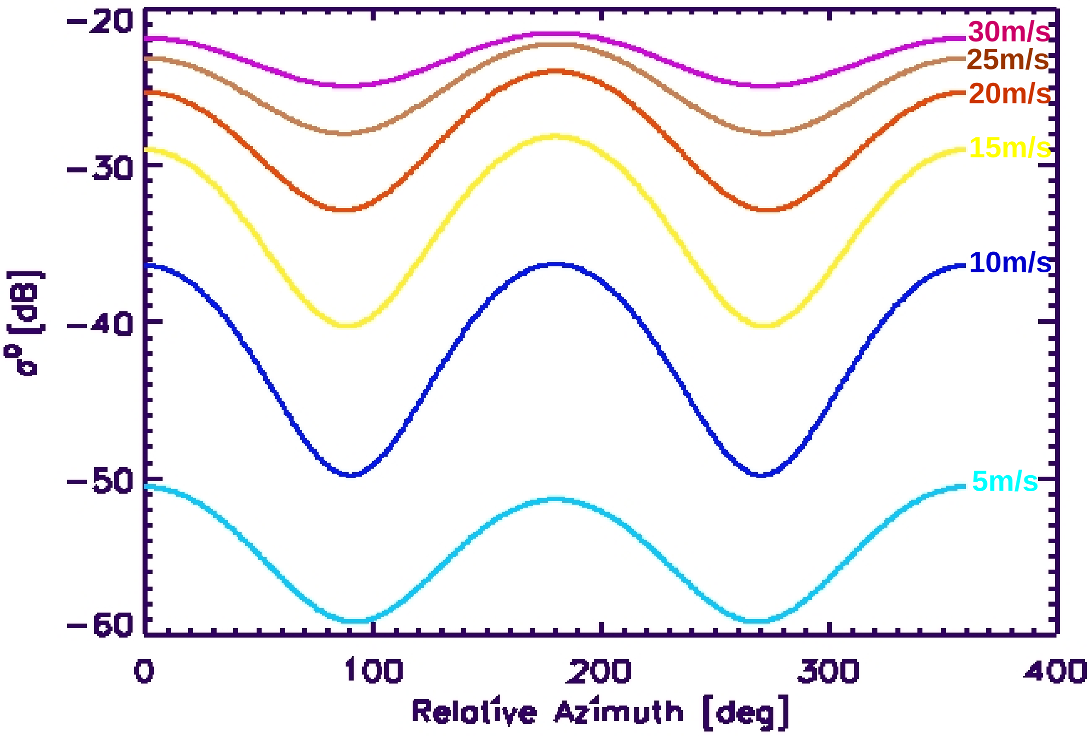

Figure 1: Ku-band radar cross section at vertical polarization as a function of the angle between wind and radar look direction for various wind speeds at an incidence angle of 40° (*courtesy Z. Jelenak*).

The GMF for ASCAT is called CMOD. The current version is CMOD5NA and CMOD6 is under development. The radar cross section measurements typically have errors of 5%, while φ, θ, p, and λ are known very accurately. Given radar cross section data at multiple azimuths as measured by a scatterometer, the GMF is inverted to compute the local wind vector (or wind vector probability distribution; see *Stoffelen and Portabella*, 2006). See also *Portabella*, 2002, and *Stoffelen*, 1998a, who describe the scientific background to wind retrieval and processing.

The radar cross section is a property of the surface itself. It is a measure of the surface roughness, z_0, and related to the wind stress vector, $\boldsymbol{\tau}$. This is in turn related to the friction wind velocity, u_* or $\mathbf{u}_*$ in vector notation. The surface wind at 10 m anemometer height, U_{10}, depends on u_* and the temperature difference between the ocean and the overlying air. To avoid the latter dependency of scatterometer winds, SAF scatterometer winds, U_{10N}, are processed at equivalent neutral stability, i.e., using equal temperature of air and sea (e.g., *Hersbach*, 2010a). In equations and following *Portabella and Stoffelen* (2009):

$$U_{10N} = \frac{u_*}{k} \ln(10/z_0) \tag{2}$$

$$U_{10} - U_S = \frac{u_*}{k} \left[\ln(10/z_0) - \psi(10/L) \right] \tag{3}$$

$$z_0 = 0.11 \frac{\nu}{u_*} + \alpha \frac{u_*^2}{g} \tag{4}$$

$$\boldsymbol{\tau} = \rho \cdot u_* \mathbf{u}_* \tag{5}$$

where $k = 0.41$ is the von Karman constant, z_0 is the roughness depth (also called roughness length), ψ is the stability function (positive, negative, and null, for unstable, stable, and neutral conditions, respectively) and L is the Monin-Obukhov length, which includes the effects of temperature and moisture fluctuations on buoyancy. ρ is the air mass density, ν is the kinematic viscosity of the air ($1.5\text{x}10^{-5}$ m^2/s), g is the gravitational acceleration at the Earth's surface (9.8 m/s^2), and α is the dimensionless Charnock parameter.

A few remarks can be made concerning systematic effects in scatterometer winds:

- A scatterometer wind is measured w.r.t. the current and not w.r.t. an earth-fixed frame like buoy and NWP winds. In the Gulf Stream or the Kuroshio current, the discrepancy may be occasionally as large as 1 m/s in speed.
- Roughness is caused by air-sea momentum exchange (stress) which depends on atmospheric mass ρ. Eq. (5) suggests such dependency, whereas eq. (4) ignores it. Typically, ρ varies by a few percent over the globe which is generally ignored in scatterometry (*Hersbach*, 2010b).
- Ocean mass density also plays a role in momentum exchange and varies by a per mille over the globe (e.g., http://en.wikipedia.org/wiki/Water_(molecule)#Density_of_water_and_ice and NOAA World Ocean Atlas). This is also ignored.
- The momentum exchange and small-scale ocean roughness at a given equivalent neutral wind may depend on variations in sea state. *Portabella and Stoffelen* (2009) found no such

dependency in a statistical assessment using the ECMWF WAM model wave parameters. In extreme conditions, particularly near the coast, such effects are quite plausible. It has on the other hand been noted that some of these conditions are flagged by the scatterometer Quality Controls at KNMI.

The following effects are also known for their systematic behavior:

- Contamination by land and/or sea ice. Land and sea ice have a much larger radar cross section than the ocean surface, so land or sea ice contamination of a cell may lead to overestimation of the wind speed. Quality Control prevents such contamination (e.g., *Belmonte* et al., 2011).
- Presence and intensity of rain. Microwave radiation is scattered into all directions by raindrops in the atmosphere and therefore less signal is received back than in the absence of rain, leading to an underestimation of the wind speed. On the other hand, rain clouds cause backscattering leading to overestimation of the wind. Moreover, splashing rain on the ocean surface disturbs the radar cross section. The former two effects are substantial at Ku-band wavelengths (NSCAT, SeaWinds, OSCAT; *Nie and Long*, 2008), but rather small at C band (ERS, ASCAT; *Portabella* et al., 2011).

Scatterometer processing starts with defining a regular grid on the Earth's surface. The area of a grid cell is larger than the area over which a single radar measurement is performed. Next, for each measurement geometry all individual radar measurements centered within a grid cell are averaged. This results in a gridded σ_0 product in which each grid cell contains exactly one σ_0 value per antenna view. The averaging process reduces the speckle noise (measurement error) that is inherent in radar observations to typically 5%.

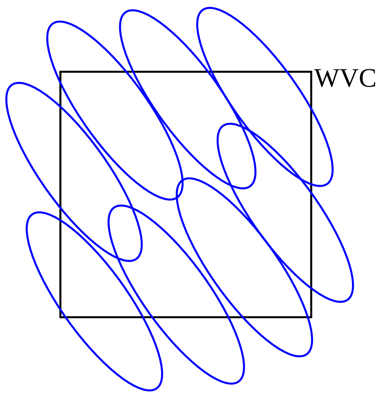

Figure 2: Averaging the radar views (blue ellipses) in the WVC (black square).

Scatterometer wind processing starts with the gridded σ_0 product. The retrieved wind is therefore representative for the grid cell, further referred to as wind vector cell (WVC). The WVC size determines the spatial resolution of the wind field, i.e., the size of the smallest wind feature visible. In practice the individual radar measurements do not cover the WVC exactly, nor are they spread homogeneously. Such effects are small and generally neglected. Multiple views in varying antenna geometry, notably in azimuth, are needed to resolve the wind vector. Due to the varying antenna orientation (see figure 2), the area sampled in a given WVC is not identical in the different views. Wind variability in the WVC area causes noise in the wind retrieval, known as geophysical noise (*Portabella and Stoffelen*, 2006). The combination of speckle and geophysical noise results in a random wind vector RMS error of about 0.5 m/s.

In order to further improve scatterometer wind biases, the following activities are ongoing:

- Ocean calibration to improve consistency between scatterometer missions;
- GMF improvements which are expected to benefit consistency of wind calibration across the swath and wind direction retrieval, particularly at winds below 4 m/s;
- Study of geophysical effects, such as those concerned with air-sea momentum exchange, e.g., effects of air mass density in generating ocean roughness;
- QC development in variable wind and rain conditions, near the coast and near the ice edge;
- Study of bias and wind variability effects due to spatial resolution, i.e., concerning wind PDF variation as a function of spatial resolution, effects of noise and the non-linear wind retrieval function.

What does a NWP surface model wind represent?

A NWP model calculates meteorological quantities like wind on a regular grid. The equations use derivatives in space and time and only structures defined over several grid points are propagated well. In NWP model resolution is commonly referred to as grid distance, but spatially resolved structures over the open oceans are usually about 5 times larger (*Skamarock*, 2005). NWP model fields are propagated in discrete time steps and the model values are also representative for a time window of several time steps. This poses, of course, limits to the effective spatial and temporal resolution of the model fields. The size of these limits depends on the model characteristics, e.g., horizontal and vertical diffusion schemes and closure of the dynamical equations. In particular, the representation of 3D turbulence on scales below 500 km is generally poor in NWP models (*Nastrom and Gage*, 1985).

The NWP surface wind vector depends on how the surface layer processes are described in the model (cf. eq. 2-4) and on the representation of boundary layer processes. Notable aspects are:

- Equivalent neutral surface winds (U_{10N}) are computed from the NWP model friction velocity, which cannot be directly calibrated. In fact, the NWP model U_{10N} is validated against buoys when stability information has been measured (e.g., *Portabella and Stoffelen*, 2009). NWP model stability tends to be too neutral (e.g., *Hersbach*, 2010a). When the advected air is much warmer than the ocean, the situation is called stable. Under such conditions the wind profile over the ocean surface changes, leading to reduced surface wind and increased turning of the wind with height. The coupling of NWP winds with the free tropospheric winds is generally too large in stable conditions, leading to strength and direction biases (occasionally > 10 degrees) in the surface stress vector (eq. 5). When the ocean is warmer than the overlying air the situation is called unstable. Underestimated instability has generally a smaller effect on the surface stress vector error than underestimated stability. Several different NWP parameterizations for the wind profile exist with differences in momentum flux of up to 30%, but 10m wind biases of NWP models are generally only a few percent. To our knowledge, this statement includes NWP models with surface layer dependency on sea state, but further feedback from the user community would be welcome here.
- NWP models do generally not describe ocean current, although developments in this direction are under way in several centers. Moreover, skilful deterministic ocean current modeling is still in its infancy. Without current representation, the relative motion between free troposphere and surface will be in error, e.g., too fast when a local current exists in the direction of the atmospheric flow. In this case and in case of moderate or high winds the surface stress and the roughness depth will be exaggerated. Subsequently U_{10N} will be estimated too high according to eq. (2). It is clear that biases result in NWP model U_{10N} due to ocean current misrepresentation, but with amplitude depending on NWP model surface layer parameterization.
- Roughness is caused by air-sea momentum exchange (stress) which depends on atmospheric mass ρ. As mentioned earlier, eq. (5) suggests such dependency, whereas eq. (4) ignores it. As in scatterometer wind retrieval, global variations in ρ of a few percent are generally ignored in NWP (cf. eq. 4).

Surface truth: buoy winds

Both scatterometer and NWP model winds lack calibration. Conventional wind sensors are calibrated, however, and are generally used as calibration standard for both scatterometer and NWP winds. In particular moored buoys are platforms dedicated to atmospheric and oceanographic measurement.

A number of moored buoys measure the wind speed and direction, together with a number of other parameters. If these include air and sea temperatures it is possible to convert the measured wind vector to an equivalent neutral wind vector at 10 m anemometer height and compare to scatterometer winds. Buoy winds are commonly given as averages over 10 minutes. Note that buoys give time-averaged winds at a fixed location, while scatterometers give a spatially averaged wind at a certain time. A typical wind speed of 7 m/s averaged over 10 minutes (600 s) corresponds to a track in one dimension of about 4 km length and a spatial scale of about 2 km. This is about one order of magnitude smaller than the typical scatterometer resolution. Thus, moored buoys and NWP and scatterometer winds each have a different spatial representation. It is important to note in this respect that spatial averaging of the wind field leads to a narrowing of the wind speed PDF and one would thus expect less extreme winds in a NWP data set than in a buoy wind data set. A narrower wind speed PDF corresponds to a lower mean wind of the wind PDF. Spatial averaging thus leads to a bias in the wind speed (reduction of the mean) w.r.t. the original data. It is clear that spatial representation has to be taken into account in calibration[1].

Moored buoy platforms do not reach 10m generally. Therefore, actual roughness depth and stress need to be estimated at the buoy measurement site and these be represented as equivalent neutral 10-m winds, U10N, in order to represent the scatterometer data. Although roughness depth and stress vector PDF's do depend on the surface layer parameterization, U10N appears rather independent of the parameterization (*Portabella and Stoffelen*, 2009).

Moored buoy wind sensors are calibrated at dedicated sites and in wind tunnels. However, the buoy measurement platform and its interaction with large waves may cause failure to accurately determine extreme winds above 20 m/s. Dedicated hurricane campaigns are conducted to calibrate extreme scatterometer winds (e.g., *Esteban* et al., 2006).

The buoy wind measurements are w.r.t. an earth-fixed reference frame and thus in case of ocean current do not provide an appropriate reference to scatterometer winds, nor provide good input for air-sea fluxes which essentially depend on the relative motion of air and sea. For the main ocean currents biases up to 1 m/s may occur (*Kelly*, 2001).

Buoy wind sensors need calibration and maintenance. To address performance anomalies, monitoring and QC are in place at several centers (e.g., *Bidlot* et al., 2002). These schemes prevent instrumental errors to propagate into calibration parameters, but, on the other hand, somewhat affect geophysical and spatial sampling.

Sampling biases may further occur when the data set used is not representative for the global wind climate. High-quality buoy measurements, for instance, are concentrated in the tropical oceans and along the coasts of North America and Europe (see figure 3 below). Therefore,

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[1] One may increase temporal averaging to match spatial representation, i.e., using Taylor's frozen turbulence hypothesis, but we note that a fixed temporal averaging implies variable spatial representation as a function of wind speed (3 hours averaging corresponds to a 20 km stretch at 2 m/s and a 200 km stretch at 20 m/s). For this reason we do not follow this approach.

alibration results may not be fully representative of the global ocean conditions and be geographically biased towards tropical and coastal wind distributions.

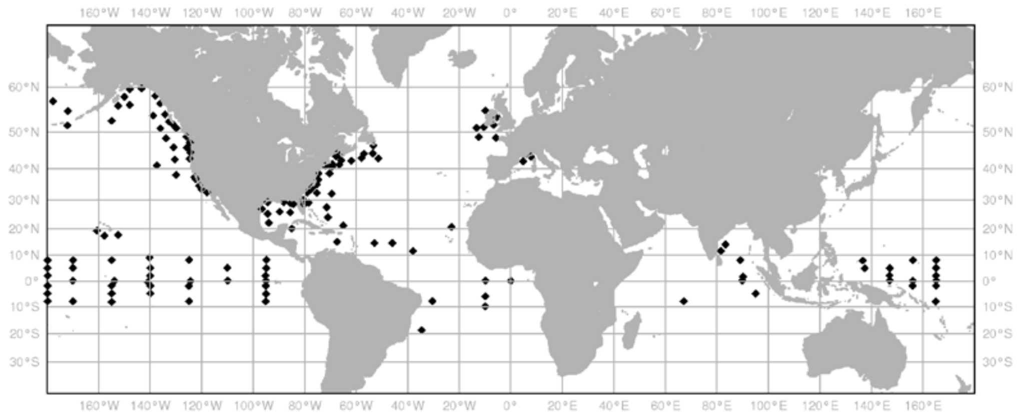

Figure 3: Irregular global distribution of moored buoys measuring high-quality winds.

How to detect biases?

Biases show up when plotting the difference between scatterometer wind and model wind. A number of such plots is made available on the web. The NWP SAF web page at www.nwpsaf.org provides links to monitoring pages of scatterometer differences with ECMWF, UKMO, and KNMI NWP models; so-called o-b and o-a differences with NWP background and analysis fields, respectively. These differences provide monitoring information on scatterometers and models. Also many error studies are published in the scientific literature and presented at IOVWST meetings for example (http://coaps.fsu.edu/scatterometry/meeting/past.php).

Systematic differences in winds occur due to

- System calibration errors; for example, speed-dependent biases will show up as geographically- and time-dependent biases, since the mean wind speed is geographically and time dependent due to weather and climate;
- Differences in spatial representation; local wind PDF’s (buoys) have more extreme values than area-mean wind PDF’s (NWP, scatterometer);
- Undetermined geophysical dependencies, e.g., currents, wind variability (e.g., downbursts in convection), sea state, etc.;
- So-called pseudo biases in wind speed due to non-linear transformation of random component errors (*Stoffelen*, 1998b);

Only categories 1 and 3 are systematic errors that need to be corrected for BLUE wind component analysis, while categories 2 and 4 need to be acknowledged, but are not incompatible with BLUE wind components.

For statistical calibration of wind components, two methods are distinguished here:

- Triple collocation. This is the most general, but also the most elaborate method. It yields (linear) calibration coefficients and error variances for three collocated data sets;
- *o* - *b* regression. Under some assumptions discussed below, also *o* - b regression may give useful results.

Regression techniques are widely used to calibrate data sets. Regression will generally lead to useful results when the dynamic range of the variables is large as compared to the errors involved. For wind components, however, the dynamic range is typically 5 m/s, while random errors are typically 1 m/s, i.e., not negligible w.r.t. the dynamic range. In such cases, the regression result will critically depend on the random error assumptions, which assumptions often will be implicit rather than explicit. Moreover, the spatial representation error has to be well taken into account in the random error attribution. We will now illustrate the two methods.

Note that data assimilation systems require BLUE wind components and specify a wind component and constant random error. We note that wind components generally behave like variables with constant random error due to the fact that a large proportion of the NWP and observation errors are due to wind variability effects. Wind variability effects on scales below 500 km are mainly governed by 3D turbulence, which in turn is well described as variations in wind component on the different scales. In fact, variations in wind speed and wind direction are more complex functions of 3D turbulence (see also *Stoffelen*, 1998).

Triple collocation calibration

Method

The triple collocation method assumes that three systems (buoys, scatterometer, and model background in the case considered here) all give information on the true value t. The buoy is chosen as absolute reference relative to which the other systems are calibrated. Assuming that the buoy is free of bias (i.e., free of systematic errors) and that linear calibration suffices for the other two systems, the values w measured by the different systems satisfy

$$\begin{aligned} w_{buoy} &= t + \delta_{buoy} \\ w_{scat} &= \alpha_{scat} t + \beta_{scat} + \delta_{scat} \\ w_{back} &= \alpha_{back} t + \beta_{back} + \delta_{back} \end{aligned} \tag{6}$$

with α and β the calibration coefficients and δ the random measurement error. Since most errors will be due to speed scaling effects and wind components can be both positive and negative, the *b* calibration coefficients are generally very small and may be ignored. Note that the triple collocation calibration procedure is not part of the NWP SAF wind processors: their output (and, hence, the OSI SAF wind products) contain the values w_{scat} and w_{back} but no buoy measurements.

Forming equations for all first and second statistical moments results in a set of equations that are further simplified by the following assumptions on the error characteristics:

- Linear calibration by α and β is sufficient over the whole range of measurement values considered for scatterometer and NWP winds;
- The reference measurement values are unbiased (see above);
- All random measurement errors δ are unbiased by definition;
- The measurement errors have constant variance over the whole range of measurement values; this is generally corroborated by combined PDF's of two wind data sets which show a rather constant width of the difference distribution as a function of wind component strength;
- The measurement errors are uncorrelated with each other since they are realized independently spatial representation errors may concern similar spatial scales and are treated separately;
- The measurement errors are uncorrelated with the measurement values; in fact, any variation that is common (correlated) in the three systems is interpreted as a dependent realization and caused by the underlying true wind field. The spatial scales represented in *t* are thus determined by the effective NWP model resolution, as this is generally the coarsest among the three systems.

Since both the scatterometer and buoy have better effective resolution than the NWP system, they both may resolve true wind variance that is not resolved by the NWP winds. This wind variance will be part of both the spatial representation error of the scatterometer and buoy, and therefore be a correlated part of the observation error. Some subtleties are involved in handling the correlated part of the spatial representation error, see *Stoffelen* (1998). The following example uses representation errors calculated from wind spectra, see *Vogelzang et al.* (2011).

Under these assumptions the error variances $<\delta^2>$ and the calibration coefficients can then be solved from equations (6), after which calibration may be performed as follows:

$$\begin{array}{l} w_{scat}^{cal} = \alpha_{scat}^{-1} w_{scat} \\ \\ w_{NWP}^{cal} = \alpha_{NWP}^{-1} w_{NWP} \end{array} \quad \Rightarrow \quad w_{scat}^{NWP} = \frac{\alpha_{NWP}}{\alpha_{scat}} w_{scat} \;, \qquad (7)$$

with superscript *cal* referring to calibration w.r.t. the buoys and superscript *NWP* referring to calibration w.r.t. the NWP model wind climate.

Example Data Set

- Buoy measurements not blacklisted by ECMWF (see figure 3);

- ECMWF forecast;
- Scatterometer data (from OSI SAF):
  - ASCAT-coastal, September 1, 2010 – November 30, 2013
  - ASCAT-12.5, October 1, 2008 – November 30, 2013
  - ASCAT-25, April 1, 2007 – November 30, 2013
  - SeaWinds-KNMI, November 1, 2007 – November 23, 2009

Results

Let $u_{cal} = a_u u + b_u$ and $v_{cal} = a_v v + b_v$ with (u,v) the wind components from the OSI SAF wind product and (u_{cal}, v_{cal}) the linearly calibrated wind (note that in the previous version of the report calibrated and uncalibrated winds were erroneously switched). The calibration constants a and b are given in the table below for the various scatterometer wind products and for the collocated ECMWF forecast

	Scatterometer				ECMWF			
Dataset	a_u	b_u (ms^{-1})	a_v	b_v (ms^{-1})	a_u	b_u (ms^{-1})	a_v	b_v (ms^{-1})
ASCAT-coastal	0.9967	0.088	1.0093	-0.062	1.0245	0.238	1.0465	0.025
ASCAT-12.5	1.0035	0.114	1.0107	-0.045	1.0250	0.249	1.0440	0.045
ASCAT-25	1.0096	0.116	1.0088	-0.016	1.0183	0.230	1.0467	0.057
SeaWinds-KNMI	1.0482	0.281	1.0304	0.011	1.0109	0.351	1.0397	0.069

Table 1: Triple collocation calibration coefficients.

The error standard deviations are given in table 2 below. The numbers are valid for the calibrated wind components (using the calibration coefficients given above). See *Vogelzang et al.* (2011) for a discussion of these values. Interestingly, the buoy data have the largest random wind error, while it constitutes the best calibrated and most direct winds. This is obviously due to the spatial representation error corresponding to the turbulent wind scales observed by the buoys, but not by the scatterometer and NWP model.

Further note that the better resolution ASCAT product shows similar errors for the buoy and the ECMWF model, but larger error for the scatterometer. This is mainly due to the spatial representation error variance that increases from about 0.6 to 0.8 m^2/s^2 when going from the 25 to the 12.5-km product, due to the poorer resolution of the ECMWF model (see *Vogelzang* et al., 2011). Since the SeaWinds-KNMI product is smoother than the ASCAT 25-km product, it has a lower spatial representation error, but that is compensated by a larger instrument error. Similarly, we noted a much superior comparison of the SeaWinds 100-km product to the ECMWF model as compared to the 25-km KNMI SeaWinds product.

Dataset	Buoy		ECMWF		Scatterometer	
	ε_u (ms^{-1})	ε_v (ms^{-1})	ε_u (ms^{-1})	ε_v (ms^{-1})	ε_u (ms^{-1})	ε_v (ms^{-1})
ASCAT-coastal	1.36	1.53	1.22	1.12	1.01	1.28
ASCAT-12.5	1.37	1.53	1.24	1.14	0.99	1.25
ASCAT-25	1.35	1.47	1.23	1.19	0.86	1.05
SeaWinds-KNMI	1.51	1.53	1.04	1.15	0.98	0.82

Table 2: Error standard deviations of buoy and scatterometer observation errors and ECMWF model error.

Calibration by regression

Method

When applying standard regression methods on differences between observed (scatterometer) and model winds, one must be cautious as to how the errors are handled. Most regression methods implicitly assume that all errors are contained in the dependent variable while *o* and *b* errors are of similar size (see table 2), but this will cause errors as depicted in figure 4.

In the figure above the observations are perfectly calibrated (dashed black curve). However, when a regression routine assumes all errors to be contained in *o*, the average for low values of *b* (red dot on the left-hand-side blue line) will lie above the true calibration curve. Similarly, the calculated average $\langle o|b \rangle$ at high values of *b* (red dot on right-hand-side blue line) will be too low. As a result, regression would yield something like the red dotted curve. In fact, a different regression is obtained when average *b* values are computed for given *o*, $\langle b|o \rangle$, implicitly assuming perfect *o* with no random error.

If, however, one can safely assume that *o* and *b* have the same error distribution, which is a more reasonable assumption than assuming either one has no error, one may apply standard regression to $o - b$ versus $(o + b)/2$, as shown in figure 5. Now standard regression will not introduce spurious biases. One may also bin the data in $o + b$ values, as indicated by the blue lines and the yellow arrows, and obtain a nonlinear calibration curve by calculating the average in each bin. In this way, calibration issues for low and/or high winds will become visible.

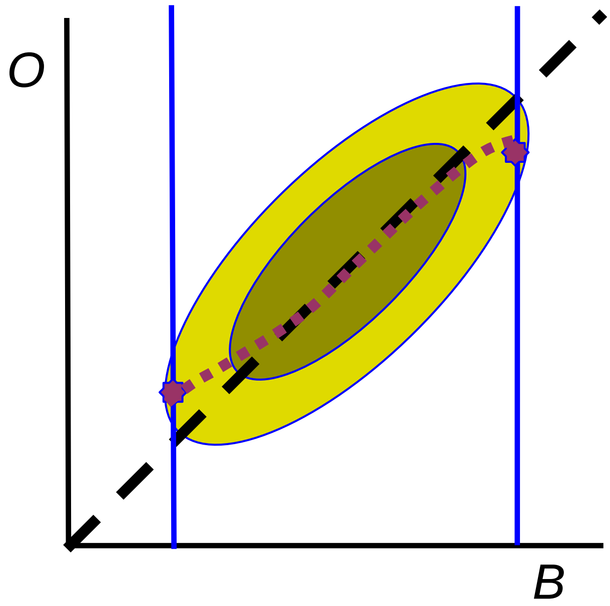

Figure 4: Bivariate *o* and *b* distribution, showing (dashed) the mean *o* as a function of *b*.

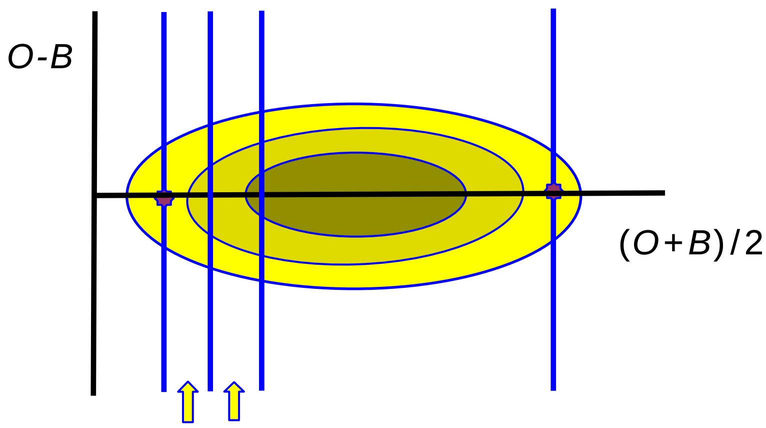

Figure 5: Bivariate *o* and *b* distribution, depicting the mean *o-b* as a function of $(o + b)/2$ (red dots).

More sophisticated regression methods take the error in both variables into account explicitly. The average values are now calculated along skewed lines with a slope determined by the ratio of the errors.

CDF matching

Stoffelen (1998b) used a technique for obtaining higher order calibration that is now commonly referred to as CDF matching, where CDF is the Cumulative probability Density Function of a variable. It follows from eq. (6) that two linearly calibrated collocated data sets (so a = 1 and b = 0) have the same underlying PDF of t. If both error PDF's are the same, both distributions must have identical CDF. Since the CDF is a monotonically rising function, the CDF's of the two data sets may be mapped onto each other. This implies a higher order calibration of the two data sets, similar to what is obtained by binning o - b against $o + b$.

CDF matching requires that both data sets have the same error variance. This will in general not be the case, but the error variances can be made equal if one assumes that the errors are Gaussian. If, $\sigma_o^2 < \sigma_b^2$, one can add a simulated Gaussian error with variance $\sigma_b^2 - \sigma_o^2$. If $\sigma_b^2 < \sigma_o^2$, one can add a simulated Gaussian error with variance $\sigma_o^2 - \sigma_b^2$ to the background. In both cases the two data sets will have equal error variance, so one can calculate the CDF's and match them.

The values of σ_o^2 and σ_b^2 can be obtained from triple collocation. However, the triple collocation results are averages over all wind speeds and all WVC's. Plotting $\sigma_{o-b}^2 = \sigma_o^2 + \sigma_b^2$ as a function of $o - b$ will reveal variations of the total variance with average wind speed and /or WVC number. The error variances can now be made equal for each $o - b$ bin and/or WVC number. This requires a additional assumptions on σ_o^2 or σ_b^2. One may choose either of them constant, or one may take their ratio constant. Some experimenting will be needed to find the assumption that suits ones goals best.

Guidance

The output of NWP SAF wind data processors (including the OSI SAF wind products) is calibrated against in situ wind data using triple collocation. NWP model wind climates may differ in quality and effective resolution. Therefore, inconsistencies in the represented spatial scales and in calibration should be determined to avoid detrimental impacts. Spatial analyses of collocated data sets are recommended to allow identical samples of NWP and scatterometer winds and therefore accurate calibration.

If a bias against observations is encountered, one can take the following measures:

- Recalibrate the scatterometer winds using the triple collocation and/or o - b regression techniques described above. In case of $o - b$ regression, it is advised to calibrate the observations w.r.t. to the model, even when the model is known to be incorrect, to ensure model consistency. Regression (or CDF matching) will be adequate when the scatterometer observation error is similar to the NWP model error in the equivalent neutral wind. The latter is NWP-model dependent, where NWP models encapsulating smaller spatial scales will generally have larger wind errors.

- Improve model physics in order to better describe the reality as it is measured and/or correct the NWP model climate. However, this is not straightforward, since it depends on many aspects and affects weather predictability. This is generally a longer term measure.
- Filter the data. If the problems occur at certain wind speed ranges, in certain geographical area's, or in certain times of the year, one may consider rejecting those data that cause problems. In this respect, we recommend to follow the quality control flags as set in the SAF wind processors, AWDP, SDP, and OWDP.
- Discard the data. Since scatterometer winds are known to be accurate and reliable, this is not a recommended strategy.

Joint observation and NWP model wind distributions are known to be seasonally dependent and it is recommended to perform calibration with a data set representative of a full year.

Monitoring of *o-b* and *o-a* differences is needed to be reassured of constant NWP model wind climates, For examples of monitoring diagnostics we refer to the web links below.

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Useful web sites

- NWP SAF monitoring pages:
  http://research.metoffice.gov.uk/research/interproj/nwpsaf/monitoring
  Under "Scatterometer reports" links are given to the web pages of ECMWF, Meteo France, and UKMO.

- OSI SAF monitoring pages at KNMI:
  www.knmi.nl/scatterometer
  Select a wind product on the right hand side of the screen and then "Monitoring information", again on the right hand side of the screen.

- IOVWST meeting presentations:
  http://coaps.fsu.edu/scatterometry/meeting/
  Various presentations on calibration and applications.