JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 99, NO. C12, PAGES 25,035–25,049, DECEMBER 15, 1994

A significant wave height dependent function for TOPEX/POSEIDON wind speed retrieval

J. M. Lefevre and J. Barckicke

Meteo-France, Toulouse, France

Y. Ménard

Centre National d'Etudes Spatiales, Toulouse, France

Abstract. The ocean surface roughness affects the radar cross section measured by altimeters. The wind speed is responsible for this roughness and most of present algorithms use the radar cross section (RCS) to infer it. A few authors (Monaldo and Dobson, 1989; Glazman and Greysukh, 1993) emphasized the influence of the sea maturity on satellite measurements. They found a marginal improvement in wind speed retrieval by including significant wave height in their algorithm. In this paper several previously established algorithms relating altimeter radar cross section to ocean surface wind speed are first analyzed. The shapes of the RCS versus wind speed curves are shown to depend mainly on the minimization methods used to generate the model functions. An empirical wind speed algorithm is then derived from the two altimeters (ALT and SSALT) on board TOPEX/POSEIDON (T/P) satellite using a quality controlled data set in which North Atlantic operational surface wind and wave analyses are collocated with altimeter ALT measurements. Unlike usual algorithms, this new function depends on both the radar cross section and the significant wave height. The improvement in the T/P wind speed estimate seems significant at the 99.9% level. The accuracy of the derived function is evaluated using an independent collocated SSALT and numerical weather prediction models data set. Here again the improvement is significant, but at the 90% level because of the smaller amount of data available. The T/P wind speed estimates are furthermore compared to collocated estimates from National Oceanic and Atmospheric Administration data buoys: the new algorithm retrieves wind speed from Geosat measurements with an accuracy compatible with usual algorithms.

1. Introduction

The present study is part of the investigations started at Meteo-France for the operational use of remote sensed measurements from altimetric satellites. Such measurements, thanks to their global and continuous coverage, provide many advantages for analyzing and forecasting winds over oceans. Despite the fact they estimate only the wind modulus along the satellite track, they can be useful for meteorological short-term forecasting, numerical model assessment [*Guillaume et al.*, 1992], and data assimilation into numerical models [*Lionello et al.*, 1992].

Radar altimeters receive a complex stochastic signal due to the reflection of the transmitted pulse over a 5-km radius footprint. The radar cross section (RCS) can thus be considered as a function of the statistic moments of the sea surface elevations and slopes. The most pertinent parameter of this function is the mean square slope. However, short-scale slopes associated with capillarity waves are mainly a function of the local wind, and large-scale slopes are mainly associated with surface gravity waves (including swell); until now, the effect of large-scale slopes has been neglected. Therefore most of geophysical model functions (GMFs) used to calculate wind speed are only related to the radar cross section. An improvement would be to consider RCS as a function of the wind speed and a new parameter which characterizes the sea state. Previous studies [*Glazman and Pilorz*, 1990; *Fu and Glazman*, 1991] emphasized the influence of the sea maturity on radar measurements in relation to the degree of development of the wind sea. The sea maturity can be estimated through the pseudo-wave age parameter [*Glazman and Pilorz*, 1990] which is a function of the wind speed and the significant wave height (SWH). Altimeter SWH can be derived from the slope of the leading edge of the return power waveform. In a recent paper, *Glazman and Greysukh* [1993] investigated the influence of the sea maturity on the altimeter wind speed retrieval from collocated Geosat/buoy measurements. The results were encouraging but the improvement was not statistically significant at a 90% confidence level due to the relatively small amount of data used (865 data points).

The launch of TOPEX/POSEIDON (T/P) with two altimeters on board (ALT and SSALT) in August 1992 appeared as an opportunity to assess the quality of the existing GMFs and to derive a new one, depending on both RCS and SWH measurements. Recent studies [*Guillaume and Mognard*, 1992; *Freilich and Dunbar*, 1993] demonstrated the interest of using data from numerical weather prediction (NWP) systems for such purposes; one of the main advantages is the

Paper number 94JC01958.
0148-0227/94/94JC-01958$05.00

wide availability of that data within a short time after the satellite launch. In this paper we propose a validation of most of the existing GMFs based on a collocated T/P altimeter/NWP data set. A method proposed by *Guillaume and Mognard* [1992] to improve the quality of NWP data sets is first implemented. Then, the impact of the additional variable SWH in wind speed algorithms is investigated. All winds are estimated from altimeters or buoy measurements at the 10-m level for neutral atmosphere stratification like *Glazman and Pilorz* [1990].

2. Collocated Data Set

2.1. The Data Set

Most of the existing wind speed model functions have been calibrated by using in situ measurements or scatterometer data. However, the use of in situ measurements yields relatively small collocated data sets. On the other hand, scatterometer data introduce uncertainties because they are similar to altimetric data (they are remote sensed and also obtained through GMFs). Using model data for the calibration of new algorithms and the validation of satellite data provides several advantages (such as the availability of large data samples), which have been promoted by *Guillaume and Mognard* [1992] and then used by *Freilich and Dunbar* [1993].

Thus a large amount of data can be available within a short time after launch. This allows for the performance of quality control for both wind speed and SWH in quasi-real time and the calibration of new wind speed model functions within a few months. Furthermore, particular areas or specific situations can be easily selected, for instance, those with high sea state conditions.

A comparison between winds from altimeter and model analyses was carried out by *Freilich and Dunbar* [1993] over the whole globe and for 1 year. The normalized variance of the difference between model and altimeter winds was found minimum in the North Atlantic. This result is not surprising because observations in this area are relatively dense. As a consequence, winds from model analyses are very inaccurate in some other areas and a regional approach is more appropriate when model data are used. The North Atlantic is large enough for strong regional effects on wind speed algorithms to be avoided insofar as the relation between wind speed and surface roughness depends on the air-sea temperature difference.

Our data set is based on collocated altimeter measurements from the geophysical data records (GDRs) provided by the AVISO center in Toulouse (archiving validation interpretation of satellite data in oceanography), and analyses from the French numerical weather prediction model ARPEGE [*Courtier et al.*, 1991] and from the operational numerical wave model VAGATLA [*Guillaume*, 1990]. The model data are available every 6 hours with a spatial resolution of about 150 km. The satellite data from cycles 9 to 31 of ALT and from cycles 9 to 41 of SSALT (corresponding to the period from December 1992 to July 1993 for ALT and from December 1992 to November 1993 for SSALT) were selected over the North Atlantic. The mean RCSs of these two samples (in Ku band since we consider only this band in the present paper for T/P measurements) are equal to the global mean RCSs (about 11.3 dB for ALT, and 11 dB for SSALT). Quality flags from GDRs were used to remove data contaminated by land, ice, rain, and data with bad measurement conditions. Then, SWHs and RCSs acquired along the track every second have been averaged over 20-s periods (corresponding to about 120 km length boxes) to match the model mesh size. The goal of this process is to reduce the difference between altimeter and model data due only to the spectral cutoff imposed by the resolution of the NWP and to get (almost) independent altimeter data. *Monaldo* [1988] suggests that completely independent wind speed estimates are made every 150 to 200 km in ground track. As a consequence, the number of independent samples should be reduced by approximately 25% for any statistical study.

A second quality control has been performed in order to reduce the amount of spurious data that had not been detected by the quality flags. This process is very similar to the one used at the European Centre for Medium-Range Weather Forecasts to compare ERS 1 data with model data. Basically, the standard deviation of the parameter (RCS or SWH) calculated in each box is regarded as an indicator of the spatial homogeneity of the measurements: the averaged value is rejected if the standard deviation is too large (higher than 25% of the mean value). Observations deviating by more than 3 standard deviations from the mean in each box or associated with an attitude greater than 0.15° were also rejected. Furthermore, boxes with less than seven data were removed. Thus about 10% of the data were removed from the data set.

When comparing satellite and model data (or buoy), differences are expected as a result of spatial and temporal disparities. Such differences were evaluated by *Dobson et al.* [1987], *Monaldo* [1988], and *Guillaume and Mognard* [1992].

According to their studies and to calculations we performed, we estimated that by adding the two effects the expected RMS difference should be of about 1.5 m/s for the wind speed and of 0.3 m for the SWH. In order to reduce these effects, we processed a double linear interpolation (spatial and temporal) to get a collocated altimeter/NWP data set. Nevertheless, because of the spatial and temporal resolutions of the models the reduction should be marginal as noticed by *Guillaume and Mognard* [1992].

The RCS distributions for different altimeters are different, with a variable peak position. The mean RCS and the peak position are very similar because of the almost Gaussian form of the distributions. The mean value is about 10.9 dB for Geosat [*Dobson et al.*, 1987]. This value is also obtained with the collocated data set used by *Glazman and Greysukh* [1993] which includes 3 years of data. We found a mean RCS of about 11.3 dB for ALT and 11 dB for SSALT in our data set. We applied a constant offset of −0.4 dB to the ALT RCS and −0.1 dB to the SSALT RCS in order to use previous functions derived for Geosat to T/P RCSs. GDR wind speeds were calculated by using the Modified Chelton-Wentz model function (MCW) function with a RCS correction of −0.7 dB for ALT data. We found a wind bias of 1.09 m/s (Table 1 and Figure 1) for the GDR ALT winds when compared to NWP winds. This bias is reduced to 0.13 m/s when MCW is used with ALT RCSs corrected by −0.4 dB (Figure 11). This result is consistent with the difference noticed between the mean Geosat RCS and mean ALT RCS.

2.2. Quality Control for Model Data

Freilich and Dunbar [1993] looked recently at the differences between products coming from independent centers in

Table 1. Summary of Mean and Standard Deviation Errors Stratified as a Function of Wind Speed Range for Geosat and Seasat Derived Algorithms

	T/P ALT-NWP Winds Differences (s.d.), m/s						
Range, m/s	GDRs	Brown	CM	SBrown	MCW	NWP3	Carter
0–5	0.1 (1.9)	0.5 (1.6)	0.1 (1.9)	0.2 (1.8)	−0.4 (1.8)	0.1 (1.7)	−0.2 (1.7)
5–10	1.1 (1.9)	0.1 (1.6)	0.8 (1.9)	−0.2 (1.6)	0.1 (1.8)	−0.3 (1.8)	0.5 (1.8)
10–15	1.9 (2.2)	−0.7 (2.1)	3.1 (3.1)	−0.6 (2.0)	1.0 (2.3)	1.5 (2.9)	1.0 (2.2)
>15	1.2 (2.1)	−0.8 (2.6)	9.9 (4.9)	−2.6 (2.0)	0.2 (2.1)	5.6 (3.4)	0.3 (2.1)
Total	1.09 (2.02)	0.07 (1.74)	1.84 (4.0)	−0.19 (1.77)	0.13 (1.95)	0.25 (2.5)	0.4 (1.9)

order to quantify errors in model analyses. The main drawback of such a method is that errors due to common behaviors of NWP models cannot be removed. For instance, it is admitted that most of the NWP models yield smoothed values for geophysical parameters. As a consequence, high surface winds are generally underestimated. An alternative method to select accurate wind speeds was proposed by *Guillaume and Mognard* [1992]. This method, which tends to reduce the amount of dubious data (for instance, when there is a lack of observations or when small-scale phenomena such as tropical cyclones, out of the resolution of the model, are present), is based on the assumptions that SWH modeling errors are mainly due to local wind errors (wave models are generally driven by model winds) and that altimeter SWHs are more reliable than model SWHs. Like Guillaume and Mognard, we compared model significant wave heights (H_{mod}) with altimeter significant wave heights (H_{sat}) and retained the model winds only if they did not differ by more than a given percentage of the mean value of H_{sat} and H_{mod} (referred to hereinafter as μ). In order to avoid the elimination of data points associated with low SWH, and because the accuracy of SWH measurements is between 0.1 and 0.5 m, we decided to retain wind data with H_{mod} differing by less than 0.25 m from H_{sat}. Finally, the model wind data were selected only if the following relationship is satisfied:

$$|H_{sat} - H_{mod}| < \max\ (\mu \times H_{mean},\ 0.25) \tag{1}$$

with

$$H_{mean} = (H_{sat} + H_{mod})/2. \tag{2}$$

Tests were performed to evaluate the sensitivity of the results to the percentage value μ. We first defined the scatter index as the ratio of the standard deviation of the difference between altimeter and model wind speed over the mean

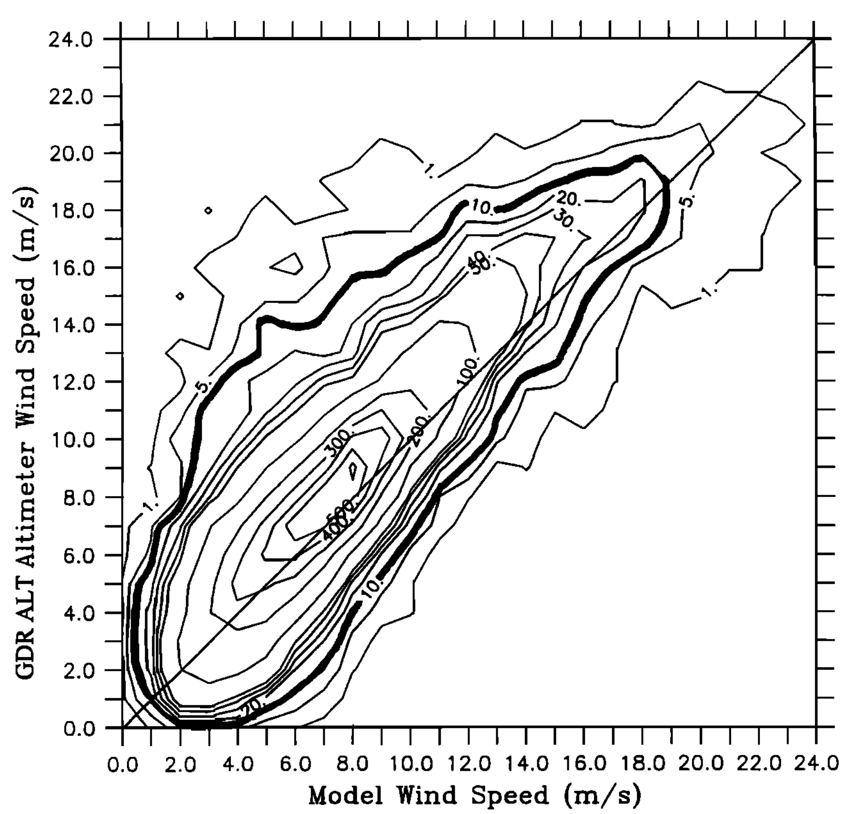

Figure 1. Scatter diagram of ALT wind speed versus model wind speed. Comparison of ARPEGE model with radar altimeter wind speeds calculated in GDR (with the MCW function and a RCS correction of −0.7 dB).

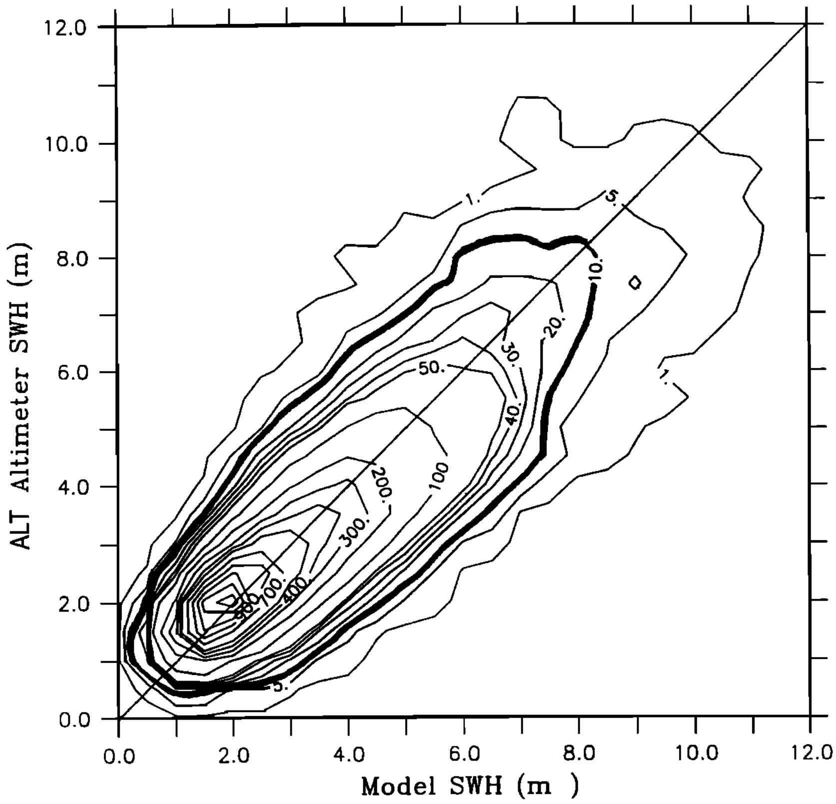

Figure 2. Scatter diagram of ALT significant wave height versus VAGATLA wave model SWH.

value of the model wind speed. The scatter index was calculated, using the Brown GMF and various values of μ. It was found to be equal to 0.28 without any selection, 0.27 for $\mu = 0.5$, and to have an almost minimum value of 0.24 for μ under 0.15. So we finally chose $\mu = 0.15$ in order to keep a large enough sample of data. We computed the bias for each class of SWH with 1 m bin as a first step of our quality control. No significant bias was found for each class of SWH contrary to ERS 1 and Geosat data [*Guillaume and Mognard*, 1992; *Queffelou and Lefevre*, 1992; *Carter et al.*, 1992]. This confirms that there is no systematic underestimation of high waves by ALT or SSALT measurements (Figures 2 and 3).

3. Review of the Classical Model Functions

3.1. Brown

One of the first wind speed model functions was proposed by *Brown* [1979] and *Brown et al.* [1981] for Seasat data. *Brown et al.* [1981] developed a logarithmic function which was calibrated using in situ measurements. A fitting process was used to determine the coefficients of the function minimizing the mean square difference between the observed RCS and the predicted RCS (function of the observed wind speed). Three sets of coefficients were calculated corresponding to three ranges of wind speed. The calibrated function introduced a statistically skewed error in wind speeds since the routine minimized the mean square difference of the RCSs instead of the winds. A second estimate of the function was derived by considering a fifth-order polynomial of the first-stage predicted wind speed to partly remove this skewed error. The coefficients were obtained by minimizing the mean square difference between the predicted wind and the observed wind.

The main drawback of Brown's logarithmic function lies in the fact that the three branches produce a multimodal distribution of the wind speed. Another limitation is due to the small amount of data considered for the calibration (184), specially for wind speeds exceeding 10 m/s (only 36 pairs of data). Moreover, one can think that a direct minimization of the wind mean square difference would have provided a very similar result as suggested on Figure 4. The "pseudo Brown" function obtained in that way with our data set and represented in dashed line (Figure 4) yields a standard deviation error of 1.77 m/s with no bias, while the Brown function (referred to as "Brown" in Table 1) yields a standard deviation error of 1.74 m/s and a mean error of 0.07 m/s as listed in Table 1. In the following items, the pseudo versions of others previous algorithms are also constructed: similar optimization procedures as the previous authors are used but with our data set.

3.2. Chelton-McCabe

In order to avoid a multimodal distribution, *Chelton and McCabe* [1985] suggested that it was imperative that any wind model function had a continuous slope everywhere. A second generation of model functions was thus proposed to compute wind speeds from the Geosat altimeter data. Unlike Brown, Chelton and McCabe used wind data from the Seasat scatterometer (SASS) for the calibration of a logarithmic function. As there were no collocated data, they used a spatial and temporal averaging technique. SASS and Geosat altimeter data were averaged over 2° by 6° areas and over 96 days, resulting in SASS wind speeds limited to the range 4 to

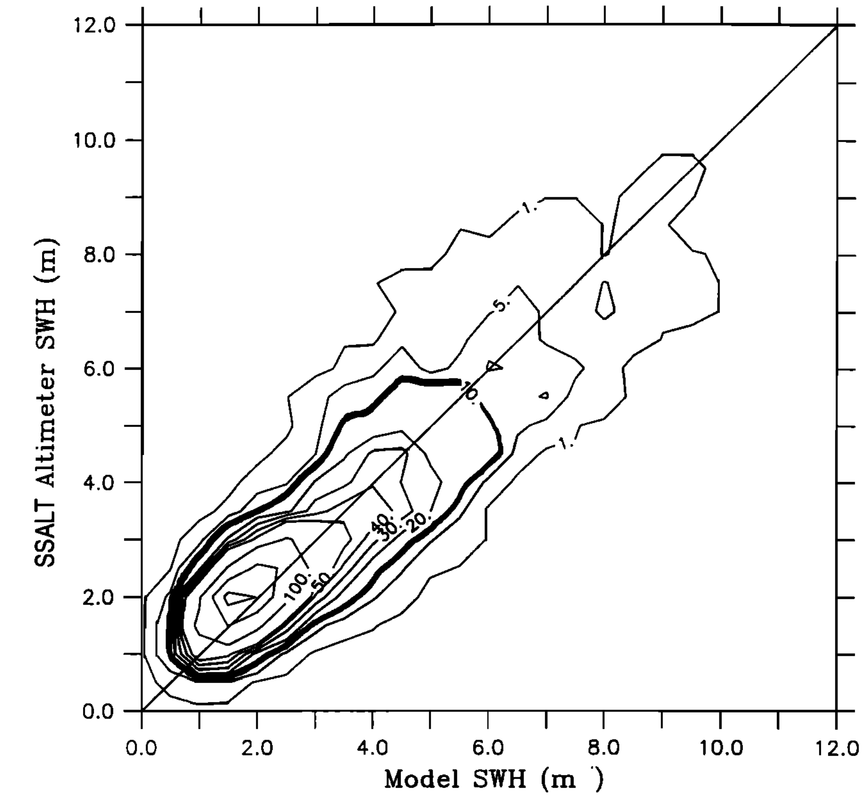

Figure 3. Scatter diagram of SSALT significant wave height versus VAGATLA wave model SWH.

14 m/s. The coefficients were determined by minimizing the mean square difference of the RCS. A discrepancy at wind speeds higher than 12 m/s was found between the new function and Brown's one, but was not considered as serious because of the paucity of data in this range. This discrepancy can also be explained by the limited degree of freedom of the prescribed logarithmic function. The strong weight of the data in the vicinity of the peak of the wind distribution as

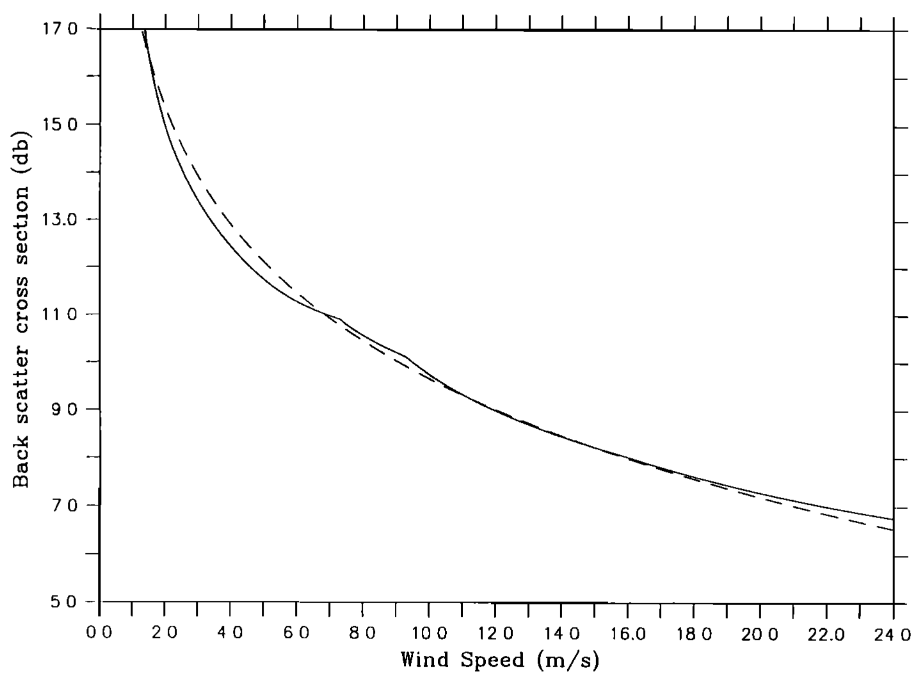

Figure 4. Comparison of the altimeter wind speed model function proposed by *Brown et al.* [1981] (three branches continuous line) and the logarithm function ("Pseudo-Brown") derived with the T/P ALT/NWP data set (dashed line).

Table 2. Summary of Mean and Standard Deviation Errors Stratified as a Function of Wind Speed Range for T/P Derived Algorithms

Range, m	P-Brown	P-SB	P-CM1	P-CM2	New GMF
0–5	1.0 (1.6)	0.8 (1.5)	−0.5 (0.2)	−0.3 (1.7)	0.9 (1.5)
5–10	−0.1 (1.5)	−0.1 (1.6)	0.2 (2.0)	−0.2 (1.8)	−0.1 (1.6)
10–15	−0.7 (2.3)	−0.7 (2.0)	3.3 (3.3)	2.0 (3.2)	−0.5 (1.9)
>15	−0.9 (2.5)	−3.5 (1.9)	11.2 (5.4)	8.2 (4.6)	−1.0 (2.1)
Total	0.0 (1.77)	−0.06 (1.75)	1.67 (5.36)	0.58 (3.3)	0.0 (1.67)

The wind speed classification is performed using the mean values of the NWP analysis with the corresponding T/P measurement. Mean differences of the T/P estimates to the NWP wind speed and, in parentheses, standard deviations, are listed for 17,094 data pairs. P denotes "pseudo" since the derived functions are close to the corresponding Geosat functions.

well as the choice of the RCS space for the fitting process are probably responsible for the overestimation of high wind speeds.

An analogous fitting was performed with our data set after correction of the data in order to simulate a systematic error in RCS such as in Seasat [*Chelton and Wentz*, 1986]. The "pseudo Chelton-MacCabe" resulting function (referred to as P-CM1 in Table 2) is represented in Figure 5 (long-dashed line). It is very similar to Chelton and McCabe's one (solid line). In particular, the curves are both flatter than Brown's function at high wind speed and yield higher values. Even without applying the Seasat correction, we found such a behavior for the fitted function (referred to as P-CM2 in Table 2) shown in Figure 5 (long-short dashed line). The "pseudo Chelton-MacCabe" GMF produces a mean error of 1.67 m/s and a standard deviation error of 5.4 m/s which is worse than 1.84 m/s and 4.0 m/s, respectively, for the mean and standard deviation error with the Chelton-McCabe function (referred to as CM in Table 1). The simulated Seasat error is responsible for very bad characteristics of the derived P-CM1 probably because of some possible inaccuracies in the Seasat error estimate. Such algorithms are very sensitive to RCS errors: mean and RMS errors obtained with the CM function are considerably reduced when the Seasat error is taken into account: the bias is 0.95 m/s and the standard deviation error is 2.27 m/s, and P-CM2 gives a 3.3 m/s RMS error (instead of 5.4 m/s).

3.3. Smooth-Brown

Another attempt to avoid a multimodal distribution for wind speed was made by *Goldhirsh and Dobson* [1985]. They fitted a fifth-degree polynomial to the original Brown data, but in wind space. Because this new function was nearly identical to the Brown one, but with a continuous shape, it was called Smooth-Brown algorithm. The high degree of freedom associated with the choice of wind space yielded an opposite effect by comparison to Chelton-McCabe. High wind speeds were underestimated and limited

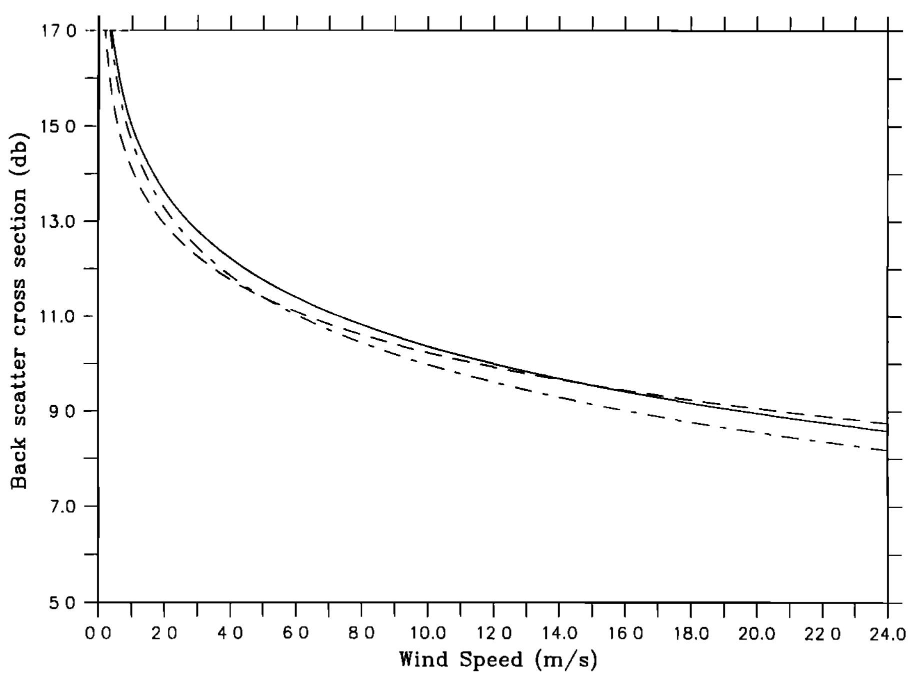

Figure 5. Comparison of the altimeter wind speed model function proposed by *Chelton and McCabe* [1985] (solid line) with the "Pseudo Chelton-McCabe" function (P-CM1) derived from the Seasat/NWP simulated data set (long-dashed line) and with the "Pseudo-CM2" derived from the ALT/NWP data set (long-short dashed line).

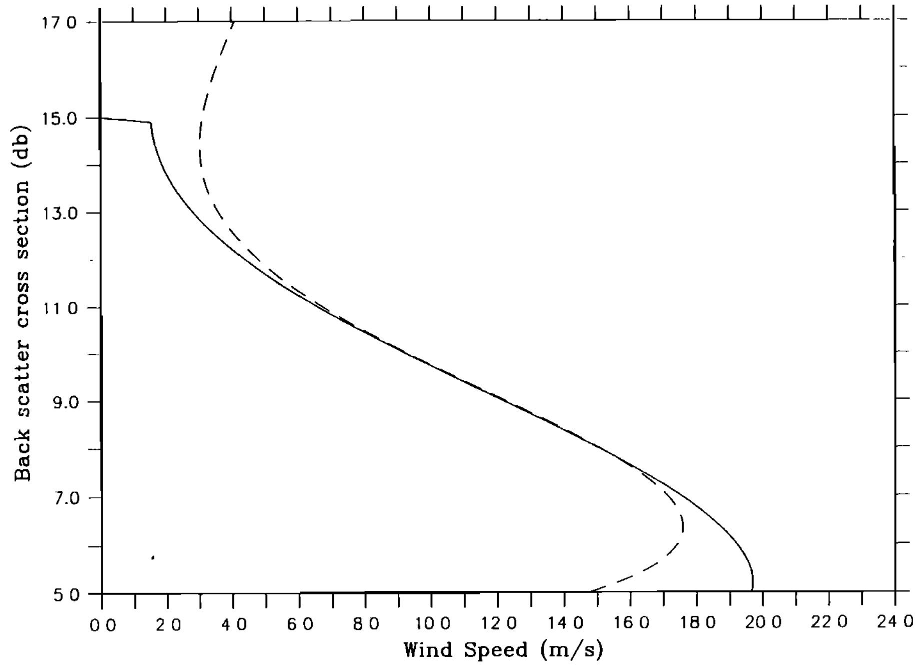

Figure 6. Comparison of the altimeter wind speed model function proposed by *Goldhirsh and Dobson* [1985], referred to as Smooth-Brown (continuous line) and the five-order polynomial ("Pseudo Smooth-Brown") derived from the ALT/NWP data set (dashed line) in section 3.1.

to 18 m/s due to the curvature of the function in this range, although *Goldhirsh and Dobson* [1985] actually suggested a 14 m/s limit for wind speed.

Here again a new fitting, also fifth-degree polynomial and RCS-dependent, was done with our ALT/NWP data set. The result is shown in Figure 6 and fits perfectly the Smooth-Brown function for wind speed in the range of 4–16 m/s. Elsewhere, the discrepancy is not surprising because of the very little amount of data used in the Smooth-Brown derivation unlike in our data set. The larger amount of data from extreme values in our ALT/NWP data set made this "pseudo Smooth-Brown" slightly different from the original one. As a consequence, the "pseudo Smooth-Brown" function is double valued at higher low speeds and lower high speeds than does the original one. Thus its range of validity is 3–17.5 m/s. The skills of the two GMFs are very similar in terms of mean error and standard deviation error; they are of −0.06 m/s and of 1.75 m/s in the "pseudo Smooth-Brown" (referred to as P-SB in Table 2) and of −0.19 m/s and of 1.77 m/s in the Smooth-Brown case (Table 1), respectively.

3.4. Chelton-Wentz and Modified Chelton-Wentz

Chelton and Wentz [1986] proposed a new method to derive wind speed from the Seasat altimeter in order to obtain a function satisfactory for high winds (for a typical range of 12–20 m/s). The limited range of wind speeds used for the computation of the Chelton-McCabe function was due to the averaging process. Their approach was thus based on comparisons between instantaneous Seasat altimeter measurements of RCS and the nearest off-nadir SASS measurements of wind speed, with a distance of about 200 km between the two. Contrary to the previous model functions, it was not necessary with this approach to assume a prescribed functional form. Starting from a first guess function of the altimeter wind speed, an iterative process was performed to minimize the difference between SASS wind speeds and the predicted wind speeds for each bin of their mean value. Chelton and Wentz' method allows a high degree of freedom for the form of the derived function. Indeed, the fitting process is different from all the previous ones. The resulting function was given in a tabular form for RCS values ranging from 19.6 to 7 dB (corresponding to 19.5 m wind speeds between 0 and 21 m/s). As a consequence, the minimization method does not yield the minimum RMS difference between the wind measurement and the wind estimate.

A comparison between Chelton and Wentz' function and the three previous ones (3.1–3.3) was performed by *Dobson et al.* [1987]. Their conclusion was that the Brown and Smooth-Brown functions behaved better when compared to buoys measurements than did the Chelton-McCabe and Chelton-Wentz functions. They pointed out that this result was not surprising since the former functions were computed by using buoy data and the latter ones by using SASS data.

Guillaume and Mognard [1992] compared the Brown, the Smooth-Brown, and the Chelton-Wentz algorithms, but using data from NWP models. Their results agreed with *Dobson et al.* [1987].

Cross comparisons between Seasat and Geosat altimeter RCS histograms for different periods were performed by *Witter and Chelton* [1991]. They found that the Geosat RCS values differed significantly from the Seasat RCS values. Together with an independent previous study of Seasat altimeter and SASS RCS, those results suggested to Witter and Chelton that the difference between the two altimeters was due to a systematic error in the Seasat RCS estimates.

They proposed another interesting method to derive a model function for a new satellite. They used a cross

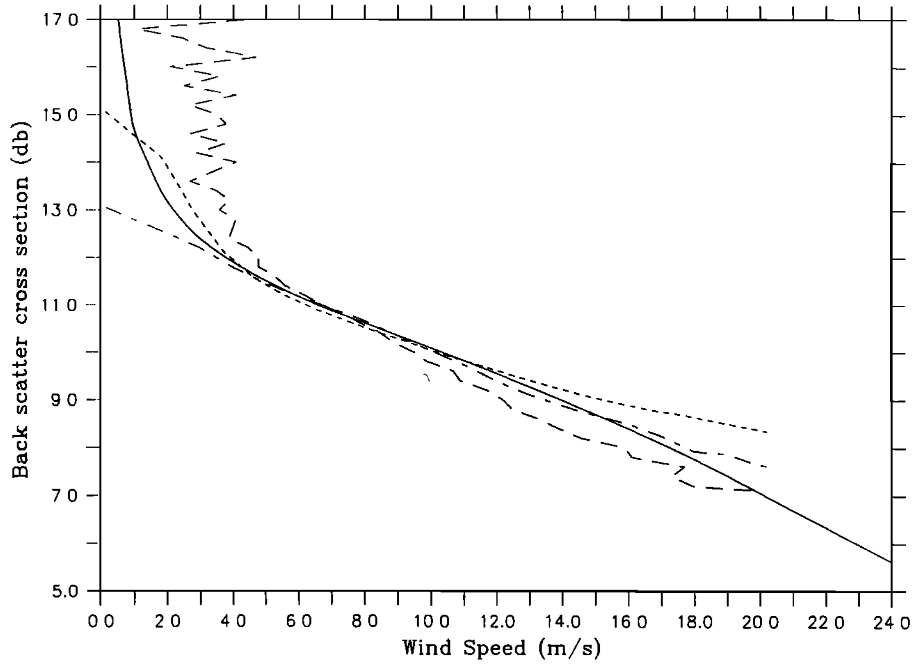

Figure 7. Comparison of the altimeter wind speed model function proposed by *Witter and Chelton* [1991], referred to as the MCW model function (solid line), the NWP3 model function proposed by *Freilich and Dunbar* [1993] (small-dashed line), and the tabular model functions derived from the ALT/NWP data set. The long-dashed line is the function obtained by averaging wind speeds in RCS bins, and inversely, the short-long-dashed line obtained by averaging RCSs in wind speed bins (as for the *Freilich and Dunbar* [1993] model function).

calibration method between RCS histograms. A model function previously established for an old spatial mission is corrected by comparing its RCS histogram to the new one. This procedure requires the stability of wind speed distributions over the same space calibration domain. The main limitation of such a method lies in the fact that the performance characteristics of the new model function cannot be improved, since it is based on previous ones.

The Seasat RCS errors were taken into account to correct the Chelton-Wentz function. The resulting function is referred to hereinafter as the Modified Chelton-Wentz model function (MCW) and is shown in Figure 7 (solid line).

A comparison with 119 National Buoy Data Center (NBDC) buoys was performed and yielded similar mean square errors (given the small amount of observations) than the Brown and Smooth-Brown functions. Unfortunately, there were very few data above 10 m/s and no data above 13.5 m/s in order to compare the functions where they differ significantly (except for the Smooth-Brown which is known to underestimate low winds and to overestimate high winds).

3.5. Freilich and Dunbar

Freilich and Dunbar [1993] used recently 1 year of global surface winds from two operational numerical weather prediction models to derive a wind speed function for the Geosat altimeter. In order to minimize the effects of NWP errors, independent NWP analyses from two agencies were used (this was valid to a certain extent, because of the common data used in the two assimilation schemes). Their relative difference was considered as an indicator of the quality of the wind and as a weighting factor in the following averaging process. For each NWP wind bin, a weighted sample mean wind speed and a weighted sample mean RCS were calculated. The results were given in a tabular form with the correspondence between RCS and wind speed from 1 m/s to 20 m/s by step of 1 m/s. Two versions of this table were computed depending on whether the data had been averaged along the satellite track or not (NWP0 for no averaging and NWP2 for 287 km along-track averaging). A NWP1 version was tuned from NWP0 to remove the high skewed distribution of RCS for very low winds. A further refined model function NWP3 (Figure 7) was derived like NWP2, but after eliminating the 20% NWP wind data with largest variance in the difference between the altimeter and NWP wind speed estimates. All the NWP-based algorithms were found to be very similar to the MCW function for wind speeds ranging from 5 m/s to 14 m/s. At high wind speeds the NWP functions overestimate the MCW one. Freilich and Dunbar performed simulations to determine the sensitivity of their model function to NWP random errors. The results suggested that random errors in the NWP analyses may account for the high wind speeds discrepancy between the MCW and NWP functions. There is another possible explanation due to the different method used to derive the functions. Indeed, for a same RCS versus wind distribution, different functions can be obtained depending on whether wind speed difference or RCS difference is chosen for the minimization process as shown in Figure 7. Freilich and Dunbar chose to minimize with respect to RCS (short-dashed line), whereas in Smooth-Brown (for instance) the wind speed was chosen. The first method yields a curve higher (short-long-dashed line) than the second (long-dashed line) for high wind speeds. In the MCW calculations, both

RCS and wind speed differences were used in the minimization leading to an intermediate curve (solid line).

3.6. Carter et al.

A simple linear relationship between RCS and wind speed was developed by *Carter et al.* [1992]. Their function is a two-stick linear fit to the collocated buoy/Geosat data set established by *Glazman and Pilorz.* [1990]. Although the results obtained were in close agreement with MCW, this function does not follow the recommendation of *Chelton and McCabe* [1985] because its slope is not continuous. The characteristics of the Carter GMF are listed in Table 1.

3.7. General Remarks

From this review of previous studies it is obvious that an important source of discrepancy between all model functions lies in the method used for their calculation, including the space chosen for the minimization process and the prescribed form of the function, if any. The method should be adapted to the goal. If the main goal is to produce the best estimate of the actual wind speed assuming that it is identical to the available wind (from buoy measurements, scatterometer data, or NWP model analyses), a method minimizing the mean square difference between the predicted wind and the true wind should be preferred. Such a method should produce the most accurate function, to the extent that the common criteria to assess a model function is the mean square difference in question. It is therefore not surprising that the Brown and Smooth-Brown functions produce winds with a smaller standard deviation error than Chelton-McCabe (after correcting RCS from measurements errors) and MCW ones. However, due to the prescribed form of the function, to the highly nonuniform wind speed distribution (with a peak around 7 m/s), and to the asymmetry of regression methods, the model function can exhibit some drawbacks in terms of wind speed dependent bias (for instance, Smooth-Brown underestimates high winds and cannot predict winds higher than 18 m/s). Thus as noticed by *Freilich and Dunbar* [1993], it is misleading to assess model function performances by comparing only an overall RMS error or mean error for the wind speed: the mean error and the associated dispersion for all wind speeds should be examined. Moreover, the regression problem is not symmetrical unless the correlation coefficient is equal to 1. This introduces a wind speed dependent bias on the fitted function. A possible way to remove such a bias is to use an orthogonal regression. Both distances in wind speed space and RCS space are used for the minimization process. The consequence is that the mean square error in each space is not minimum. Another way to reduce the asymmetry of the problem is to find other parameters which explain partly the error variance. The more variance is explained, the less asymmetrical the problem is. Another possible parameter for a wind speed model function is the significant wave height since it has been proven that the radar cross section should depend on both the sea maturity and the wind speed [*Glazman*, 1991].

4. A SWH Dependent GMF

4.1. Determination of a SWH Dependent GMF for ALT

Recent studies investigated the effect of the sea maturity on wind speed algorithms. *Monaldo and Dobson* [1989] first suggested that the information from the significant wave height should be used for wind speed prediction. They introduced SWH or excess of SWH (due to the presence of swell and estimated as the difference between SWH and maximum SWH for a given wind speed) as an additional parameter of the function. They used a multiple linear regression analysis to evaluate the benefit of introducing these new variables into the regression model. Unfortunately, the resulting residual reduction obtained by addition of the new variables was not statistically significant at a sufficient level, because of the small volume of collocated independent Geosat/buoy observations considered (236 data points). Then *Glazman and Greysukh* [1993] derived new SWH-based model functions. A previous study had demonstrated that the altimeter derived wind speed was correlated with the sea maturity. Thus they used an estimation of the magnitude of the sea maturity, proposed by *Glazman and Pilorz* [1990]: the pseudo-wave age which is a function of both the wind speed and the SWH. However, the improvement in the accuracy of the function resulting from the additional SWH information was again not significant because of the relatively small number of collocated independent Geosat/buoy observations (865 data points were used but only half could be considered as independent, since each satellite measurement was associated to two buoy measurements made within 1 hour). Since the pseudo-wave age is a function of both the wind speed and the SWH, and since the pseudo-wave age influences the radar cross section, an empirical GMF for wind speed can be expressed as a function of SWH and RCS [*Glazman and Greysukh*, 1993]. Following this approach, but without any a priori theoretical idea on the functional form, we adjusted a polynomial U(RCS, SWH) developed in the canonical form. Several polynomials with different degrees on RCS and SWH were fitted using the same ALT/model data set.

Polynomials until third degree were derived but no significant improvement was found between the second-degree and third-degree polynomials. A complete second-degree polynomial in RCS and SWH was finally retained, improving significantly the results at the 99.9% level over just using RCS alone. The function is defined as follows:

$$U = a_{00} + a_{10}h + a_{01}\sigma + a_{11}h\sigma + a_{20}h^2 + a_{02}\sigma^2 \qquad (3)$$

where

$$\sigma = (2\sigma_0 - \sigma_{\max} - \sigma_{\min})/(\sigma_{\max} - \sigma_{\min})$$

is a normalized RCS and has no unit

$$h = (2H - H_{\max} - H_{\min})/(H_{\max} - H_{\min})$$

is a normalized SWH and has no unit

σ and h vary within the interval $[-1; 1]$ for

$$\sigma_{\max} = 20 \text{ dB}, \ \sigma_{\min} = 5 \ dB, \ H_{\max} = 12 \text{ m}, \ H_{\min} = 0.5 \text{ m}$$

σ_0 is the radar cross section in decibels provided by the GDRs with an additional offset of -0.4 dB for ALT, H is the altimeter significant wave height in meters provided by GDRs. Besides,

$$a_{00} = 5.385, \ a_{10} = -0.530, \ a_{01} = -12.877$$

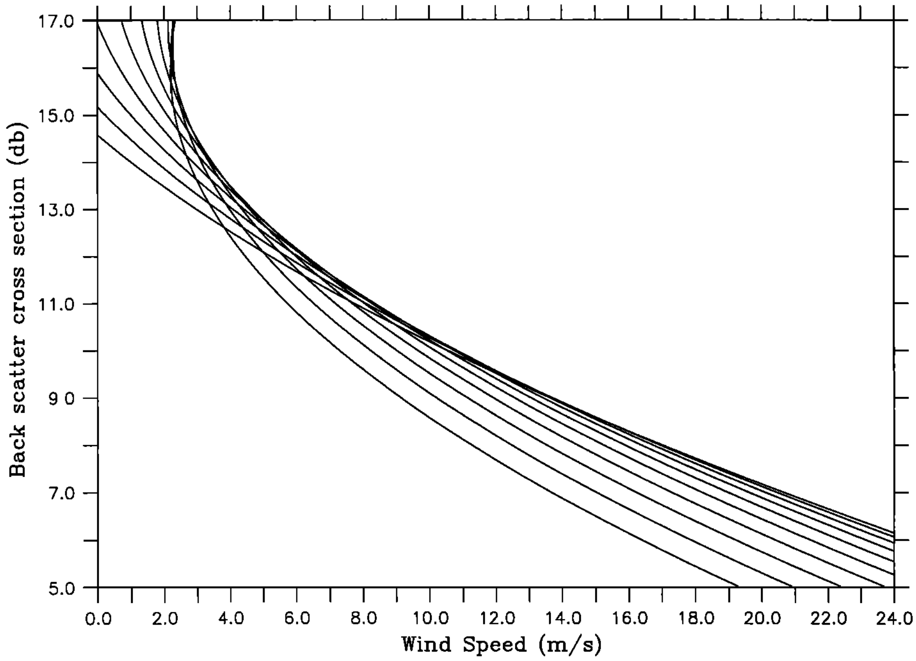

Figure 8. The new model function derived in section 3: RCS versus wind speed for SWH varying from 1 to 10 m by 1 m step from left to right in the lower part of the diagram, respectively. Only parts of the curves are valid.

$$a_{11} = -5.970, \; a_{20} = -2.350, \; a_{02} = 8.023$$

The new model function obtained (represented in Figure 8 for SWH varying from 1 to 10 m by 1 m steps) was compared to the usual functions usually obtained from distributions such as shown in Figure 9. It was shown by *Witter and Chelton* [1991] that the Chelton-McCabe and Chelton-Wentz model functions should not be applied to Geosat data. *Guillaume and Mognard* [1992] evaluated the Chelton-Wentz, the Smooth-Brown, and Brown model functions by using NWP model winds and significant wave heights. The two last functions produced similar results better than those

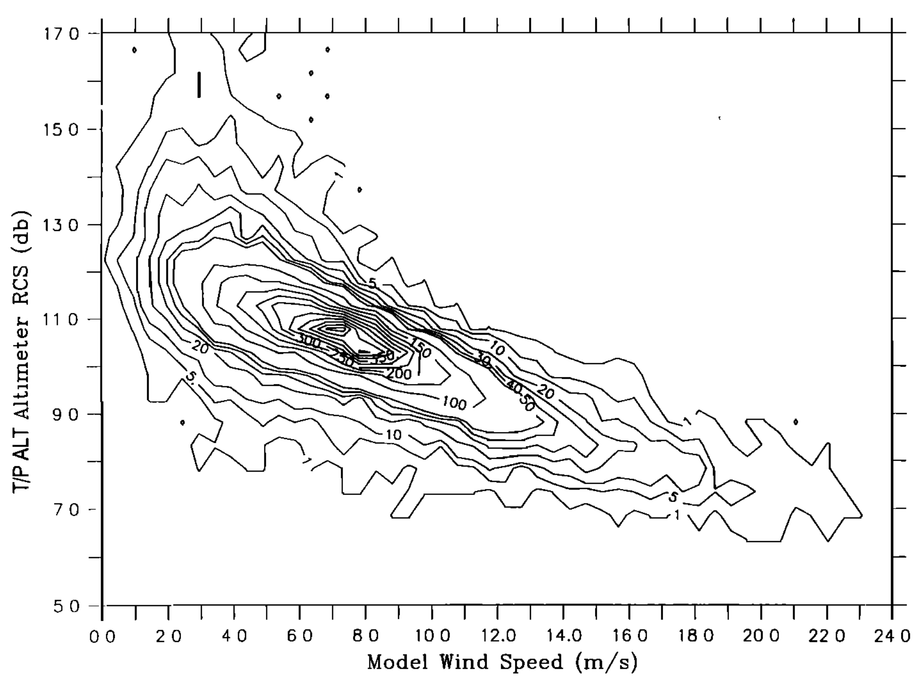

Figure 9. Radar cross section (RCS) from 17,094 T/P ALT measurements as a function of the ARPEGE 10-m wind speed.

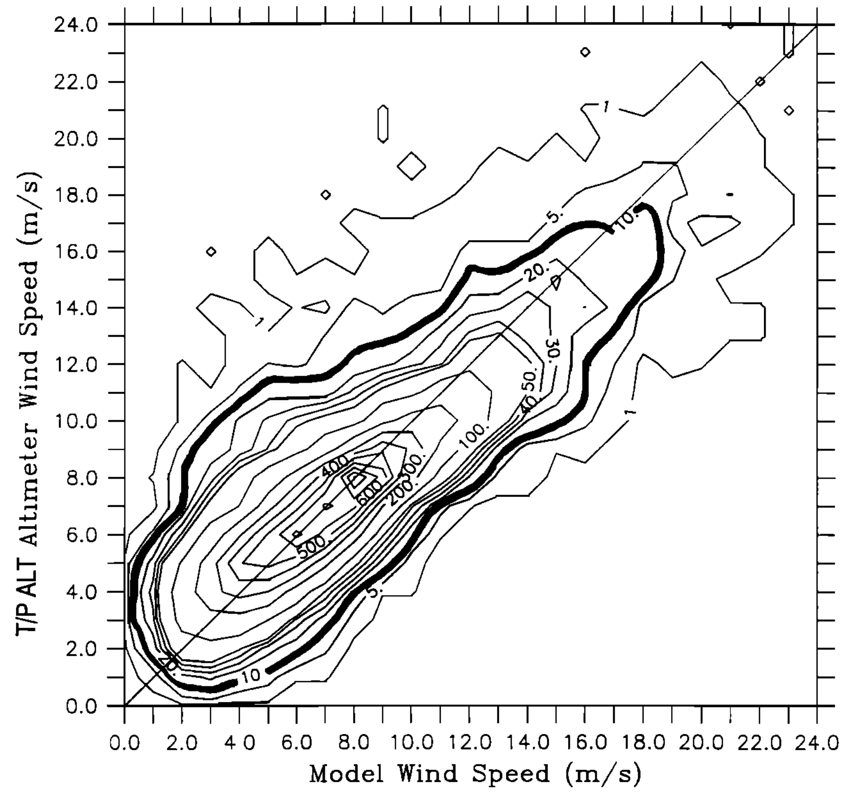

Figure 10. Scatter diagram of ALT wind speed versus model wind speed. Comparison of ARPEGE model with radar altimeter wind speeds using the Brown function.

of the first one (1.8 m/s and 2.4 m/s for the standard deviation error, respectively. The Smooth-Brown algorithm was calibrated for wind speed lower than 15 m/s. It strongly underestimates high winds and cannot predict winds above 18 m/s. We thus compared the new GMF with the Brown and MCW ones. Scatterplots of ALT wind speed versus model wind speed have been derived for the Brown (Figure 10), the MCW (Figure 11), and the new model function (Figure 12). The amount of entries per 1 m/s wide square is represented.

The global standard deviation error is larger for the MCW function (1.95 m/s or 27% of the mean wind value) than for the Brown one (1.74 m/s or 24%) and the new function (1.67 m/s or 23%). With the MCW function the standard deviation error is worse than with the two others for wind speed lower than 15 m/s, but the behavior is better than in Brown case at high wind speeds (above 15 m/s) as shown in Table 1 and Table 2. The new algorithm yields the smallest dispersion for all wind speed. In terms of bias, we found 0.07 m/s, 0.13 m/s, and no bias for Brown, MCW and the new GMFs, respectively. We then calculated a parameter characterizing the asymmetrical bias, if any. Introduced by *Bauer et al.* [1992] for comparisons between altimeter and model SWH, the symmetric slope is defined as the geometric mean of the slopes of the two regression lines obtained with a linear regression analysis ($y = ax + b$ and $x = a'y + b'$). This slope is very close to the one of the line obtained by minimizing the sum of the orthogonal distances of the data points to the regression line. In our calculations a symmetric slope greater than 1 indicates an underestimation of the high values of the altimeter wind speed and an overestimation of the low values. We found a symmetric slope of 1.14 for Brown, 0.90 for MCW, and 1.17 for the new model function.

Such a behavior can be easily attributed to the fitting method used for the Brown and new GMFs (choice of the wind speed space for the minimization). The examination of the scatter diagrams (Figures 10, 11, and 12) indicates that all these symmetric slopes are associated to small trends. The correlation coefficients were of 0.84 for the Brown and MCW functions, and of 0.855 for the new model function, respectively.

In order to demonstrate that the improvement of the function is due to the introduction of the additional variable SWH, we derived model functions based on our data set but depending only on the RCS variable. We thus derived a logarithm function and polynomials until fifth degree. We also derived a function in a tabular form. All minimization were made relative to the wind speed difference. For all these functions we found a global standard deviation error larger than 1.74 m/s. The total amount of data (17,094) is big enough to make the improvement of the new function significant with a confidence level higher than 99.9% (the reduction of variance, from 1.74^2 to 1.67^2 $(m/s)^2$ is 0.24 $(m/s)^2$ and corresponds to a significant level higher than 99.9% when 17,094 independent data are considered).

In terms of regression analysis, our function can be considered as the extension of a second-order polynomial in σ including the additional variables h, $h\sigma$, and h^2. If the residuals are reduced by a statistically significant amount, then the addition of these extra variables is concluded to improve the function performance. Since the second-order

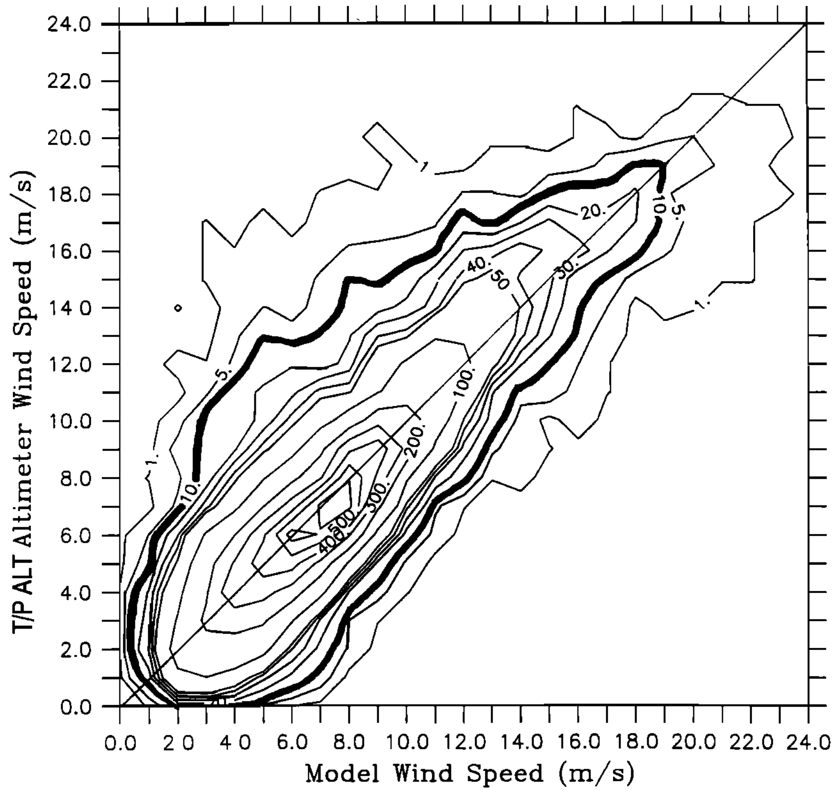

Figure 11. Scatter diagram of ALT wind speed versus model wind speed. Comparison of ARPEGE model with radar altimeter wind speeds using the Modified Chelton-Wentz function.

polynomial in σ produces a standard deviation error of 1.74 m/s and since no higher degree polynomial in σ produces significant improvement, the addition of h dependent variables into the GMF introduces new information and yields a significant improvement at the 99.9% level.

As mentioned by *Monaldo and Dobson* [1989], two physical mechanisms can be involved in the h dependence of the new function. For a given wind speed, the presence of preexisting swell can increase the mean square slope of the sea surface (MSS) and then reduce the backscatter cross section. On the contrary, the swell or nearly fully developed wind sea reduces the transfer of energy from the wind to the wave and therefore the MSS. The two effects compete with each other.

4.2. Validation of the New GMF With the T/P SSALT/NWP Data Set

We applied the new T/P ALT model function to an independent collocated T/P SSALT/NWP data set obtained between December 1992 and November 1993 (cycles 9 to 41). The data were processed by using the same procedure as for ALT and 5531 data points were selected. We first performed a comparison between the SSALT and model SWH. The correlation coefficient is similar to that obtained with ALT (0.89 instead of 0.88) and the symmetric slopes, too (they are both equal to 1.1). We then selected the data points by using the same criteria as before. In the resulting data set, 2587 points were used for the assessment of the new model function. We found a standard deviation error of 1.75 m/s (22% of the mean NWP wind) and a mean error of -0.27 m/s (as indicated in Table 3).

We compared the new function to the Brown and MCW ones, using this selected SSALT/NWP data set. Again, we found that the latter ones have less favorable characteristics: the mean bias is -0.38 m/s for the Brown function and -0.33 m/s for the MCW one, and the standard deviation error is 1.81 m/s (23% of the mean NWP wind) and 2 m/s (25% of the mean NWP wind), respectively.

We also applied the other "pseudo Geosat" functions we derived in section 3 to this SSALT/NWP data set. The results were performed in terms of biases and standard deviations. The lowest standard deviation error we obtained was of 1.82 m/s, close to the Brown case. Therefore the minimum reduction of the variance error, from 1.81^2 to 1.75^2 $(m/s)^2$ is 0.21 $(m/s)^2$ and corresponds to a significant level of 90% when 2587 independent data are considered.

4.3. Validation of the New GMF With NDBC Buoy Data Set

Although we reduced the amount of dubious NWP winds, possible systematic biases in NWP models should be reflected in our algorithm. For its validation (and hence that of the NWP winds), one should compare the results with independent, near-surface measurements. Because a large enough collocated buoy and T/P data set is not yet available, an alternative approach consists in using altimeter data from previous missions; indeed, the "pseudo Geosat" functions we derived with our T/P data set are very similar to the original ones.

A data set of collocated buoy and Geosat measurements was established by Glazman. This data set, including 3 years of the Geosat mission, is described by *Glazman and Pilorz*

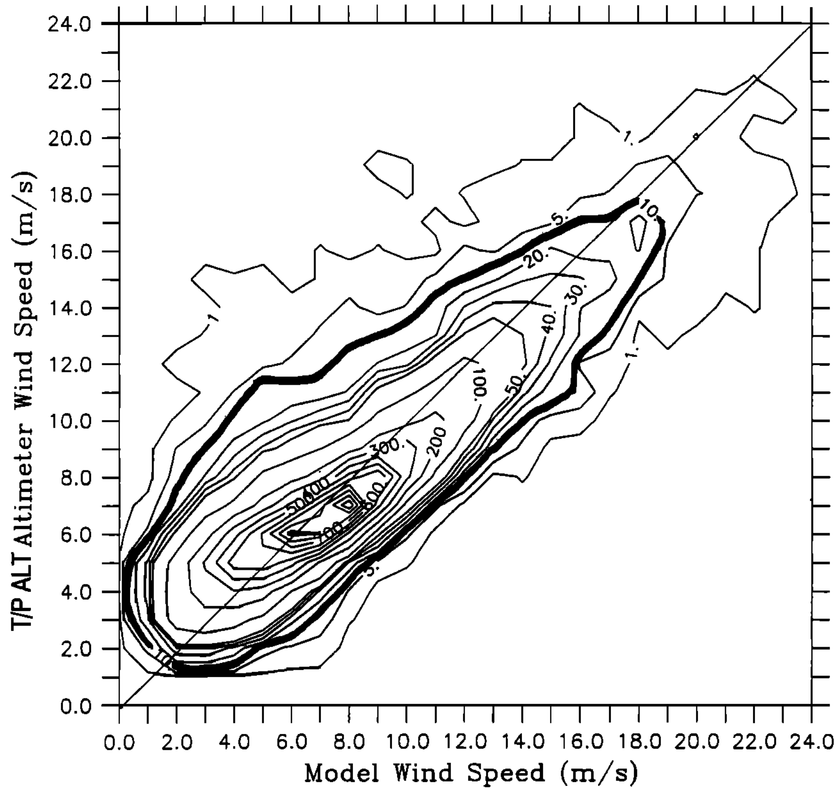

Figure 12. Scatter diagram of ALT wind speed versus model wind speed. Comparison of ARPEGE model with radar altimeter wind speed using the new model function derived in section 3.

[1990]. Geosat parameters were extracted when the satellite footprint was within a 1-degree box centered on the location of 20 buoys of the U.S. National Buoy Data Center (NDBC) of the National Oceanographic and Atmospheric Administration and when the time difference between the satellite pass and the buoy measurement was less than 1 hour. Because two buoy measurements made at an interval of 1 hour were generally associated with one satellite datum, we interpolated the buoy data at the time of the satellite pass to remove this duplication. Like *Carter et al.* [1992] and *Glazman and Greysukh* [1993], we also cleaned the data. We removed records with RCS above 20 dB and below 6 dB, and with SWH above 12 m. We corrected the derived altimeter SWH in order to avoid the underestimation found by *Carter et al.* [1992]. We applied the empirical algorithm developed by *Glazman and Greysukh* [1993] to the Geosat SWH. We then averaged the altimeter data in each box.

One crucial problem with the Geosat data lies in the relatively bad satellite attitude (off-nadir). Moreover, the estimation of Geosat attitude is not good as noticed by *Carter et al.* [1992] and makes any RCS correction difficult. There is almost a factor of 10 between the T/P and Geosat mean attitudes. Since the effect of the attitude on RCS may be large in certain cases, especially at low winds, when the RMS wave slope becomes comparable to the satellite attitude [*Glazman and Pilorz*, 1990], the small positive impact of the new SWH variable in any algorithm can be lost.

Thus we applied the MCW, Brown, and new functions to the buoy/Geosat data set, with different criteria of data selection: the results in terms of means and standard deviation errors are stratified as a function of antenna pointing and are listed in Table 4. A further selection is done by rejecting the data with a wind buoy measurement below 4 m/s. At large attitudes, above 0.75°, the MCW function yields the best characteristics; a mean error of 0.05 m/s and a standard deviation of 1.62 m/s. According to Table 4, the differences in the standard deviations of the three algorithms decrease with the satellite attitude or with the elimination of data associated with low winds (below 4 m/s). The minimum standard deviation error is obtained with the new function (1.33 m/s) when the satellite attitude is below 0.5° and the wind speed is above 4 m/s (Figure 13). Then, the MCW algorithm produces the worse mean error (0.55 m/s). How-

Table 3. Summary of Mean and Standard Deviation Errors Stratified as a Function of Wind Speed Range for Two Geosat Derived Algorithms and for the New One

	T/P SSALT-NWP Winds Differences (s.d.), m/s		
Range, m/s	Brown	MCW	New GMF
0–5	0.5 (1.4)	−0.6 (1.6)	0.8 (1.3)
5–10	−0.4 (1.7)	−0.5 (1.6)	−0.4 (1.6)
10–15	−1.3 (2.0)	0.6 (2.0)	−0.9 (1.8)
>15	−0.6 (3.0)	0.2 (2.4)	−0.7 (2.6)
Total	−0.38 (1.81)	−0.33 (2.0)	−0.27 (1.75)

The wind speed classification is performed using the mean values of the NWP analysis with the corresponding T/P measurement. Mean differences of the T/P estimates to the NWP wind speed and, in parentheses, standard deviations, are listed for our 2587 data pairs.

Table 4. Summary of Mean and Standard Deviation Errors Stratified as a Function of Antenna Pointing

Off Vertical, deg	Number of Points	Geosat-Buoys Winds Differences (s.d.), m/s Brown	MCW	New GMF
		All Winds		
1.	552	−0.12 (1.67)	0.05 (1.62)	−0.37 (1.78)
0.75	368	0.13 (1.57)	0.39 (1.52)	−0.17 (1.66)
0.5	148	0.32 (1.58)	0.60 (1.45)	−0.12 (1.53)
		Buoy Winds > 4 m/s Only		
1.	465	−0.37 (1.58)	−0.02 (1.58)	−0.73 (1.60)
0.75	313	−0.10 (1.46)	0.32 (1.46)	−0.51 (1.47)
0.5	132	0.14 (1.45)	0.55 (1.34)	−0.39 (1.33)

Mean differences of the Geosat estimates to the NDBC buoy wind speed and, in parentheses, standard deviations, are listed. Three algorithms are considered.

ever, most of the values listed in Table 4 are not significantly different at a sufficient confidence level because of the small amount of data used (for instance, a standard deviation error in a 132 data sample is significantly different from 1.33 m/s at the 90% level if it is above 1.43 m/s or below 1.23 m/s). So, it seems prudent not to conclude whether the effect of SWH on wind speed algorithms is positive. A larger sample of data, with more accurate attitudes, would be more conclusive. Thus the new GMF retrieves wind speed from Geosat measurements with an accuracy compatible with usual algorithms. In particular, no serious systematic biases were found in the new algorithm.

5. Summary and Conclusion

This study confirms the interest of using data from numerical weather prediction models to calibrate satellite data and to derive new wind model functions. The use of wave model data enables a quality control of the 10-m wind speed from the NWP analyses. Most of the existing model function, derived for previous altimeters, with other kinds of data (from scatterometer or buoys), are very similar to the functions derived by using the same methods but with the T/P data set. The method used, including the quantity to be minimized and the form of the function, if any, appears to be determinant for the accuracy of the derived algorithm. The unimodal form of the wind distribution with a pronounced peak, together with the choice of the function, are responsible for a possible important asymmetrical wind bias (Chelton-McCabe and Smooth-Brown with opposites high asymmetrical bias). The RCS dependent GMF producing the lowest RMS wind error should be derived in a tabular way. However, such an algorithm was not found significantly more accurate than an algorithm derived from a well-chosen function and minimizing the appropriate quantity. This suggests that any improvement on the accuracy of the altimeter wind speed may be due to the introduction of new variables. Because theoretical studies and analyses of derived wind speeds together with sea state condition measurements demonstrated that the RCS is affected by sea state conditions, the altimeter SWH was introduced in the wind speed calculation. A model function depending on both the significant wave height and the radar cross section was thus derived in a polynomial form. The accuracy of that new

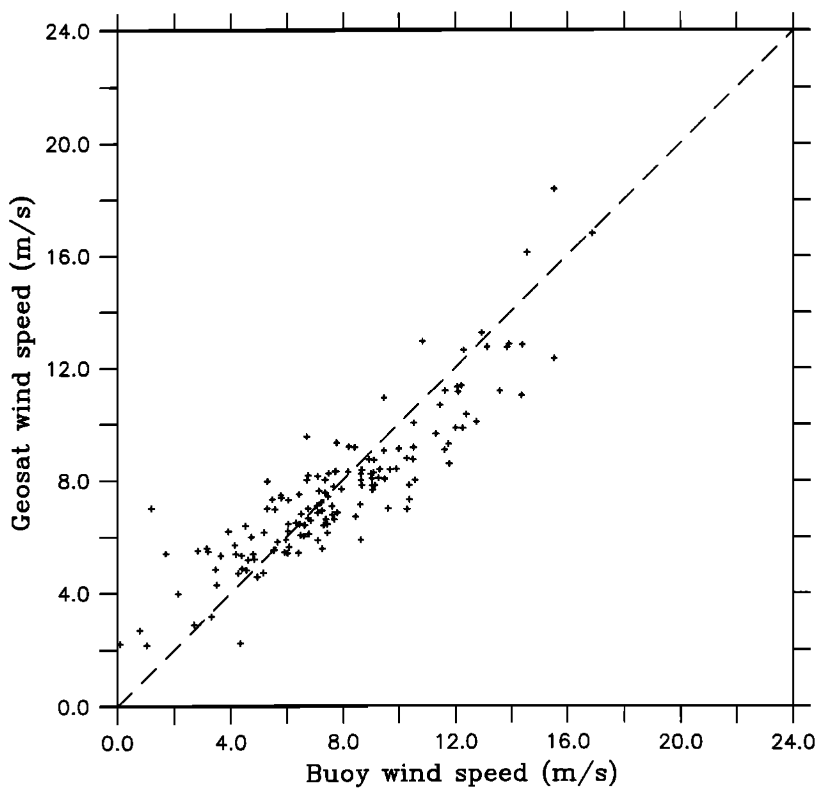

Figure 13. Comparison of 148 wind speeds from Geosat (using the new model function derived in section 3 with Geosat RCSs with attitude under 0.5°) and collocated NDBC buoy data.

model function is significantly improved compared to that of the existing ones at the 99.9% confidence level. The standard deviation error is reduced to 1.67 m/s (23% of the mean wind speed value) instead of 1.74 m/s (24%) and 1.95 m/s (27%) for the Brown and MCW functions. The global standard deviation error obtained with the MCW function is higher than with the Brown one but the MCW function is more accurate than most of all GMFs examined in this paper at high wind speed (above 15 m/s). However, the new model function performs better at all wind speeds.

The new algorithm was validated with an independent collocated Geosat/buoy data set, although the quality of the T/P RCSs is better than that of Geosat, due to larger off-nadir incidence angles for Geosat. We found that it retrieves wind speed from Geosat measurements with an accuracy compatible with usual algorithms.

The increased accuracy of wind speed determination allowed by the introduction of the SWH variable found by *Glazman and Greysukh* [1993] with a small data set (865 data points) is confirmed by this study. However, one major difficulty in the development of new model functions lies in the inaccuracy of RCS, wind speed, and SWH measurements or estimations. Investigations to improve the quality of large enough collocated data sets should be done in the future.

Acknowledgments. This work carried out at Meteo-France has been partly supported by CNES (French Space Agency). We are grateful to R. E. Glazman of the Jet Propulsion Laboratory for providing the collocated NDBC/Geosat data set used in this study.

References

Bauer, E., S. Hasselmann, K. Hasselmann, and H. C. Craber, Validation and assimilation of Seasat altimeter wave heights using the WAM model, *J. Geophys. Res.*, *97*, 12671–12682, 1992.

Brown, G. S., Estimation of surface winds using satellite-borne radar measurements at normal incidence, *J. Geophys. Res.*, *84*, 3974–3978, 1979.

Brown, G. S., H. R. Stanley, and N. A. Roy, The wind speed measurement capability of space borne radar altimeters, *IEEE J. Oceanic Eng.*, *OE-6*(2), 59–63, 1981.

Carter, D. J. T., P. G. Challenor, and M. A. Srokosz, An assessment of Geosat wave height and wind speed measurements, *J. Geophys. Res.*, *97*, 11383–11392, 1992.

Chelton, D. B., and P. J. McCabe, A review of satellite altimeter measurement of sea surface wind speed: With a proposed new algorithm, *J. Geophys. Res.*, *90*, 4707–4720, 1985.

Chelton, D. B., and F. J. Wentz, Further development of an improved altimeter wind speed algorithm, *J. Geophys. Res.*, *91*, 14250–14260, 1986.

Courtier, P., C. Freydier, J. F. Geleyn, F. Rabier, and M. Rochas, The ARPEGE project at Meteo-France, paper presented at ECMWF workshop, Eur. Cent. for Medium-Range Weather Forecasts, Reading, England, September 1991.

Dobson, E. B., F. M. Monaldo, J. Goldhirsh, and J. Wilkerson, Validation of Geosat altimeter-derived wind speeds and significant wave heights using buoy data, *J. Geophys. Res.*, *92*, 10719–10731, 1987.

Freilich, M., and R. S. Dunbar, Derivation of satellite wind model functions using operational surface wind analyses: An altimeter example, *J. Geophys. Res.*, *98*, 14633–14649, 1993.

Fu, L.-L., and R. E. Glazman, The effect of the degree of wave development on the sea state bias in radar altimetry measurements, *J. Geophys. Res.*, *96*, 829–834, 1991.

Glazman, R. E., and A. Greysukh, Satellite altimeter measurements of surface wind, *J. Geophys. Res.*, *98*, 2475–2483, 1993.

Glazman, R. E., and S. H. Pilorz, Effects of sea maturity on satellite altimeter measurements, *J. Geophys. Res.*, *95*, 2857–2870, 1990.

Glazman, R. E., Statistical problems of wind-generated gravity waves arising in microwave remote sensing of surface winds, *IEEE Trans. Geosci. Remote Sens.*, *29*, 135–142, 1991.

Goldhirsh, R. E., and E. B. Dobson, A recommended algorithm for the determination of ocean surface wind speed using a satellite-borne radar altimeter, *Rep. JHU/APLS1R85U-005*, Appl. Phys. Lab., Johns Hopkins Univ., Laurel, Md., 1985.

Guillaume, A., Statistical test for comparison of surface gravity wave spectra with application to model validation, *J. Atmos. Oceanic Technol.*, *7*, 551–567, 1990.

Guillaume, A., and N. M. Mognard, A new method for the validation of altimeter-derived sea state parameters with results from wind and wave models, *J. Geophys. Res.*, *97*, 9705–9717, 1992.

Guillaume, A., J. M. Lefevre, and N. M. Mognard, The use of altimeter data to study wind wave variability in the western Mediterranean Sea, *Oceanol. Acta*, *15*(5), 555–561, 1992.

Lionello, P., H. Günther, and P. A. E. M. Janssen, Assimilation of altimeter data in a global third-generation wave model, *J. Geophys. Res.*, *97*, 14453–14474, 1992.

Monaldo, F. M., Expected differences between buoy and radar altimeter estimates of wind speed and significant wave height and their implications on buoy-altimeter comparisons, *J. Geophys. Res.*, *93*, 2285–2302, 1988.

Monaldo, F. M., and E. B. Dobson, On using significant wave height and radar cross section to improve radar altimeter measurements of wind speed, *J. Geophys. Res.*, *94*, 12699–12701, 1989.

Queffelou, P., and J. M. Lefevre, Validation of ERS-1 altimeter wave and wind fast delivery product, paper presented at ERS-1 Geophysical Validation Meeting, Eur. Space Agency, Penhors, Brittany, France, April 27–30, 1992.

Witter, D. L., and D. B. Chelton, A Geosat altimeter wind speed algorithm and a method for altimeter wind speed algorithm development, *J. Geophys. Res.*, *96*, 8853–8860, 1991.

J. Barckicke and J. M. Lefevre, Meteo-France, 42 avenue Gustave Coriolis, 31057 Toulouse Cedex, France.

Y. Menard, Centre National d'Etudes Spatiales, 18 avenue Edouard Belin, 31055 Toulouse Cedex, France.

(Received April 25, 1994; revised July 29, 1994; accepted July 29, 1994.)