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EVIDENCE OF THE UNDERESTIMATION OF THE MEAN FREQUENCY OF SHORT WIND WAVES IN TROPICAL LATITUDES BY THE WAM MODEL

VIOLANTE-CARVALHO, N.[1] & RAMOS, A,V.C.[2]

[1]Department of Oceanography. Rio de Janeiro State University UERJ
Rua São Francisco Xavier 524, 20550-013. Rio de Janeiro - Brazil
violante_carvalho@yahoo.co.uk

[2]Department of Applied Mathematics. Rio de Janeiro Federal University UFRJ
Rio de Janeiro - Brazil
adriane@labma.ufrj.br

ABSTRACT

Violante-Carvalho, N. & Ramos, A,V.C. 2006. Evidence of the Underestimation of the Mean Frequency of Short Wind Waves in Tropical Latitudes by the WAM Model. Braz. J. Aquat. Sci. Technol. 10(1):17-26. ISSN 1808-7035. The WAM, the first proposed and most widely used third generation wave model, is employed to compare its estimated mean frequency against buoy measurements acquired in deep tropical ocean waters in Campos Basin, off Rio de Janeiro, Brazil. This model is noteworthy for being extensively tested and validated over a period of many years and is implemented operationally at several weather forecast centers in the world. However most of its validation tests were performed over a single wave parameter, that is significant wave height, using data covering all oceanic basins yielded by altimeters onboard satellites. Most, if not all of its assessment studies using detailed spectral buoy data are restricted to high latitude locations due to the sparseness of in situ measurements in low latitude waters. The standard frequency discretization used in the WAM cycle 4 model produces good scaling behavior for wind speeds ranging from 15 to 25 m/s, which is way below the typical wind conditions encountered in tropical areas. It is shown that due to the standard frequency discretization employed the model underestimates the mean frequency of short waves measured in Campos Basin. This is indication that the cut-off frequency must be extended to a higher value, specially when the initial stages of wave growth are important.

Key words: wind waves, Campos Basin, WAM wave model, Heave-Pitch-Roll Buoy Measurements.

INTRODUCTION

Our understanding of the dynamics of wave generation and growth have improved substantially over the last few decades but there are still many unknowns in the fundamental processes which have been left to be elucidated. The better estimation through numerical simulations of the wave field using past forcing winds to compute the climatologies (hindcasts) or for wave forecasts has practical importance such as for ship routing, offshore activities, coastal management and fisheries among several others.

The interest in this field of research is, however, not only limited to the economic and engineering concerns. Wind waves are the interface between the ocean and the atmosphere and are therefore closely connected to the exchange processes like for example transfer of mechanical energy, momentum, sensible and latent heat and gases (Donelan, 1990, Komen *et al.*, 1994, Csanady, 2001). Energy is transferred from the atmosphere to the ocean driving the circulation of the upper ocean. Energy from the ocean, on the other hand, is fed back to the atmosphere affecting the atmospheric circulation and the climate. The wind drag coefficient is affected by the wave age and by the wave spectrum but there is still, however, considerable uncertainty on how to model its dependency on the sea state. A better description of air-sea interaction and its consequences, for example on the world climate, has to take into account the role played by the waves on the fluxes across the interface. The studies using sophisticated numerical climate simulations considering the coupling between ocean and atmosphere and its interface using wave models are increasingly expanding. This is a field of exciting possibilities and several forecasting centers are investigating the feasibility of combining such models.

The high spatial and temporal variability of surface processes needs to be properly considered in any investigation of the dynamics of wind waves. High resolution models combined with detailed spectral satellite data seem to offer the best opportunity to provide global analysis and predictions. Since the advent of satellite oceanography the field of wave data assimilation has experienced a fast development. So far only Significant Wave Height (SWH) from altimeters have been assimilated by operational forecasting centers but with the improvement of the schemes for the retrieval of the wave spectrum from Synthetic Aperture Radar (SAR) images the natural trend is that this picture is going to change (see for example Violante-Carvalho & Robinson 2004, Violante-Carvalho *et al.* 2005). The cumbersome task of redistributing the energy from an integral parameter like SWH over the spectrum seems pointless since reliable global estimates of the full directional spectrum are becoming available. The combination of measurements and numerical estimations can be translated into better and more physically consistent model parameterizations. Inverse modeling techniques consist of estimating optimal parameters that minimize a function describing the difference between observed and estimated conditions, therefore improving the model parameters. Such approaches in oceanography have been already pursued (see the examples listed in Wunsch, 1996), although its application in wave modeling is in its infancy (de las Heras *et al.* 1994, Hersbach 1998).

Over the last 30 years major research efforts have been made and we now have suitable parameterizations of the source terms that describe the dynamics of wind waves. This has been reflected in the development of advanced third generation wave models such as WAM, WaveWatch and SWAN that compute the directional spectrum by direct integration of the energy balance equation based on the structure of the terms that describe the input of energy from the wind, the nonlinear interaction among wave components and the dissipation of energy due to whitecapping. Although their performances, specially of the WAM model, have already been demonstrated by several validation tests (see for example the comparisons of the WAM estimates against buoy and satellite measurements in Komen *et al.* 1994) these wave models have room for improvement where their main deficiencies lay in: 1. the numerical resolution; 2. the numerics, such as the propagation schemes and the integration of the nonlinear interactions; 3. the physical representation of the terms of input and dissipation of energy.

The aim of this work is to investigate the performance of the WAM, the most widely used and tested model, in estimating the mean frequency of wind waves through intercomparisons with heavy-pitch-roll buoy data acquired in deep tropical water in the South Atlantic. Most of the validation exercises carried out so far for the WAM have focused on the performance of the model in computing a single parameter, that is SWH, comparing its value against satellite altimeter data due to the lack of detailed spectral measurements available. However the use of an integral parameter like SWH to perform a validation test does not take advantage of the detailed spectral information yielded by a third generation model. Moreover the wind waves measured by buoys can assess the quality of the model estimates in more complicated conditions, such as turning winds or on early stages of development when the performance of the approximation of the nonlinear interactions and the numerical resolution of the model, respectively, can be analyzed.

THE WAM WAVE MODEL

A brief summary of the main characteristics of the third generation WAM wave model is presented and more detailed information is described in WAMDI Group (1988), Günther *et al.* (1992) and Komen *et al.* (1994).

A third generation model such as WAM does not introduce assumptions about the shape of the spectrum (SWAMP Group 1985), where the directional wave spectrum is determined by the integration of the transport equation which will be used in the numerical prediction model, that is

$$\frac{D}{Dt}F \equiv \frac{\partial F}{\partial t} + \frac{1}{\cos\phi}\frac{\partial}{\partial\phi}(\dot{\phi}\cos\phi F) + \frac{\partial}{\partial\lambda}(\dot{\lambda}F) + \frac{\partial}{\partial\theta}(\dot{\theta}F)$$

$$= S_{in} + S_{nl} + S_{ds} \qquad (1)$$

where $F=F(f,\theta,\phi,\lambda,t)$ is the two dimensional directional wave spectrum as a function of the frequency f, the direction θ on a spherical grid of latitude ϕ and longitude λ and

$$\dot{\phi} = \frac{d\phi}{dt}$$

$$\dot{\lambda} = \frac{d\lambda}{dt}$$

$$\dot{\theta} = \frac{d\theta}{dt}$$

represent the rate of change of the position and direction propagation along a great circle path for waves in water of infinite depth. The source terms for the infinite depth case are represented by the wind input (S_{in}), the nonlinear transfer (S_{nl}) and the dissipation term (S_{ds}).

The wind input term represents the transfer of energy from the wind to the ocean, producing waves. Short waves are produced in the high frequency part of the spectrum whenever the wind is blowing on the sea surface. The wind input source term S_{in} adopted in the WAM cycle 4 is based on Miles' theory for laminar flow given by the expression presented by Snyder *et al.* (1981)

and later modified (Janssen 1989; 1991) which describes the wind-wave momentum transfer. In this theory the wind input depends in a a *quasi-linear* way on the wave spectrum:

$$S_{in} = \gamma_{in} F$$

where γ_{in} is the growth rate parameter. The stress in the air surface layer is affected by the waves through their orbital velocity, the so-called wave-induced stress. Therefore the momentum transfer from air to ocean is dependent on the sea state, which is taken into account in the model.

The nonlinear wave-wave interactions are extremely important for the understanding of the evolution of the directional spectrum. The role of the nonlinear term is to redistribute energy from the short wave components to the long ones resulting in waves that otherwise would not be generated directly by the wind. The term S_{nl} describes the energy transfer due to nonlinear wave-wave interactions when a set of four waves of different wave lengths, called a quadruplet, interact with each other satisfying the resonance conditions

$$\mathbf{k}_1 + \mathbf{k}_2 = \mathbf{k}_3 + \mathbf{k}_4$$

$$\omega_1 + \omega_2 = \omega_3 + \omega_4$$

where **k** is the wavenumber vector and ϖ is the angular frequency ($2\pi f$). The exact calculation of S_{nl} is too time consuming to be used in operational models so a parameterization is employed, the discrete interaction approximation (DIA) (Hasselmann & Hasselmann 1985, Hasselmann *et al.* 1985a). It is still not very clear whether the DIA represents correctly the nonlinear interactions in more complex sea states such as in situations of turning or ceasing winds where wind sea-swell transition and turning wind sea are present (Young, 1999).

Dissipation of energy may occur in deep water by wave breaking in a process called whitecapping when the wave amplitude increases beyond a certain level—this term was introduced to differentiate it from depth-induced wave breaking. The dissipation term S_{ds} implemented in WAM cycle 4 is based on the whitecapping theory (Hasselmann, 1974), uses the parameterization proposed by Komen *et al.* (1984) and takes into account the wave induced stress (Janssen 1991). Like the wind input, S_{ds} is quasi linear in the wave spectrum and is represented by

$$S_{ds} = \gamma_{ds} F$$

with the dissipation rate γ_{ds} depending on integral spectral parameters. The parameter S_{ds} is the least well known of the three source functions and its value was adjusted to ensure that the action balance equation (1) achieves an agreement with measurements in fetch-limited growth.

The WAM model runs operationally at most forecasting centers and has been validated on statistical basis against buoy data (see for example the results presented in Komen *et al.* 1994). The comparisons of significant wave height estimated by the model against Geosat altimeter measurements show an overall good correlation with small values of bias (Romeiser 1993). However significant discrepancies were encountered in some individual cases and have been attributed to errors in the forcing wind or to inadequate spectral resolution of the model.

Altimeter wave height data have been assimilated by the European Centre for Medium-Range Weather Forecasts (ECMWF) since August 1993 ERS-1 into their WAM wave model using an optimal interpolation scheme. In this work a workstation version of the WAM model is run without the implementation of data assimilation which means that the outputs from the model are the result of integration of equation (1) which makes the comparison of the model against buoy data more meaningful. If one seeks to search for deficiencies in the numerical model through detailed spectral comparisons against buoy measurements the spurious influence of the assimilation of altimeter data would make the interpretation of the discrepancies more complicated.

The two dimensional spectra are computed using the WAM cycle 4 every hour on a latitude-longitude grid with a spatial resolution of 1^o covering the whole South Atlantic basin from the Equator line to 72^o *S* and from 74^o *W* to 30^o *E*, which totals 7488 grid points. The spectrum is evaluated up to a high frequency cut-off which depends on the wind speed and on the wave age, and beyond this point an f^5 tail is added with the same directional distribution as the cut-off region. The wave spectrum is discretized in 25 logarithmically spaced frequencies with $\Delta f / f = 0.1$ spanning a frequency range from 0.042 to 0.41 Hz and 24 directions with 15^o of resolution. The source and the advection terms have a time step of 12 minutes for all the 600 spectral components. The wave model is driven using the wind field at 10 meters height (u_{10}) computed by the Atmospheric General Circulation Model (AGCM) which is run operationally by ECMWF with the Re-Analysis (ERA) data set with a latitude-longitude resolution of 1.125^o and computed every 6 hours.

METHODOLOGY

In Situ Measurements

The buoy data analysis is comprehensively explained in Violante-Carvalho *et al.* (2004) and for completeness a brief description follows.

Campos Basin (Figure 1), in the coast off Rio de Janeiro, is the most important petrolic basin in Brazil. Tens of platforms are located in this area responsible for over 75% of the oil produced by the country with several offshore operations taking place daily. In addition the surrounding area holds a high urban concentration with strong commercial and industrial activities. Due to the remarkable importance of this region, the Brazilian Oil Company PETROBRAS carried out an extensive experiment to study the main meteo-oceanographic features of Campos Basin deploying a heave-pitch-roll buoy—in addition to mooring lines—during a period of more than four years in a depth over 1000 m around 150 km offshore at position 22º 31' *S* and 39º 58' *W* from March 1991 to March 1993 and from January 1994 to July 1995. The wind speed and direction were measured hourly from the buoy by two Young propeller-vane anemometers at a height of 3.78 m and 4.43 m and later converted for the height of 10 m.

This data set yields a unique opportunity to investigate the performance of the WAM wave model. In the first place directional buoy measurements in deep water are scarce. The buoys under the supervision of the National Oceanic and Atmospheric Administration (NOAA) are located mainly in relatively shallow waters and are almost all omni-directional. The location of buoys in shallow waters imposes an additional complication to any sort of analysis due to the spatially high gradients of the wave parameters compared to the more homogeneous situations encountered in the open ocean. Another interesting characteristic of the wave measurements used in this work is their geographical location. Right under the line of the Tropic of Capricorn Campos Basin is strongly affect by swell all the year

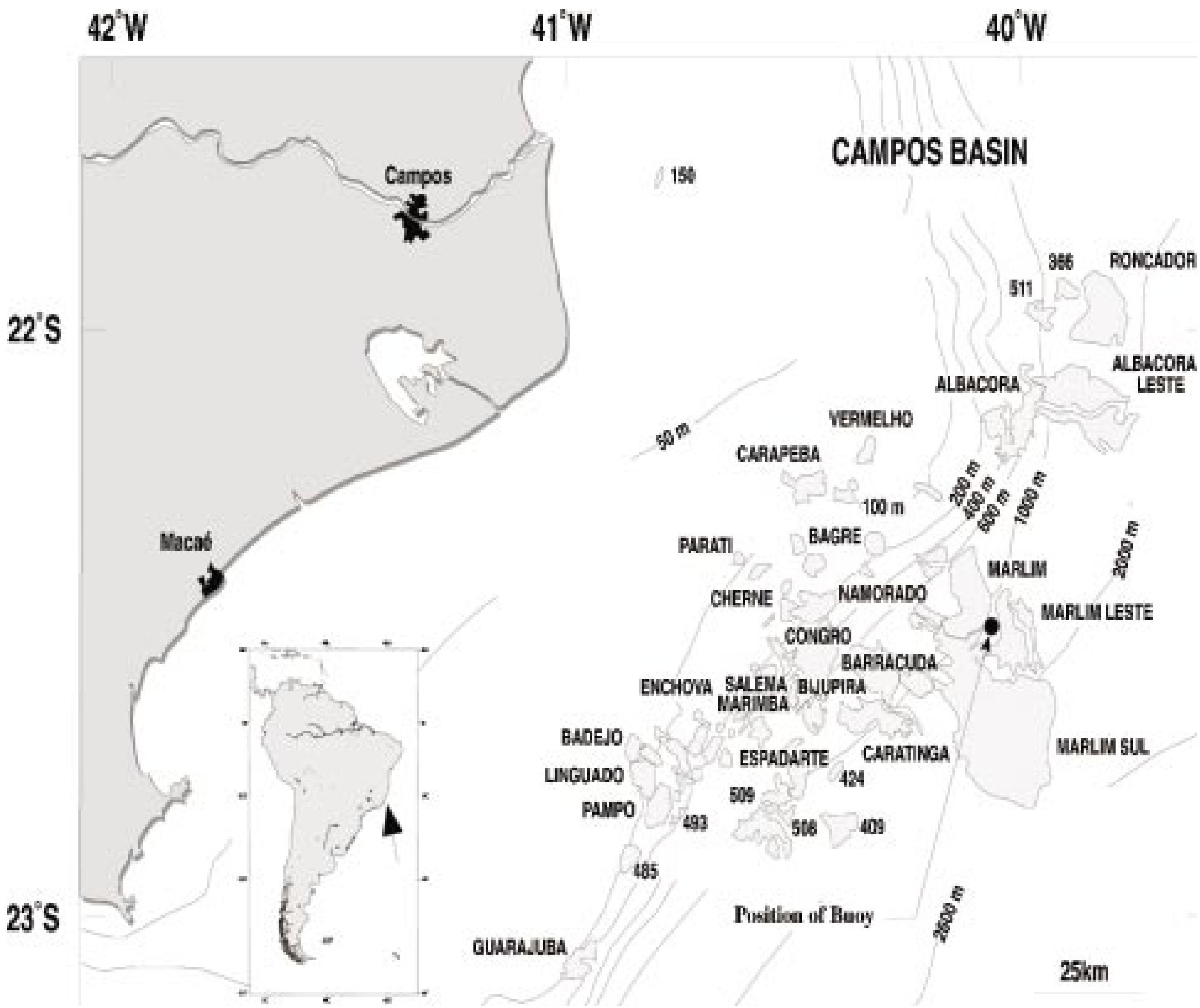

Figure 1 - The position of the buoy in Campos Basin, Brazil. The oil fields are represented by the shaded areas.

round with the low frequency band containing most of the spectral energy measured by the buoy.

The time series acquired by the buoy were sampled at a rate of 1 *Hz* during 20 minutes eight times a day every three hours and the spectral estimators were obtained using the Welch Method (see for example Marple Jr., 1987). Records consisting of 1024 data points were segmented in 16 partitions of 64 points yielding 32 degrees of freedom and frequency resolution of 0.015625 *Hz*. A fast Fourier transform (FFT) was applied employing a Hanning window and 50% overlap between adjacent segments. The directional spectrum $F(f, \theta)$ is reconstructed using the nonparametric maximum entropy method (MEM) (Lygre & Krogstad, 1986).

Collocated Data Set

For the present analysis, one year of buoy measurements is employed comprising the period from May, 1994 to April, 1995. A data set was constructed yielding a total of 105 spectra, distributed over the whole year of analysis, which matches the WAM spectra with the corresponding data from the wave buoy (see more details about the collocated data set in Violante-Carvalho (2005) hereafter referred as VC05).

Two approaches were employed for the assessment of the mean frequency estimated by the wave model. In the first, wave systems extracted from the two dimensional directional spectra using a partitioning method based on Gerling (1992) are cross assigned and their mean frequencies are intervalidated. Wave systems from the WAM wave spectrum are cross assigned with wave systems from the buoy spectrum. In the present work the wave systems extracted using the partitioning scheme proposed in Hasselmann *et al.* (1996) are used for the intercomparison. In the second approach, the directional spectra estimated by the model are integrated in direction to provide the frequency spectrum, which is yielded directly from the buoy heave data, and the comparisons are performed over specific frequency bands.

In the first approach wave systems from the WAM spectra are cross assigned to their counterpart in the buoy spectra based on four criteria (the cross assignment criteria are described in fully detail in VC05 and a brief description is presented for completeness). The first criterion states that the coordinates of the two partitions must be close enough in **k** space, that is below an arbitrary value, reading

$$\frac{(k_x^w - k_x^b)^2 + (k_y^w - k_y^b)^2}{(k_x^{w\,2} + k_x^{b\,2}) + (k_y^{w\,2} + k_y^{b\,2})} \leq 0.75,$$

where a wave system from the WAM spectrum with wave numbers (K^w_x, K^w_y) is cross assigned with a wave system of the buoy spectrum with wave numbers (K^b_x, K^b_y). Furthermore in order to eliminate spurious wave systems peaks must be above an arbitrary threshold value

$$e_{min} = \frac{20 \cdot 10^{-6}}{f_p^4 + 3 \cdot 10^{-3}}$$

where f_p is the peak frequency of the wave system. The third criterion expresses that wave systems are cross assigned if they are of the same type, that is if both are pure wind sea or both wave systems are swell (Hasselmann *et al.* 1996). And finally if more than one partition fulfills the previous conditions the closest one in **k** space is chosen.

Each independent wave system is generated by a different meteorological event and its mean frequency can be determined by integrating over the spectral interval (f, θ) to which the partition belongs, defined as (Hasselmann *et al.* 1996)

$$\frac{E_t}{\int F(f,\theta) f^{-1} df\, d\theta} \qquad (2)$$

where

$$E_t = \int F(f,\theta)\, df\, d\theta$$

is the total energy of a wave system.

However the cross assignment of different wave systems has a drawback. The main difficulty in the cross assignment is the association of a wave system in the WAM spectrum with its counterpart in the buoy spectrum, for example to intercompare the wind sea system estimated by the model with the wind sea system measured by the buoy. Quite often one spectrum contains more partitions than the other, possibly due to noise in the measurements or to limitations in the wave model. Although the four criteria above seem to be rigorous enough to guarantee the right selection, non-associated wave systems may be selected. Therefore a second approach is applied in the investigation where the one dimensional spectrum $F(f)$ rather than the two dimensional spectrum $F(f, \theta)$ is used for the intercomparison. On the one hand from the first Fourier components directly measured by the buoy one can reliably retrieve the one dimensional spectrum and on the other the two dimensional directional spectra computed by the WAM model is integrated (in direction) yielding the frequency spectrum. The comparisons are made using specific frequency bands—4 s to 6 s, 6 s to 8 s and so on till 16 s to 18 s and the mean frequency is calculated as follows:

$$\frac{e_t}{\int_{f_{min}}^{f_{max}} F(f) f^{-1} df} \quad (3)$$

where

$$e_t = \int_{f_{min}}^{f_{max}} F(f) df$$

is the total energy over the frequency band where f_{min} till f_{max} delimit the interval.

The main advantage of this approach is that the intercomparison is performed over specific frequency bands of the one dimensional frequency spectrum rather than individual wave systems extracted from the two dimensional directional spectrum which will ensure that only related information will be intercompared. Although the second approach seems to be more rigorous than the cross assignment of wave systems both approaches will be discussed in the following.

RESULTS AND DISCUSSION

Figure 2 shows the scatter plot of mean frequency of WAM estimates against buoy measurements using (2) and the statistics of the point by point comparison are presented in Table 1. The overall statistics of the WAM-Buoy comparison appears to be good with small values for standard deviation and normalized RMS error and good correlation, with a correlation coefficient of 0.82. The reason why the number of partitions that were cross assigned is greater than 105 is that more than one partition per spectrum was selected, that is, one spectrum may have two partitions (wind sea and swell) selected for the cross-assignment. From the point by point comparison shown in Table 1 it is not clear whether the wave model performs better for longer or shorter wave systems, although the cluster around the line of slope unity in the low frequency band is an indication of the better performance of the wave model for the estimation of the mean frequency of longer waves. Therefore the data should be examined more carefully for the spectral detail.

In order to analyze the mean frequency estimated by the model in more spectral detail their values are calculated over specific frequency bands using (3). Figure 3 shows that the WAM model tends to underestimate the mean frequency of short waves (with negative bias for periods shorter than 8 s) and overestimate the mean frequency of long waves (with positive bias for periods longer than 14 s). Standard deviation and normalized RMS error tend to decrease with wave period. It is worth noting that the standard deviation in the band of periods from 4 to 8 s is 5 times larger than for periods greater than 16 s, which is evidence of the poorer performance of the WAM model computing short waves.

One of the possible causes to explain the larger errors encountered in the band of short periods in Figure 3 could be a wrong wind input used to drive the wave model where the underestimation of the mean frequency represented by the negative bias would be related to an overestimation of the predicted wind speeds. The deficiencies of meteorological models in computing the wind at sea in the Southern Hemisphere are well known due to the sparseness of available observations. Therefore the wind measurements acquired offshore by the meteorological station on the pitch-roll buoy yielded a good opportunity to validate the wind fields calculated by the ECMWF model as well. The scatter plot of the wind speeds measured by the buoy and the wind speeds estimated by the ECMWF atmospheric model are shown in Figure 4. The point by point comparison shows an overall good agreement (correlation coefficient of 0.70) and normalized rms error of 36%. The ECMWF model presents negative bias, about 6% of the mean wind speed measured by the buoy, although its spread is relatively high with a standard deviation of the order of 50% of the mean buoy wind speed. The negative bias represents an underestimation of the modeled wind speed and therefore it seems that the wind input is not the cause for the poorer agreement in the high frequency band encountered in Figure 3.

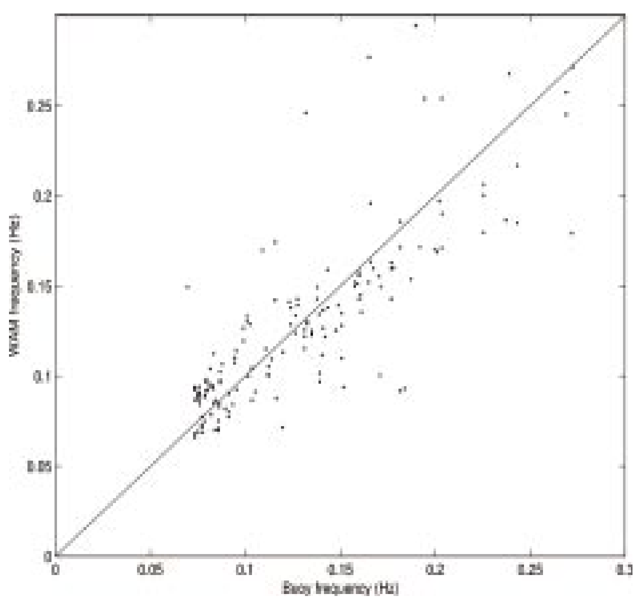

Figure 2 - Scatter plot of the mean frequency of the WAM estimates and buoy measurements with the line of slope unity drawn passing through the origin. The comparison statistics is shown in Table 1 and mean frequency is calculated using (2).

Table 1 - Statistics of the comparisons against buoy measurements of the mean frequencies of the wave systems calculated using (2), respectively bias, standard deviation (st dev), RMS error normalized with the RMS buoy mean frequency (nrmse) and correlation coefficient (corr)—bias and standard deviation in Hertz.

points	bias	st dev	nrmse	corr
156	-0.0017	0.0299	0.21	0.82

Another possibility for the underestimation of the mean frequencies of short wind sea waves could be related to the spectral discretization employed by the model. A third generation wave model such as WAM computes the two dimensional directional wave spectrum integrating the energy balance equation (1) without restrictions on the spectral shape (Komen *et al.* 1994, Young 1999). The nonlinear interactions are responsible, in the initial growth of wind waves, for the migration of energy from higher frequencies to frequencies near the spectral peak forcing a high frequency decay in a manner inversely proportional to frequency (Young & van Vledder 1993). Thus the estimation of the wave spectrum in the initial phases of growth is connected to the discretization for high frequencies employed by the model, where beyond the maximum high frequency the wave growth cannot be simulated properly since the transfer of energy from higher frequencies through nonlinear interactions will be neglected. Therefore the selection of the highest frequency is fundamental for the modeling of the wave growth since the wind sea peak starts to develop around the cut-off frequency due

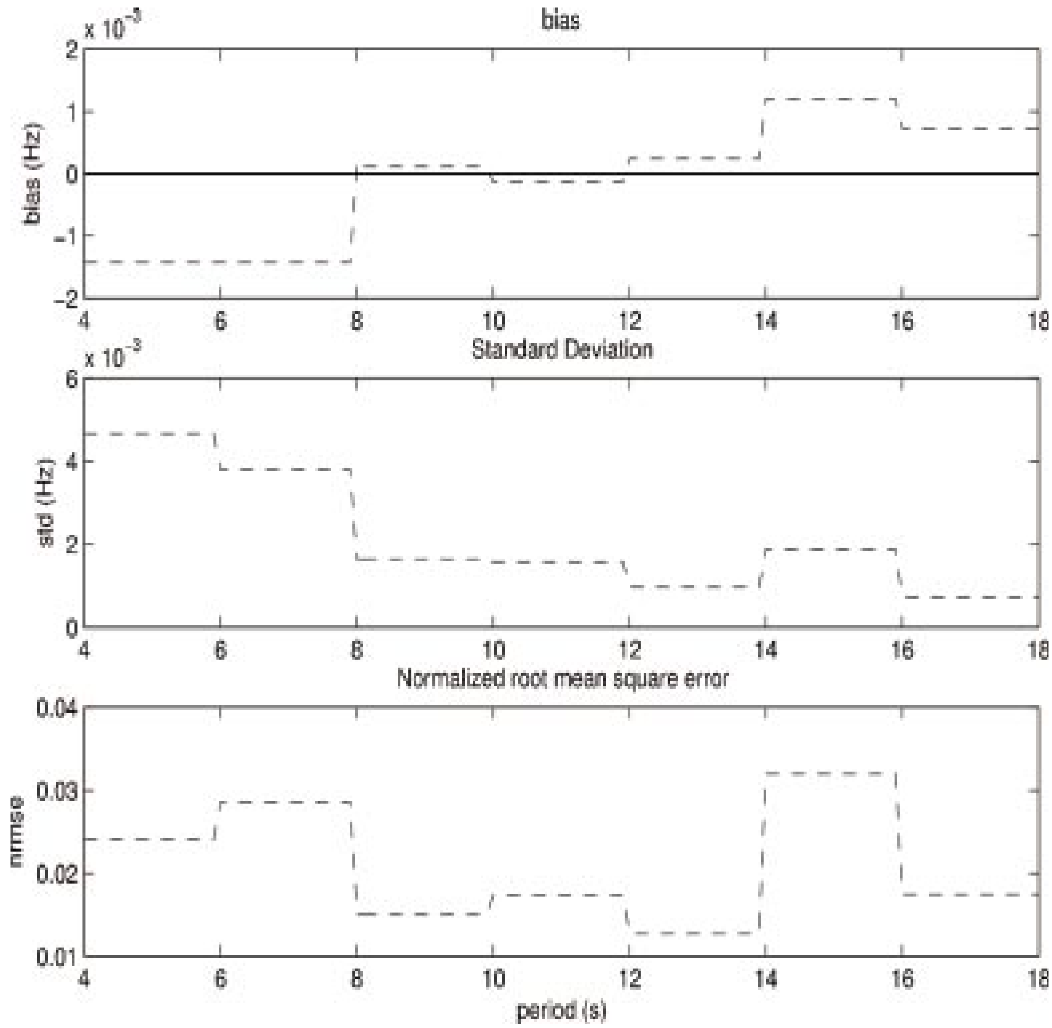

Figure 3 - Values of the mean frequency over frequency bands using (3), respectively bias, standard deviation and RMS error normalized with the RMS buoy mean frequency.

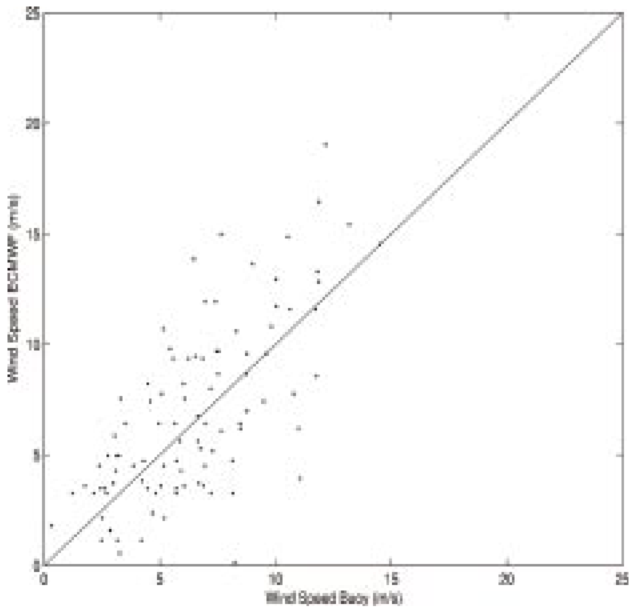

Figure 4 - Scatter plot of the wind speed measured by the buoy and estimated by the ECMWF model (in m/s for a reference height of 10 m) with the line of slope unity drawn passing through the origin. The mean wind speed measured by the buoy is 6.5 m/s (the comparison statistics is shown in Table 2).

to the direct input by the wind and the nonlinear interactions begin to act only when it attains a higher spectral level when then the peak migrates to lower frequencies.

Tolman (1992) has investigated numerical errors in wave models and the influence of the frequency discretization on the initial stages of growth. The choice of the highest discrete frequency is fundamental since it will impose the initial position of the peak and it will determine the time interval necessary for the nonlinear interactions to become effective. Considering scaling laws Tolman concludes that the frequency discretization used in the WAM model and applied in this work produces good scaling behavior for wind speeds of 15 to 25 m/s whereas for lower winds the mean wave energy is overestimated and the mean frequency is underestimated. This wind speed range is high for the region of Campos Basin, where in 10 years of wind measurements acquired on an oil platform 97% of the wind speeds observed are below 15 m/s and 74% are below 9 m/s (Violante-Carvalho *et al.* 1997). From the data analysed there is no clear evidence of overestimation of the mean wave energy with the WAM results being virtually bias free over the whole spectral domain (not shown here, see VC05).

The underestimation of the mean frequency by the WAM in the early stages of wave growth as observed in Figure 3 could be related to the diagnostic tail added beyond a dynamic (rather than fixed) high frequency cut-off f_{hf}. The wave spectrum estimated by the model consists of a prognostic part which extends up to 2.5 times the mean frequency $\{f\}$ (or maximally up to $f_{max} = 0.41\ Hz$) and beyond this point a diagnostic part represented by an f^{5} tail, given as

$$F(f,\theta) = F(f_{hf},\theta)\left(\frac{f}{f_{hf}}\right)^{-5} for\ f > f_{hf},$$

is employed where

$$f_{hf} = min\ \{f_{max}, 2.5\langle f\rangle\}.$$

Thus beyond the cut-off frequency of 0.41 Hz the model cannot simulate properly the initial growth of the waves since the nonlinear transfer is only triggered after a certain level resulting in a delay in the development of the wind sea peak which, in addition, is located at lower frequencies. The effect of the extension of f_{hf} to a higher value of 0.97 Hz is also demonstrated in Tolman (1992) resulting in wave energies and mean frequencies closer to non-dimensional theoretical growth curves.

Some discrepancies have been identified between the mean frequency of short waves estimated by the WAM and measured by a pitch-roll buoy moored in a tropical region where the typical wind speeds encountered in the area are way below the standard optimal range of the wave model. The underestimation of the mean frequencies computed by the WAM model obtained in this work may be explained by an inadequate cut-off high frequency employed, that is the point beyond which a diagnostic tail is added in order to evaluate the nonlinear transfer in the prognostic range. This appears to cause a delay in the development of the local wave peak in early stages of development which is more easily detectable through detailed spectral intercomparisons over specific frequency bands. This limitation of the WAM model in estimating the initial growth of wind waves, when its standard frequency range is employed, is less likely to be found when the comparison is performed over the whole spectral domain

Table 2 - Statistics of the comparisons of the wind speed measured by the buoy and estimated by the ECMWF model, respectively bias, standard deviation (st dev), RMS error normalized with the RMS buoy wind speed (nrmse) and correlation coefficient (corr).

points	bias	st dev	nrmse	corr
98	-0.41	2.90	0.36	0.70

or on a global scale as most of its validation exercises have been so far.

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