Ocean Modelling 70 (2013) 116–131

Contents lists available at SciVerse ScienceDirect

Ocean Modelling

journal homepage: www.elsevier.com/locate/ocemod

The effect of statistical wind corrections on global wave forecasts

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ARTICLE INFO

Article history:
Available online 12 November 2012

Keywords:
WAVEWATCH III
Wind wave models
Wind forcing
Operational wave forecasting
Wind corrections

ABSTRACT

The skill of modern wave models is such that the quality of their forecasts is, to a large degree, determined by errors in the forcing wind field. This work explores the extent to which large-scale systematic biases in modelled waves from a third generation wave model can be attributed to the forcing winds. Three different sets of winds with known global bias characteristics are used to force the WAVEWATCH III model. These winds are based on the Australian Bureau of Meteorology's ACCESS model output, with different statistical corrections applied. Wave forecasts are verified using satellite altimeter data. It is found that a negative bias in modelled Significant Wave Height (H_s) has its origins primarily in the forcing, however, the reduction of systematic wind biases does not result in universal improvement in modelled H_s. A positive bias is present in the Southern Hemisphere due primarily to an overestimation of high H_s values in the Southern Ocean storm tracks. A positive bias is also present in the east Pacific and East Indian Ocean. This is due both to the over-prediction of waves in the Southern Ocean and lack of swell attenuation in the wave model source terms used. Smaller scale features are apparent, such as a positive bias off the Cape of Good Hope, and a negative bias off Cape Horn. In some situations, internal wave model error has been compensated for by error in the forcing winds.

1. Introduction

The ability to forecast wind waves relies largely on numerical models. Current third generation wave models such as WAM (Wamdig et al., 1988) and WAVEWATCH III® (WW3, Tolman, 1991; 2009) have been found by many studies to produce accurate forecasts several days in advance. The skill of these models is such that the quality of the wave forecast is, to a large extent, determined by errors in the forcing wind field (e.g. Cardone et al., 1996; Rogers and Wittmann, 2002).

The Australian Bureau of Meteorology (Bureau) has recently replaced all the existing operational Numerical Weather Prediction (NWP) systems (e.g. GASP (Seaman et al., 1995)) with the Australian Community Climate and Earth System Simulator (ACCESS) system (NMOC, 2010), which is based on the UK Met Office Unified Model/Variational Assimilation (UM/VAR) system (Rawlins et al., 2007). Durrant and Greenslade (2012) performed an assessment of the marine surface winds from ACCESS. Comparisons against QuikSCAT scatterometer data identified a negative bias, with surface winds speeds (U_{10}) underestimated by approximately 8%. Within this overall negative bias, significant regional variation was also apparent.

During testing of WW3 for operational implementation at the Bureau, Durrant and Greenslade (2011) identified a negative bias in the modelled H_s. Based on the findings of Durrant and Greenslade (2012), this was attributed largely to the negatively biased forcing. A number of means of removing these wind biases through statistical corrections were proposed by Durrant (2011) and Durrant et al. (Submitted to Weather and Forecasting). The present work analyses the effect of these statistical wind corrections on global wave biases, further exploring the extent to which large-scale systematic biases in the modelled waves can be attributed to the forcing winds.

The paper is arranged as follows. Some background is given in Section 2. Details of the data sources used are provided in Section 3 and the overall approach is described in Section 4. The results are presented and discussed in Section 5 and Section 6 contains some further discussion. Sections 7 and 8 present the conclusions and some closing remarks.

2. Background

Spectral wave modeling is based on the decomposition of the surface elevation variance across wave numbers k and directions θ. The development of the spectral density F in space and time is governed by the wave transport or energy balance equation:

$$\frac{DF}{Dt} = S_{in} + S_{nl} + S_{ds} \quad (1)$$

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http://dx.doi.org/10.1016/j.ocemod.2012.10.006

Non-conservative sources and sinks of wave energy on the right consist, in deep water, of the input of wave energy by wind (S_{in}), nonlinear interactions between waves (S_{nl}) and dissipation due to wave breaking or 'whitecapping' (S_{ds}).

The non-linear interactions term represents a process that shifts energy between spectral components, but does not change the total wave energy. In modern operational third generation wave models, these are modelled using the discrete interaction approximation (DIA) of Hasselmann et al. (1985). The most commonly used source terms are the combination of the wind input term of Janssen (1991) and the dissipation term tuned according to Bidlot et al. (2007) (hereafter referred to as BJA[1] terms) and the default WW3 terms of Tolman and Chalikov (1996) (hereafter referred to as TC96 terms). A detailed description of these source terms is not given here: In addition to the referred papers, the relevant descriptions of the physics of wave generation and dissipation, and their representation in modern source terms, can be found in the reviews of Wamdig et al. (1988) and Komen et al. (1994) with more up to date details of recent advances summarized in WISE Group (2007).

The source terms applied to the evolution of the wave spectrum, though physically based, contain a number of tunable parameters. In general, the determination of tuning parameters is first performed based on their ability to reproduce simple idealized cases, such as known duration and fetch limited growth curves (e.g. Komen et al., 1984; SWAMP Group, 1985; Tolman and Chalikov, 1996). These tunings are then refined according to their ability to reproduce realistic wave fields in variable wind conditions. This is done through their application in large-scale wave models used to simulate case studies for which observations exist (e.g. Tolman, 2002; Tolman et al., 2002; Bidlot et al., 2002,2007; Ardhuin et al., 2008, 2010).

This process relies on the availability of high quality wave observations. Historically, data coverage over the ocean has been poor. For research applications, many studies have benefited from intensive measurement campaigns such as the JOint North Sea WAve Project (JONSWAP; Hasselmann et al., 1973) and the Surface Wave Dynamics Experiment (SWADE; Weller et al., 1991). In operational applications, throughout the formative years of the WAM model, available wave data was primarily obtained from moored buoys. By nature, these observations are few, located in selected areas, generally along coastlines, and can only provide local error estimates. Additionally, these data have historically come from the major North American and European buoy networks, potentially biasing the tuning of these models to conditions in the Northern Hemisphere.

The advent of satellite altimetry provided a boon for wave model verification and tuning, and for the first time, the open ocean could be reliably observed. The TC96 source terms in WW3 relied heavily on altimeter data during developmental tuning (Tolman, 2002; Tolman et al., 2002). Significant adjustments were required to the idealized tunings in order to achieve realistic wave fields on a global scale. It was found, for example, that swell dissipation due to opposing or weak winds was overestimated, requiring significant retuning. Additionally the model tuned in the classical way to fetch-limited growth for stable conditions was found to underestimate deep-ocean wave growth requiring a subsequent retuning for effects of atmospheric stability (Tolman, 2002).

As demonstrated by Tolman (2002), the use of altimeter data to assess the spatial variation in the modelled H_s error provides a powerful means of identifying sources of systematic model error. This approach has been used by a number of subsequent studies. Tolman (2003), for example, showed that an overestimation of wave heights in the tropics could be easily traced to missing wave blocking from island chains that were too small to be explicitly resolved by the grid. Greenslade and Young (2004) identified a distinct negative bias in the Bureau's previous operational model AUSWAM in the region of the Southern Ocean storm tracks. The global validations and tuning of the recent parameterizations of Ardhuin et al. (2008, 2010) have relied heavily on the minimization of spatial bias over the globe as a tuning diagnostic.

While knowledge of the spatial wave field error is valuable information, corresponding biases in the forcing winds are necessary to confidently attribute this error to wave model deficiencies. The translation of error in the forcing winds into the wave model is not straightforward. Locally, wind errors will produce errors in newly generated wind sea. These errors will also present as errors in the swell propagating away from the generation region. Hence, the wave error at any given point associated with incorrect wind forcing is a result of the integration of wind error over a window of time and space. The addition of error due to an imperfect wave model makes the attribution of error a non-trivial exercise.

There have been several studies dealing with the accuracy of atmospheric predictions from the perspective of the wave modeller (e.g. Komen et al., 1994; Cardone et al., 1995, 1996; Khandekar and Lalbeharry, 1996; Janssen et al., 1997; Tolman, 1998b). In general, these studies have employed two methods: (1) compare both wind and wave model data with all the available measurements and/or (2) cross-compare results obtained using several combinations of atmospheric and wave models. The efficiency of the first method alone has historically been limited by the sparseness and intermittency of the measured data, complicated by the difficulty in making inferences based on local conditions alone. By comparing a number of different models containing different error characteristics, sources of error can be further isolated.

The inability to make simple, local inferences regarding wind/wave error attribution is reduced somewhat by examining single, intense storm events (e.g. Cardone et al., 1996). Under such conditions, where high frequency energy dominates the wave spectrum, error attribution can essentially be done locally. Similarly, by examining enclosed basins, the influence of propagating error is reduced (e.g. Bertotti and Cavaleri, 2004; Ardhuin et al., 2007).

In a more general sense, there have been a number of studies examining the contribution of systematic bias in the forcing winds to that of the modelled waves in the open ocean. Rogers and Wittmann (2002) compared surface winds from the (US) Navy's Operational Global Atmospheric Prediction System (NOGAPS), run at Fleet Numerical Meteorology and Oceanography Center (FNMOC), and the National Centers for Environmental Prediction (NCEP) Global Forecasting System (GFS) analyses to QuikSCAT scatterometer data. They found that both analyses tend to be biased low at high wind speeds, this tendency being relatively slight with the GFS analyses, and stronger in the NOGAPS analyses, particularly in the north-east Pacific. Rogers (2002) made similar direct wind evaluations, and similarly suggested that strong surface wind events in the NOGAPS analyses were biased low. They were led to conclude that the dominant source of error in predictions of low-frequency wave energy in FNMOC's global models was inaccuracies in the wind forcing. Bias associated with the wave model itself was believed to be only secondary.

This work was repeated following upgrades to the atmospheric model NOGAPS in the second half of 2002 (Rogers et al., 2005). This led to improvement in the operational global wave model. Following these changes, the authors conclude that wind error was no longer the primary cause of total wave model error. These studies, however, focused on comparisons with a number of buoys around the United States (US) coast, and interpretation on global scales remains difficult using these point-based measurements.

[1] Note that the BJA terms are incorrectly referred in several papers as the "BAJ" terms (e.g. Ardhuin et al., 2007; Ardhuin et al., 2010, Durrant and Greenslade, 2011).

In recent years, scatterometer data has become a valuable source of data for the study of marine surface winds (e.g. Kelly, 2004). These data have been extensively used for verification of NWP winds (e.g. Rogers and Wittmann, 2002; Yuan, 2004; Isaksen and Janssen, 2004; Schulz et al., 2007). Research examining the spatial variability of the operational European Centre for Medium-Range Weather Forecasts (ECMWF) and NCEP analyses (Chelton and Freilich, 2005) has shown that these two products contain significant spatial structure in the overall bias. As discussed above, knowledge of the spatial H_s bias has greatly enhanced the ability to diagnose and address sources of systematic error in modern wave model source terms. However, while the contribution of bias in the forcing winds is often considered in a general sense, the extent to which a spatial variation in systematic wind speed error contributes to that of the waves has not received a lot of attention.

Where systematic errors in the wind field are known *a priori*, they can be removed with statistical corrections (e.g. Tolman, 1998b; Greenslade et al., 2005). While such adjustments provide a useful means of removing known biases in the forcing winds, these simple corrections come with a number of limitations. The first is the inability to account for spatial variation in the wind error; winds corrected in this way can be expected to retain significant regional biases. The second limitation is the need to continually monitor changes in systematic wind biases in atmospheric models, which themselves are frequently undergoing upgrades. The reality of changed forcing is an issue for any 'downstream' model. Part of the motivation for performing such wind corrections is an acknowledgement that these wind error characteristics are likely to change. Adjustment of statistical wind corrections with these changes is less burdensome than the retuning of the wave model itself. However, maintaining such wind corrections still requires considerable effort.

Despite the acknowledged impact of wind error on the quality of wave forecasts it is an oft-ignored facet of current operational wave model tuning. Where the provision of accurate wave estimates is paramount, such as in the context of operational wave forecasting systems, the model is set up, verified and tuned. This tuning is often done based on the forcing as it is, not as it should be. A knowledge of the role of the forcing wind on the accuracy of the wave forecast, while an important research question, is secondary to the provision of accurate wave forecasts under whatever forcing is available. However, where systematic errors in the forcing winds exist, tuning the wave model in isolation in this way is likely to result in the wave model tuning compensating for these errors.

This raises an interesting question regarding the tuning of wave models in general. While modern wave model parameterizations are the result of a great many contributors, the source terms primarily in use today are BJA and TC96. Global tuning of these terms has been performed with ECMWF (Bidlot et al., 2007) and NCEP (Tolman, 2002) wind products respectively. The previously mentioned work of Chelton and Freilich (2005) examined and compared the operational winds from these two institutions, demonstrating not only significant spatial structure in the overall bias, but also significantly different bias characteristics between them. The question then arises, for the purposes of producing accurate wave forecasts using a given set of source terms, are winds that closely match reality the desired forcing product, or those that most closely resemble the winds under which the source terms were developed?

In applications such as operational forecasting, it could be argued that wind errors that compensate for wave model deficiencies are a good thing. However, for the purposes of wave model development, such compensation serves to hinder the identification of sources of systematic wave model error, and delays addressing the causal issue. Knowledge of the wind error, and an understanding of how this manifests in the wave model, is hence an important aspect of the further refinement of the source terms.

This study aims to assess the contribution of systematic error in the forcing surface winds to that of the global modelled wave field. Specifically, the following questions are addressed

- To what extent can large-scale systematic biases in the waves be attributed to biases in the forcing winds?
- Can statistical adjustments which remove these wind biases lead to better wave forecasts?
- What are the residual wave biases when forced with unbiased winds?

3. Model and data

3.1. Wave model

The model used in this work is the most recent release of the WW3 model, version 3.14 (Tolman, 2009). The set up and verification of WW3 under ACCESS forcing is documented in Durrant and Greenslade (2011). Evaluation of a number of hindcasts was conducted, examining the impact of the choice of source terms and numerics. Care was taken to minimize sources of external error. Third order numerics were used, minimizing numerical error. All global runs were performed with 1° spatial resolution; sufficient for evaluation of the large-scale error that is the focus here. Bathymetry data was supplemented with a coastal polygon data set in the construction of the grids, sub-grid-scale blocking was employed to minimize the error associated with unresolved island blocking (e.g. Tolman, 2003) and an observation-based, daily updated, explicit sea ice edge was included.

In all the hindcasts performed in Durrant and Greenslade (2011), a negative H_s bias was present. Within this overall negative H_s bias, TC96 was found to over-predict in the long fetches of the Southern Ocean, resulting in over-predicted H_s values on the Australian west coast. BJA terms were found to produce a more consistent negative bias over the globe, with the exception of the eastern tropical Pacific, due to a lack swell attenuation within these terms (discussed below). Based on these results, the BJA terms were chosen for operational implementation at the Bureau, and are the focus of this study. Sections 5.1–5.3 present results with BJA source terms, with some comparative results for TC96 terms given in Section 5.4.

3.2. Surface winds

As noted above, the forcing winds are obtained from a test configuration of the Bureau's recently implemented ACCESS system. These ACCESS surface winds have been examined in Durrant and Greenslade (2012). Verifications against QuikSCAT data were conducted, including an analysis of the spatial structure of the error over the globe. During the 4 month time period examined here, the uncorrected ACCESS winds were found to have an overall negative bias of $-0.52\ \mathrm{ms}^{-1}$ and root-mean-square error (RMSE) of $1.57\ \mathrm{ms}^{-1}$ in comparison to QuikSCAT observations.

Building upon the above verifications, Durrant et al. (Submitted to Weather and Forecasting) explored a number of techniques for correcting these winds, based on comparisons against scatterometer observations. In the present work, the effect of two of these corrections on the wave field are assessed, and we refer to these as 'static homogenous corrections', and 'spatially and temporally varying learned corrections'. These are briefly described below:

Static homogeneous corrections – These consisted of a single correction, applied uniformly over the entire global domain. Based on comparisons with scatterometer data an approximate 6% increase in U_{10} was found to be appropriate. This reduced the overall surface wind speed bias to $-0.068\ \mathrm{ms}^{-1}$ and RMSE to $1.49\ \mathrm{ms}^{-1}$.

While such corrections produced overall improvements in the wind speed statistics, they were unable to adequately account for regional and/or temporal variation in the error characteristics. To address this, Durrant et al. (Submitted to Weather and Forecasting) further considered corrections that varied in space and time.

Spatially and temporally varying learned corrections – This method involved the application of independent corrections at each model grid point that varied in time with the recent historical bias of the model at that grid point. Extending the point based, learned corrections of Durrant et al. (2009), these automatically-evolving gridded corrections were calculated from a moving window of historical comparisons between scatterometer observations and preceding forecasts. A number of spatial and temporal learning windows were explored, with a 30 day learning window found to give the best results. This effectively targeted the removal of synoptic scale systematic biases, while applying independent corrections at each model grid point enabled the removal of persistent biases on fine spatial scales, such as those present along coastlines and in the lee of islands. Correcting winds in this way eliminates the need to monitor and manually adjust these corrections with time. The corrected winds had an overall small positive bias of 0.049 m/s and RMSE of 1.44 m/s. Importantly for this work, regional biases were almost eliminated over the entire global domain.

In summary, three different sets of forcing winds over a 4 month time period are used: uncorrected ACCESS winds; ACCESS winds corrected with static homogeneous corrections; and those corrected using spatially and temporally varying learned corrections, as described above. Further details on the specifics and development of these corrections can be found in Durrant et al. (Submitted to Weather and Forecasting).

3.3. Observations

The wave model verification carried out in this work relies heavily on altimeter data. The two altimeters used here are the Poseidon-2 altimeter onboard Jason-1 (Menard et al., 2003; Carayon et al., 2003) and the RA-2 altimeter of Envisat (Resti et al., 1999). The real time data streams were used here, taken from the Bureau's operational archive. H_s from these two data sources was corrected according to Durrant and Greenslade (2011). Quality control consists of a first check based on the standard deviation of the 20 Hz and 10 Hz H_s values following Mackay et al. (2008), and nearest neighbor comparisons are performed to remove any remaining obvious errors. In order to match the spatial scales of variability between model and observations, "super-obs" are then calculated by performing 1° along-track averages, consisting of 15–20 individual observations (e.g. Tolman et al., 2002; Janssen, 2008). Model data is then interpolated to match the time and location of the altimeter to make up a set of co-locations, from which statistics are calculated. Over the July–October 2008 period examined here, this analysis resulted in more than 580,000 co-locations. Calculating statistics based on these co-locations gives an overall description of the error.

To determine the spatial variation in error, co-locations are distributed into latitude–longitude bins, and statistics are calculated for each bin separately. When choosing an appropriate latitude/longitude box size, a balance must be struck between resolution and the robustness of the resulting statistics for each box due to increased number of observations. 3° was found to be a good compromise here. It is worth noting that the physical size of a 3° box reduces at higher latitudes. However, due to the orbital characteristics of the satellite, the density of the observations also increases at higher latitudes, maintaining sufficient observations in these smaller boxes. Over most of the globe there are around 150 co-locations for each $3^\circ \times 3^\circ$ bin.

Satellite scatterometer observations are used to a small extent in the present work. The reader is referred to Durrant (Submitted to Weather and Forecasting) for details on the treatment of the QuikSCAT scatterometer data.

4. Approach

In evaluating error sources in modelled H_s, Rogers et al. (2005) employ three condition-interpretation pairs. These are given in the first column of Table 1. The context in which these tests are applied by Rogers et al. (2005) differ somewhat from that here. In that study, conclusions are drawn from comparisons at a number of point locations, namely buoys, around the US coast. The authors reason that by looking at the Northern Hemisphere winter, they remain focused primarily on wind-sea and young swell in these conditions, and hence are able to draw conclusions based on local wind/wave conditions. Here, the distribution of wind and wave bias is considered spatially over the whole globe, and while this approach adds to the breadth of conclusions that can be drawn, it also complicates the issue of error separation, and attribution of error becomes a non-local exercise.

This point is well illustrated by the numerical simulations conducted by Alves (2006). He broke the global domain into 13 swell generation areas, and for each region a run was performed with wind kept active only for that region. By analyzing the swell propagating away from each generation region, its relative influence on global wave climate could be gauged. One of the major conclusions of that study was that swells generated in extratropical areas of the Southern Oceans spread energy throughout the entire global ocean, and are a potentially important component of the wave climate in most ocean basins in both hemispheres. It was also noted that these areas generate robust swell systems that propagate westward against the predominant storm advection direction. Durrant (2011) further noted that H_s biases in the swell dominated eastern Pacific are more sensitive to adjustments in the extratropical winds than to adjustments to the local winds.

Some amendments are thus required to these simple tests to meaningfully interpret the results. These are stated in the second column of Table 1. Test 1 was not actually used by Rogers et al. (2005) because of the difficulty in proving small bias in the wind field, and the requirement to separately evaluate the sensitivity of the wave model to wind field bias. In the present work, the wind fields used have been extensively evaluated and appropriate corrections to those winds have been made. Indeed, the winds that have been corrected with spatially and temporally varying learned corrections are now known to contain small bias over the whole domain, allowing this test to be confidently applied here, in amended form.

A word of caution is introduced, however, regarding Test 1. The assertion of an unbiased wind field does not imply a wind field without error. Random error remains, though the time scales at which the wave model responds to these errors makes this less of a concern here. What is of potential concern is error which may remain in the distribution of U_{10} across the range of wind speeds. This is especially relevant in the generation regions of the extratropics. Many of the boundary-layer processes in these parts of the world are highly non-linear and involve strong temporal (and spatial) covariances (e.g. Simmonds et al., 2005). The non-linear response of the waves to this forcing means that the overall wind bias gives only a first order indication of wind induced wave bias (e.g. Chawla et al., 2009,2011). The U_{10} distribution for the corrected wind fields was examined in Durrant et al. (Submitted to

Table 1
Condition-interpretation pairs used to evaluate error sources in this work. Column 1 shows statements employed by Rogers et al. (2005). Amendments used in this work are given in the second column.

	Rogers et al. (2005)	Amendments
(1)	If a model is forced with a wind field that contains small bias, then nontrivial bias observed in energy predictions from a wave model forced by these wind vectors implies a probable bias associated with the wave model itself	*Such inferences cannot, however, be drawn from a simple local comparison. This test must be applied in the context of knowledge of the influence of propagating error*
(2)	If a model is forced with a wind field with a bias of known sign, and nontrivial bias of opposite sign is observed in energy predictions from a wave model forced by this wind field, this implies a probable bias associated with the wave model itself. (No conclusions are drawn if the bias is of the same sign)	*A bias of the same sign in both the wind and the waves is interpreted as suggestive evidence of wind bias being a contributor to the wave bias. This evidence is reinforced in areas where the reduction of the wind bias leads to a reduction of the corresponding wave bias. As with Test 1, this test must be applied in the context of a knowledge of the influence of propagating error.*
(3)	If hindcasts and wave model-data comparisons are chosen such that the bias from numerics and resolution is small, then the nontrivial bias in the wave model itself (i.e., internal bias) is probably associated with the model source/sink term parameterizations	

Weather and Forecasting) and though improved, these remain imperfect.

For Test 2, forcing with two alternate wind fields of opposite sign is cited by Rogers et al. (2005) as a valuable means of assessment. However, wind fields from different models can be expected to have differing error characteristics in addition to bias alone. Forcing the model here with winds that are almost identical, except for their local bias characteristics, allows for more certainty in the allocation of systematic H_s error associated with each forcing. Additionally, the ability to monitor both the wind and wave bias spatially over the globe provides a powerful diagnostic tool, allowing more reliable interpretation than was possible by the site-based comparisons of Rogers et al. (2005). The statement of Test 2 has hence been somewhat strengthened.

With respect to Test 3, Rogers et al. (2005) focus on comparisons against North American buoy observations, in the Northern Hemisphere winter, thus primarily considering wind sea and young swell in these conditions, and minimizing error associated with propagation. Here, global results are considered, and any errors associated with propagation numerics or resolution are not easily isolated. As noted in Section 3.1 and described in Durrant and Greenslade (2011), care has been taken to minimize such error. The ability to compare results from different source terms within the same model framework is also advantageous here. Where the origin of error is suspected to be from sources other than the physical formulation of the source terms, comparison with the same model set-up, using different source terms, can provide corroborative evidence for this.

Poor specification or non-specification of currents and/or air-sea temperature differences for the purposes of stability present additional sources of external error. These are not expected to have a significant impact overall (Rogers et al., 2005). Comment is made in the text, however, where such omissions are locally relevant.

5. Results

Results from three different forcing winds are analyzed; uncorrected ACCESS winds, those corrected with static homogeneous corrections, and those corrected using spatially and temporally varying learned corrections. For brevity, runs are referred to simply by their corrected wind labels, e.g. reference to the static homogeneous winds refers to winds that have been corrected with this method. Reference to static homogeneous waves refers to waves resulting from forcing the model with these corrected winds, etc. Section 5.1 qualitatively examines the broad scale attribution of wind/wave error, and a more quantitative assessment of the effect of U_{10} corrections on the modelled H_s results is presented in Section 5.2. Finally, confident that the systematic error in the forcing winds have been reduced by the spatially and temporally varying learned corrections, the remaining bias characteristics of the modelled H_s are discussed in Section 5.3.

5.1. Qualitative attribution of large scale systematic error

The global time averaged bias of each of the three wind fields against scatterometer data and the resulting wave field bias is shown in Fig. 1. Statistics are calculated using 1° latitude-longitude boxes for U_{10}, and 3° boxes for H_s. Gaussian smoothing has been applied over 5 boxes in the case of the 1° U_{10} bias, and 2 boxes for the 3° H_s bias. Considering first the uncorrected ACCESS winds, Fig. 1(b) shows a negative bias over most of the globe in modelled H_s when compared to altimeter data (Durrant and Greenslade, 2011). Fig. 1(a) reveals a similar negative bias in the forcing wind field against scatterometer data (Durrant and Greenslade 2012). It seems reasonable then that the bulk of the bias in the wave field can be attributed to the forcing winds in this case. In the context of an evaluation of WW3 under ACCESS forcing, this is a strong result and effectively answers one of the major questions of this paper. In a more general sense, the impracticality of assessing wave model error in isolation is made clear.

However, when an unbiased wave model is forced with winds that are negatively biased, a negative bias in the waves is an expected result. The sensitivity of modelled H_s to spatial variation in wind bias is not easily assessed with this case in isolation. With the exception of the east Pacific, the wave model is negatively biased over the entire global domain. Further insight can be gained here by contrasting H_s bias resulting from runs performed using the two corrected winds.

We consider first the Southern Ocean, as the conclusions made here have some broader relevance in the overall discussion. The general under-prediction is well explained by the negative wind bias in this region for uncorrected winds. In the case of static homogeneous corrections, it could be speculated that the positive bias in the waves in the Southern Ocean is attributable to the corresponding positive bias in U_{10}. The fact that these biases remain in the case of the spatially unbiased winds, suggests that the wave model is inherently over-predicting H_s in this region.

Within this general over-prediction in the Southern Hemisphere, a number of smaller scale features are apparent. Across all three runs, a local H_s bias maximum can be seen in the Amundsen sea, along the Antarctic ice edge, between 100°W and 140°W. A local minima is also present in the Drake Passage, south of Cape Horn in all three cases. In the case of the spatially unbiased winds,

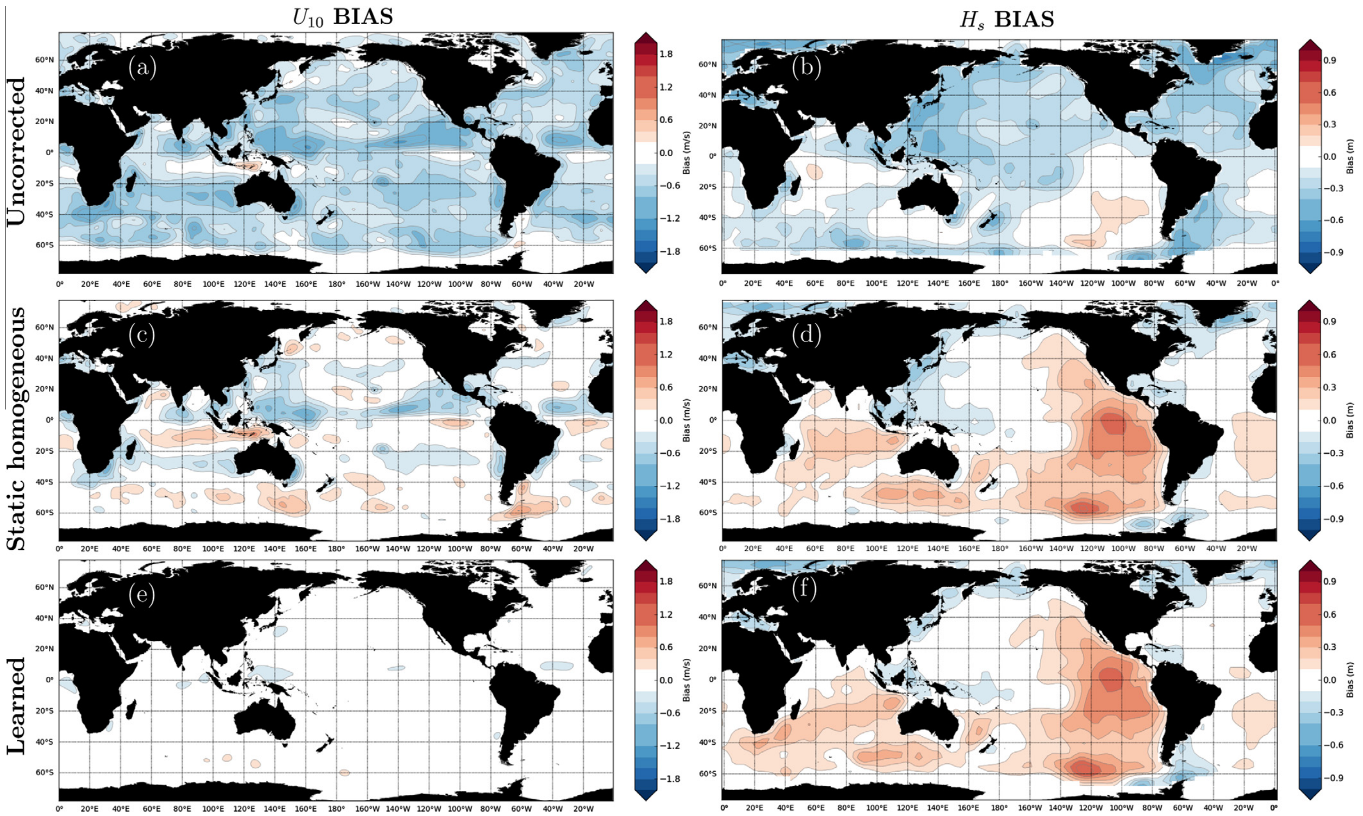


Fig. 1. Bias over the whole 4 month period for U_{10} (left column), and H_s (right column) relative to scatterometer and altimeter data respectively for uncorrected ACCESS winds (first row), winds corrected using static homogeneous corrections (second row) and those corrected using spatially and temporally varying learned corrections (third row). Gaussian smoothing has been applied over 5 boxes in the case of the 1° U_{10} bias, and 2 boxes for the 3° H_s bias.

overestimated H_s is evident off, and downstream of the Cape of Good Hope. This appears to be offset by regions of local, negatively biased wind speeds in both of the other cases. Possible causes of these features are discussed further below.

All three runs show a positive H_s bias in much of the eastern tropical Pacific. In the case of both corrected wind runs the possibility of over-predicted waves correctly propagating from the South Pacific remains. This is supported by the fact that this area is highly sensitive to U_{10} in the Southern Ocean (Alves, 2006; Durrant, 2011). However, the presence of this bias, particularly in the case of negative bias in the Southern Ocean in the case of uncorrected winds, strongly suggests a systemic issue with the wave model. A similar pattern can be seen in the east Indian Ocean. These features are clearly the result of excessive swell propagation into these regions.

Negative H_s biases are present in the western tropical Pacific and the Gulf of Mexico corresponding with negative U_{10} biases in both the uncorrected, and static homogeneous corrected cases. These H_s biases are reduced when forced with spatially corrected winds, though low mean H_s and U_{10} in these regions (Figures not shown) increase relative observational uncertainty, requiring some caution here.

The situation in the Indian Ocean is less clear. In both the static homogeneous, and spatially and temporally varying learned cases, a positive H_s bias associated with excess swell propagation from the Southern Ocean is present. Over-prediction around the Cape of Good Hope exaggerates this in the case of the latter. Biases in the static homogeneous winds show a lot of spatial variation, and attribution of wave bias remains difficult as waves propagate through these regions. There is, however, some suggestion of wind-induced wave bias. Features such as the slight positive bias in the Arabian Sea, and a slight negative bias in the Mozambique Channel, common to both wind and waves, are reduced with the spatially and temporally varying wind corrections. In general, tropical regions which are not significantly affected by propagating errors from the Southern Ocean appear to show biases that, to a large degree, reflect those of the winds.

With the exception of the eastern Pacific, systematic H_s bias in the Northern Hemisphere appears to be well explained by U_{10} biases. In the static homogeneous case, negative H_s biases in the western tropical Pacific, northwest Pacific and North Atlantic correspond to negative U_{10} biases in these regions. Removal of the U_{10} biases in the case of spatially and temporally varying corrections improves these H_s biases. Once again, regions that are not affected by propagating errors from the Southern Ocean show biases that, on the large scale, reflect those of the winds.

Considering coastal regions, a negative bias in the ACCESS U_{10} is particularly noticeable on the Australian and South African east coasts. A corresponding negative bias in the waves can be seen in these regions. After the application of static homogeneous corrections, the coastal biases remain in the winds. Corresponding negative biases remain for H_s, despite positive bias in the neighboring regions. The removal of these coastal wind biases in the case of the spatially and temporally varying learned corrections appears to improve H_s bias in these areas. Though suggestive that much of these coastal H_s biases are wind induced, the existence of strong boundary currents in these regions could also be influential. This is discussed further in Section 5.3.

5.2. Quantitative effect of statistical wind corrections on the modelled wave field

Following from the qualitative discussion above, a more quantitative assessment is now presented. Verification statistics both

Table 2
Regional statistics for H_s relative to altimeter data for BJA source terms when forced with uncorrected winds as well as those corrected with a static homogeneous correction and spatially and temporally varying learned corrections. Percentage improvement refers to % improvement in RMSE relative to the 'uncorrected' case.

Run	Bias (m)	RMSE (m)	SI	% Imp.	N
Global					
Uncorrected	−0.27	0.506	0.150		581926
Static-Hom.	0.057	0.476	0.171	4.0	581926
Learned	0.070	0.486	0.174	2.0	581926
Northern Hemisphere Extratropics					
Uncorrected	−0.277	0.449	0.178		103791
Static-Hom.	−0.059	0.378	0.189	15.8	103791
Learned	−0.033	0.371	0.186	17.4	103791
Tropics					
Uncorrected	−0.163	0.330	0.143		198969
Static-Hom.	0.090	0.346	0.166	−4.8	198969
Learned	0.106	0.349	0.166	−5.8	198969
Southern Hemisphere Extratropics					
Uncorrected	−0.235	0.462	0.134		409749
Static-Hom.	0.126	0.470	0.153	−1.7	409749
Learned	0.138	0.481	0.156	−4.1	409749

globally and separately for the tropics (25°S–25°N) the Northern extratropics (North of 25°N) and the Southern extratropics (South of 25°S) are given in Table 2. Focusing initially on the static homogeneous corrections, recall from Section 3 that the 6% increase in U_{10} reduced overall U_{10} bias to near zero and improved the RMSE by about 5% in comparison to scatterometer observations. The waves show a corresponding improvement, with the previous negative bias of 0.27 m now presenting as a slight positive bias. RMSE has been reduced by 4%, though the Scatter Index (SI; standard deviation of the difference between model and observations normalized by the observed mean) has degraded. For spatially and temporally varying learned corrections, improvements are surprisingly less than those for the static homogeneous corrections, despite the wind speeds verifying better (Durrant et al., Submitted to Weather and Forecasting). Again, overall bias has been reduced and SI has degraded. The improvement in RMSE over uncorrected winds is just 2%.

Examining regions separately however, presents a more complex picture. The Northern extratropics show impressive reductions in H_s RMSE, with spatially and temporally varying learned corrections producing a 17% improvement, with negligible remaining bias. These corrections also produce better results than the static homogeneous corrections. H_s RMSE has, however, degraded in the tropics and the Southern extratropics. Previous negative biases are now positive, though are less severe. In both cases, the spatially and temporally varying learned corrections degrade wave model performance slightly more than static homogeneous corrections. This is partly due to regions of negative U_{10} bias in the static homogeneous case compensating for inherently positively bias H_s, such as in the eastern tropical Pacific and the Cape of Good Hope. These features are discussed further in Section 5.4.

Focusing only on results from the spatially and temporally varying wind corrections, this spatial variation is more clearly visualized in Fig. 2, showing percentage improvement in H_s RMSE for each model grid point. Significant improvement is seen in most of the Northern extratropics, parts of the South Atlantic and despite the now positive bias, even parts of the Southern Ocean show gains. However, in line with the discussion above, large parts of the Southern Ocean show degradation. The overall reduction in skill in the tropics seen in Table 2 shows large regional variation. Of most note is the large improvement in RMSE evident in the western tropical Pacific and dramatic degradation in the eastern tropical Pacific. This, and the similar, though less dramatic presentation in the tropical Indian Ocean, is consistent with the observed biases above due to excess swell propagation.

H_s probability density functions (PDFs) constructed from model/altimeter co-locations are shown in Fig. 3. Observed and modelled H_s PDFs are shown on the left hand side, on the right are error PDFs (model - observed). Results here are mixed. Over the whole globe, the distribution is better overall in the case of the corrected winds, though the peak at around 2 m is better captured in the uncorrected case. Higher wave heights are improved in the corrected winds cases. The error PDFs are now closer to zero centered, however the error standard deviations have been increased in all regions (the difference PDFs have been broadened).

Fig. 4 shows box and whisker plots of the differences between modelled and observed H_s, as a function of observed H_s (with a minimum of 100 observations required in each bin here). A clear overestimation in the tropics (Fig. 4(c)) is apparent in the range of 0–4 m for corrected runs, consistent with excessive swell energy. In the Northern extratropics (Fig. 4(b)), the corrected wind has improved the H_s distribution throughout the wave range, with a slight over-estimation apparent in the 6–8 m range. In the Southern extratropics (Fig. 4(d)), wave distributions again appear to be well captured by the corrected wind hindcast up to 6 m. Above this, an increasing positive bias is evident, though the magnitude of the bias is less than the negative bias in this range for the uncorrected winds.

Though this representation of the data well illustrates the H_s bias characteristics as a function of H_s, some caution must be applied here. The effect of observational error is not accounted for is this analysis, and a spurious over estimation of low H_s and underestimation of high H_s, could be expected (see for example Freilich (1997) and Tolman (1998a)). The observed over-estimations of high waves for the corrected winds are particularly noteworthy in this context. This suggests that the bulk of the positive bias in the Southern Ocean, seen in Fig. 1(f), can be attributed to these high wave heights. This tendency is explored further in Section 5.4 below, discussing residual systematic wave error.

Improvement in the wind bias as a result of corrections is not matched in the modelled H_s results overall. However, large regional variation is apparent, with gains in some areas offset by degradation in others. Where inherent bias in the wave model is compensated for by bias in the winds, improving the forcing degrades H_s verifications. This is most apparent in the east Pacific, where the best wave model results are achieved with uncorrected winds, due to the fact that positive bias internal to the wave model is compensated by negatively biased forcing. Such compensation is easily identified here by examining the spatial distribution of the bias in both fields.

5.3. Residual systematic wave bias

The results presented above have identified a number deficiencies that appear independent of the forcing winds. The discussion here focuses on features evident from the H_s results when forced with a wind field with near zero bias, i.e. that corrected using the spatially and temporally varying learned corrections (Fig. 1(e) and (f)). By reducing wind biases to near zero everywhere in the spatial domain, remaining biases in modelled H_s can be more confidently attributed to deficiencies in the wave model itself. The previously discussed issues surrounding propagating errors dictate some caution here however; systematic wave bias remains a non-local consideration.

5.3.1. Over-prediction in the Southern Ocean

It is clear that the wave model is over-predicting H_s in the Southern Ocean when forced with unbiased winds. This raises a number of questions. Given the time of year, the wind speeds in

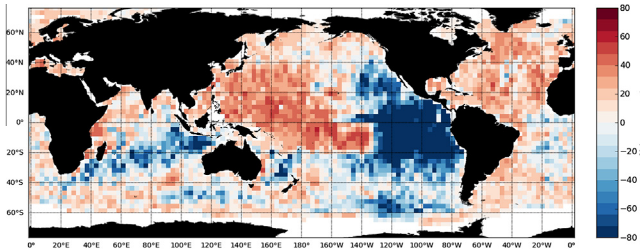


Fig. 2. Percentage improvement in modelled H_s RMSE achieved by correcting the forcing winds with spatially and temporally varying learned corrections using BJA source terms.

the Southern Ocean far exceed those of the North Pacific or North Atlantic. So is this a case of the model over-predicting H_s in strong wind conditions, or is this over-prediction specific to the Southern Ocean? This could be explored by performing a similar analysis for the Northern Hemisphere winter months. There is, however, some reason to expect that there are conditions unique to the Southern Ocean that could cause this strong positive bias.

Both the Northern and Southern mid-latitudes winters are dominated by low-pressure systems. However, the continuous eastward procession of these systems in the Southern Ocean contrasts with that in the North Pacific, where their migration is far more variable (e.g. Bender, 1996). Southern Hemisphere extratropical synoptic activity is particularly strong in the winter and spring period examined here, when the semi-annual oscillation dictates that the Antarctic circumpolar trough is at its strongest (e.g. Simmonds and Jones, 1998; Simmonds, 2003). The combination of these persistent westerly winds, and the largely unbroken expanse of sea, produces potentially enormous fetches, resulting in the Southern Ocean experiencing higher wave heights for longer periods than any other body of water (e.g. Young, 1999).

Bender (1996) evaluated the WAM4 source terms for implementation in the Bureau's AUSWAM model, and found these terms to consistently over predict H_s values when compared to buoys on the southern Australian coast. Through a series of simulations using extremely long fetches of 20,000 km to represent the conditions of the Southern Ocean, he showed a significant degree of residual wave growth above the 'fully developed' Pierson and Moskowitz (1964) (PM) values for high wind speeds (although the relatively large uncertainty in the fully developed PM values must also be acknowledged, e.g. Alves et al. (2003)). Under constant 20 ms^{-1} winds, H_s growth continued for several days, well above the PM predicted value of 9.86 m. This residual growth was reportedly absent for 10 ms^{-1} U_{10}, and increased for 30 ms^{-1}. Recent simulations using the operational WAM model under a constant and uniform 18.45 ms^{-1} wind, representing a saturated PM value of slightly less than 8 m, show H_s still growing after several days, approaching 11 m (Cavaleri, 2009). This suggests that similar residual growth is present for the BJA formulations used here[2].

Sustained winds of this magnitude are, of course, unrealistic. However, in the dynamically evolving Southern Ocean, persistently large waves are present. A strong storm does not require days to build waves of this magnitude from a calm ocean, as in these simple fetch limited experiments. Conditions of 20 ms^{-1} winds with waves approaching these PM saturation limits occur with some frequency. Fig. 5, for example, shows the percentage of time over the four months examined here that H_s over 10 m, and U_{10} over 20 ms^{-1} occur simultaneously in the modelled values. In the Southern Ocean, regions where these extreme conditions are present more than 5% of the time are apparent. This strongly resembles the baroclinic eddy rate for this time of year (Simmonds and Lim, 2009). The modelled U_{10} has also been shown to be under-predicted at these extremes Durrant et al. (Submitted to Weather and Forecasting) suggesting that this is an underestimation of the actual frequency of such occurrences.

A correlation can be seen between these areas, and the maximum biases seen in Fig. 1(f), as well as areas downstream of these maxima. It is clear from the box plots presented in Fig. 4 that the positive bias in the Southern extratropics occurs mainly for waves above 6 m. This suggests that the residual wave growth from the BJA source terms at extreme values may be responsible for much of the overall positive bias in the Southern Ocean. Air-sea momentum transfer under high wind speed conditions remains poorly understood, with a lack of quality observations in these extreme conditions partly to blame. The work of Powell et al. (2003) and Donelan et al. (2004) suggests that at high wind speeds, the drag saturates, or even decreases with wind speed. This is not currently represented in the BJA source term formulations, and may be contributing to the positive biases at high H_s values here. In any event, the existence of positive Southern Ocean H_s biases, despite the fact that U_{10} has been shown to be under-predicted at high wind speeds, flags this as a significant internal wave model deficiency.

An additional source of error in the Southern Ocean is offered by the recent work of Ardhuin et al. (2011), who suggest that significant wave energy is lost due to blocking by icebergs in the Southern Ocean. By including this effect in the form of a temporally varying sub-grid-scale blocking grid in WW3, they are able to reduce this bias. This may also be playing a part in the positive H_s bias in the Southern Ocean in general, and the local bias maxima seen in the Amundsen Sea in particular.

5.3.2. Under-attenuation of swell

The second obvious feature in Fig. 1(f) is the positive H_s bias in the eastern Pacific and to a lesser extent the tropical Indian Ocean. As discussed previously, from this case in isolation, the possibility of swell correctly propagating from an over-predicted Southern Ocean wave field exists. The fact that this east Pacific bias is present even in the case of uncorrected winds (Fig. 1(b)), where H_s in the Southern Ocean is negatively biased, strongly suggests a systemic issue with the wave model. Indeed, this is a known deficiency in the WAM4 variant source terms, such as BJA. Verification studies such as Tolman (2002) and Rogers (2002) first suggested the presence of too much swell in the east Pacific from these terms. It is clear from several recent studies (e.g. Ardhuin et al., 2008, 2009) that the lack of swell attenuation in the BJA source term formulations produces unrealistic swell propagation, leading to positive biases on the eastern sides of the major ocean basins. Forcing the model with unbiased winds here simply further exposes this deficiency.

Unlike WAM variant terms, swell dissipation is notably accounted for in the TC96 terms, in the form of a negative wind input for waves travelling faster than, or at large angles to the wind. The importance of swell dissipation on global scales, originally determined heuristically in this case (Tolman, 2002), has subsequently been more explicitly defined in the work of Ardhuin et al. (2010), based on observed swell decay rates (Collard et al., 2009). It should also be noted that the lack of swell attenuation in the BJA terms has been addressed in the ECMWF operational WAM model with the introduction of a negative wind input term (Bidlot, 2012b).

5.3.3. Ocean surface current considerations

The effects of currents on the wave field have been ignored in the model simulations carried out in this work. Over most of the ocean these are negligible, however, more scrutiny is required in

[2] Note that a recently discovered error in the DIA code used in WAM by ECMWF, affecting the downshifting of spectral energy, may account for some of this residual growth (Bidlot, personal communication, September 2012a). It is not clear whether this may also be present in the WW3 code.

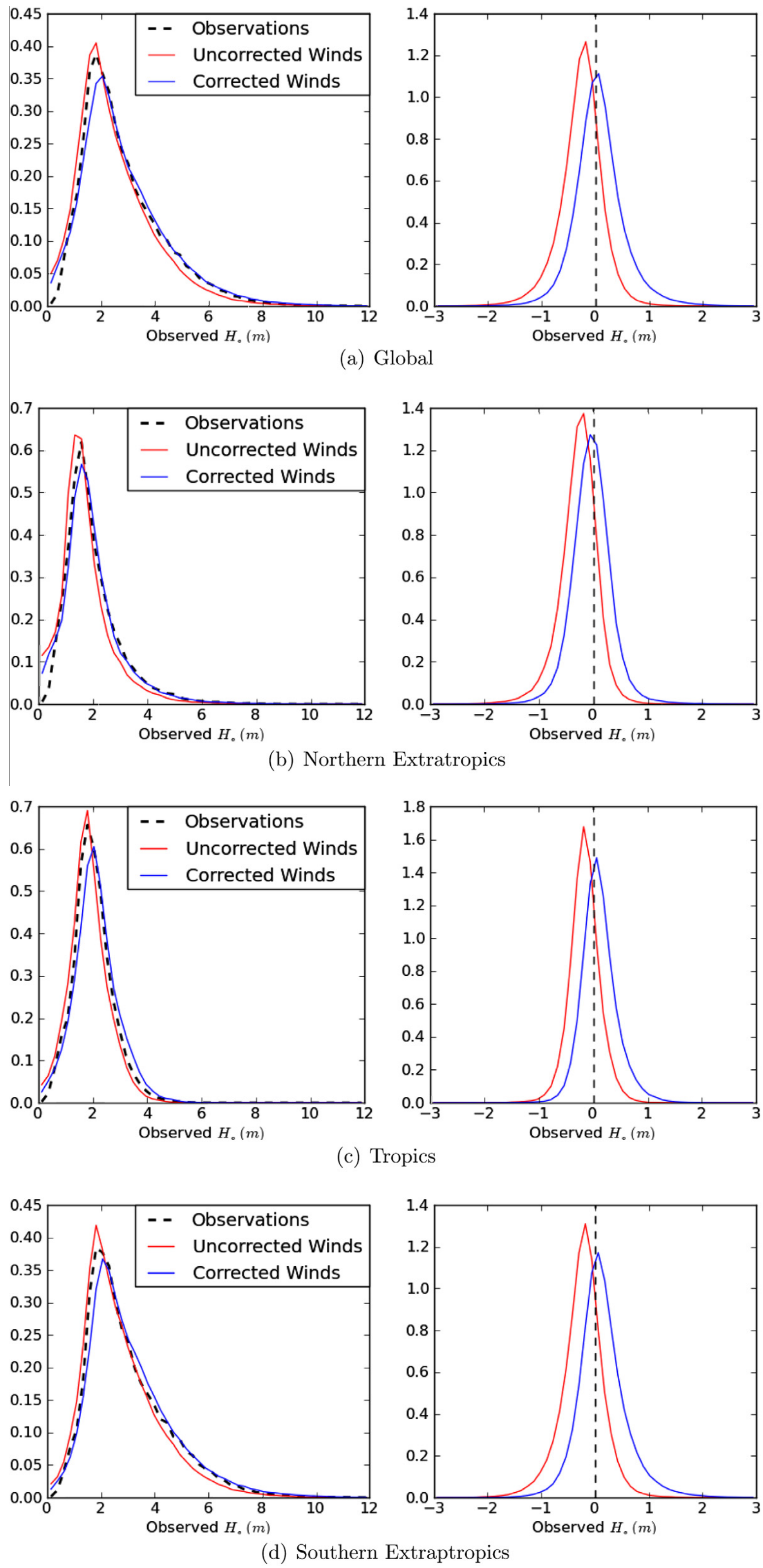
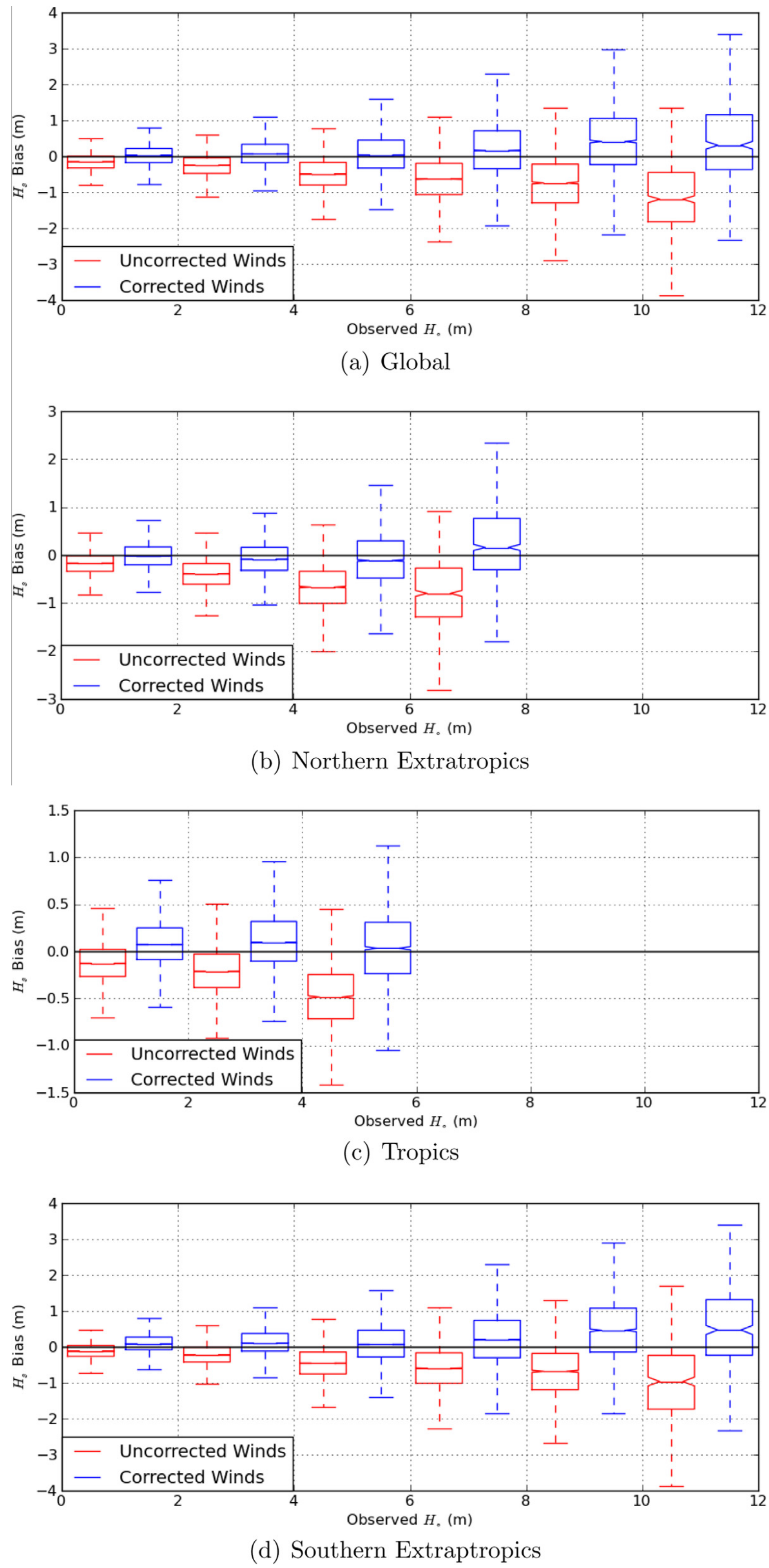


Fig. 3. PDFs of altimeter observed H_s and co-located modelled H_s (left) and differences (right) for simulations using both corrected and uncorrected winds. Corrected winds in this case refer to those corrected using spatially and temporally varying learned corrections (see text for details).

areas of strong, persistent currents. On the scales considered here, two current related effects are of relevance: wave-current interactions and the correct estimation of the true wind speed with respect to the moving sea surface. The relative contribution of the inclusion of each effect was quantified in a recent series of experiments at ECMWF (Hersbach and Bidlot, 2008; Bidlot, 2010, 2012a).

Wind stress is associated with the vector difference between the surface wind speed and the movement of the ocean surface. The issue of relevance here is that the scatterometer is measuring



(a) Global

(b) Northern Extratropics

(c) Tropics

(d) Southern Extraptropics

Fig. 4. Box and whisker plots of the differences between altimeter observations and co-located model H_s for BJA source terms, forcing with both uncorrected and corrected winds, using learned spatially and temporally varying corrections. The center band of the box indicates the median, the top and bottom of the box represent the upper and lower quartiles respectively and the whiskers show the most extreme values within 1.5 times the inner quartile range. A minimum of 100 co-locations is required in each bin.

U_{10} relative to the moving surface, while the NWP model estimates U_{10} relative to a fixed frame of reference. By correcting the modelled wind speeds according to scatterometer data, the effects of currents on the wind speed felt by the waves is crudely accounted for in the mean. However, currents are dynamic. The wind correction method applied here relies on the previous 30 days data, and it is the effect of the mean current over these preceding 30 days that is applied at any given model time. If currents are indeed having a

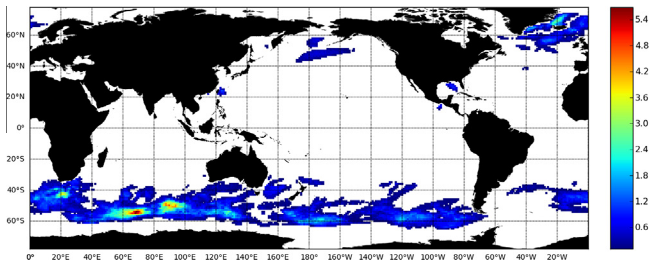


Fig. 5. Percentage of time over the four months examined here that the modelled H_s values over 10 m and U_{10} over 20 ms^{-1} occur simultaneously.

significant effect on wind corrections, and those currents show large variation on shorter than monthly timescales, this may present a significant shortcoming of the applied method.

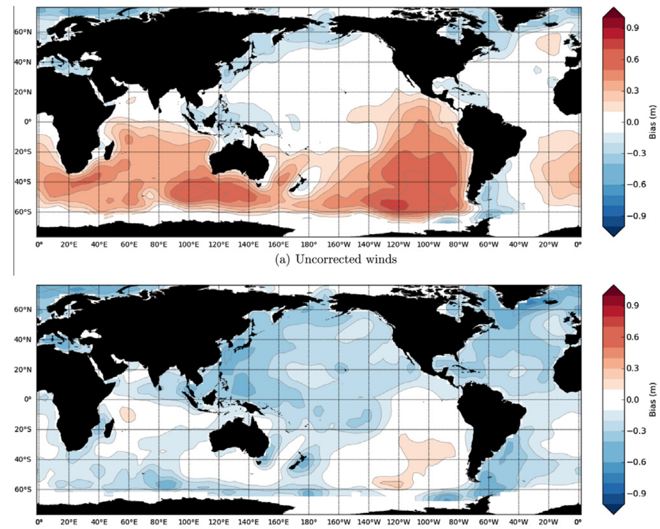
Consider, for example, the Agulhas return current off the Cape of Good Hope. In the case of the spatially and temporally varying learned corrections, where U_{10} in this region now agrees well with scatterometer observations, the waves are over-estimated (Fig. 1(e) and (f)), both here and downstream. The neglect of wave-current interactions could be expected to produce such a result. A significant reduction in mean H_s in this region is apparent in the experiments of Hersbach and Bidlot (2008) and Bidlot (2010, 2012a) in which the effects of currents on wave advection are included.

Wave steepening, leading to increased dissipation, could also be expected to reduce mean H_s. The effect of meanders of this current on the wind corrections method remains a significant question however. Similar issues arise in the Drake Passage, as the Antarctic Circumpolar Current (ACC) flows between the southern tip of South America and the Antarctic Peninsula. Unlike the Agulhas current, the ACC and the wind in this region are, on average, aligned. This results in scatterometer measured wind speeds that are lower than absolute wind speeds. This could explain the local positive maxima visible in the U_{10} bias for both the uncorrected, and the static homogeneous corrected winds (Fig. 1(a) and (c)). Where wind is corrected according to the local scatterometer data, a low H_s bias results (Fig. 1(e) and (f)). Again it is unclear if the wind is being mis-corrected here, or this is simply the result of a lack of wave-current interactions in the wave model. In general, the role of currents, both in terms of their contribution to the modelled H_s biases, and the potential contaminating effects on the wind speed correction methodology appear to be significant. Further work is needed here.

5.3.4. Atmospheric stability considerations

The issue of stability on scatterometer wind retrievals may be relevant here. Wind retrievals are calibrated to the equivalent neutral-stability wind at a reference height of 10 m above the sea surface, while NWP products are estimates of the actual 10 m wind. Not accounting for this difference, though commonplace and justifiable overall, results in local bias features due to sea surface temperature fronts. Further discussion can be found in Durrant and Greenslade (2012).

It is well established that in unstable conditions, wind wave growth is enhanced (e.g. Komen et al. (1994); Young, 1998). Both BJA and TC96 terms have the ability to account for stability effects on wave growth (Bidlot (2012b) and Tolman (2002) respectively), requiring the ingestion of ocean-atmosphere temperature difference grids by the model. The effect on global scales is small (e.g. Tolman, 2002; Rogers et al., 2005), and this has not been included here. The exclusion of stability effects from both the wave model and the scatterometer retrievals may have the unintended effect of offsetting each other to some degree. By correcting the wind



(a) Uncorrected winds

(b) Corrected winds

Fig. 6. H_s bias for TC96 source terms relative to altimeter data when run under (a) uncorrected and (b) corrected winds.

to match the scatterometer measured U_{10}, stability effects are crudely accounted for in the mean. As with the currents above, daily variation in stability is not accounted for however, potentially introducing variable error.

Overall, H_s bias associated with atmospheric stability on the large scale is expected to be small. However, both atmospheric stability and currents could be a factor in the H_s biases seen on mid-latitude east coasts. Strong, warm-water, boundary currents (e.g. Gulf Stream, Kuroshio, Agulhas and East Australian Currents) will likely promote atmospheric instability, enhancing wind-wave growth. As discussed previously, the existence of coastal wind biases has been established by several studies, however, the influence of ocean currents on the assumed neutral stability scatterometer winds used here may also be contributing to the negative U_{10} bias in these regions. Wind corrections based on scatterometer data could then simply be resulting in overestimated U_{10}, compensating for the lack of inclusion of stability effects on the wave growth. This is speculative however.

Overall, the BJA source terms appear to respond well to spatially and temporally varying learned wind corrections in the Northern extratropics. On the large scale, spatial bias in the H_s field is greatly reduced when forced with spatially unbiased winds, and RMSE is reduced by about 17%. However, results are degraded in the Southern extratropics and tropics, due primarily to an overestimation of large waves in the Southern Ocean storm tracks, and the under-attenuation of swell.

5.4. Comparative results for TC96 source terms

The discussion above has focused on runs performed using the BJA source terms. Some comparison is made here with results obtained using the TC96 source terms. The above analysis is not repeated, rather some specific differences in error characteristics associated with these two sets of source terms are discussed.

Fig. 6 shows H_s bias for TC96 source terms when run under both (a) uncorrected and (b) spatially and temporally varying corrected winds. Similar to the BJA case (see Fig. 1(b) and (f)), the negative bias has been reduced in the North Atlantic and North Pacific. The increase in the mean H_s in the Southern Ocean has resulted in the previous small negative bias now presenting as a large positive bias over most of the Southern Ocean. This is consistent with the discussions of the inherent over-prediction in the Southern

Table 3
Regional statistics for H_s relative to altimeter data for TC96 source terms when forced with uncorrected winds as well as those corrected with spatially and temporally varying learned corrections. Percentage improvement refers to % improvement in RMSE.

Run	Bias (m)	RMSE (m)	SI	% Imp	N
Global					
Uncorrected	−0.215	0.49	0.159		581926
Learned	0.122	0.533	0.187	−8.8	581926
Northern Hemisphere Extratropics					
Uncorrected	−0.326	0.485	0.181		103791
Learned	−0.089	0.39	0.192	19.6	103791
Tropics					
Uncorrected	−0.188	0.335	0.138		198969
Learned	0.096	0.331	0.158	1.2	198969
Southern Hemisphere Extratropics					
Uncorrected	−0.147	0.433	0.137		409749
Learned	0.227	0.535	0.164	−23.6	409749

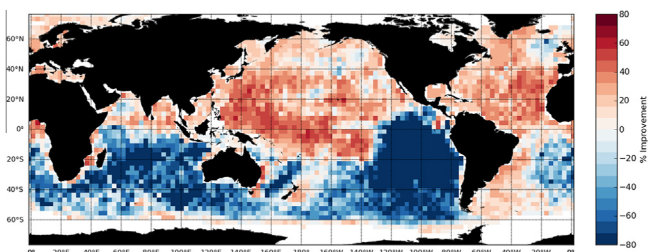


Fig. 7. As Fig. 2 for TC96 source terms.

Ocean by the TC96 source terms in Durrant and Greenslade, (2011). Despite a much stronger positive bias in the South Pacific, the northeast Pacific bias is not as strong as in the BJA case. This is due to the previously discussed better handling of swell attenuation in the TC96 terms.

Verification statistics for TC96 runs with and without wind corrections applied are presented in Table 3. Unlike the slight improvement seen for the BJA terms, global results show significant degradation here. The large differences seen between the hemispheres are even greater, with the Northern extratropics showing almost 20% improvement in RMSE and great reduction in the negative bias, while the Southern extratropics have degraded by almost 24%. Previous negative biases have been replaced with even stronger positive ones. These differences are easily visualized when comparing the spatial percentage improvement in H_s RMSE for TC96 terms, shown in Fig. 7, with the corresponding BJA results (Fig. 2). Gains appear spatially similar in the Northern extratropics, with degradation appearing both more severe and more widespread in the Southern extratropics.

Under unbiased winds, both BJA and TC96 model runs share a tendency to overestimate H_s in the Southern Ocean, with the tendency being greater for TC96. The nature of this positive bias also differs somewhat. Box and whisker plots comparable to those for BJA of Fig. 4 are shown in Fig. 8 for TC96. H_s appears to be well predicted in the Northern extratropics; the corrected wind has improved the H_s distribution throughout the wave range, with the slight over-estimation seen in the BJA terms in the 6–8 m range absent here. In the Southern extratropics, TC96 terms exhibit over-estimations for waves below 10 m, with no bias in the 10–12 m range. This is in contrast to BJA, which shows good statistical agreement with observations below 6 m and over-estimations above. This is likely due to the fact that the TC96 wind input term imposes a maximum allowed drag coefficient, pragmatically matching the qualitative behavior observed by Powell et al. (2003) and Donelan et al. (2004), providing more realistic input at high wind speeds (this limit is set here to 2.5×10^{-3}). Unlike BJA, where the bulk of the positive bias seen in the Southern Ocean appeared to have its origin in large waves, it is in the middle H_s ranges that this bias occurs for the TC96 terms.

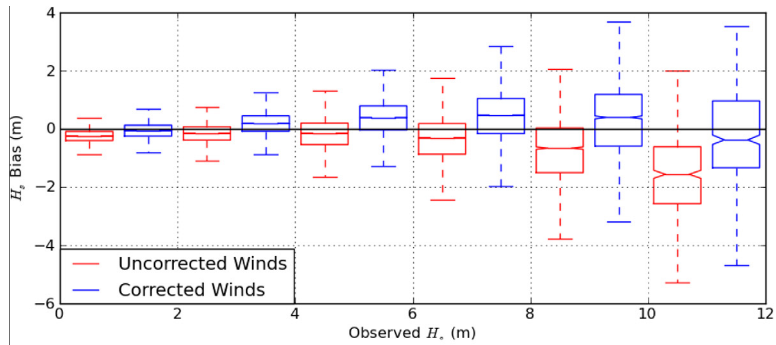
Overall, TC96 terms appear to respond well to spatially and temporally varying wind corrections in the Northern extratropics, similar to the BJA results. On the large scale, spatial bias is greatly reduced when forced with spatially corrected winds, and RMSE is reduced by almost 20%. Again, similarly to the BJA terms, TC96 results are degraded in the Southern extratropics, even more so in the case of the latter. Where low and moderate waves appear well captured by the BJA results, they are overestimated by TC96 terms, while TC96 produces better values for large waves.

6. Discussion

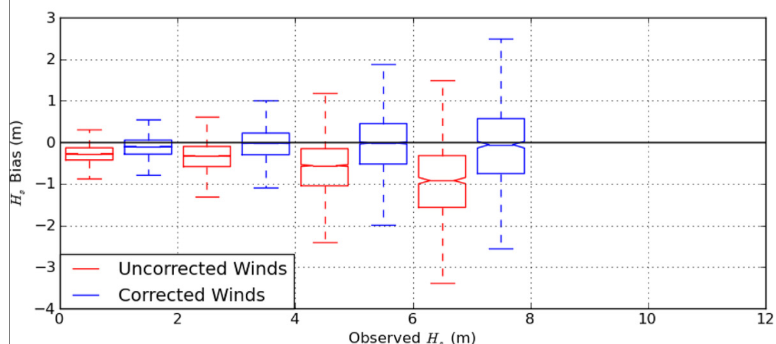
The use of spatially and temporally varying learned corrections, based on comparisons between past forecasts and scatterometer observations, provides a robust means of correcting the surface winds (Durrant and Greenslade, 2012). However, forcing the wave model with these winds produces mixed results in terms of modelled H_s. Greater gains are seen in the Northern extratropics than the Southern for both BJA and TC96 source terms. As discussed above, this may be a seasonal effect. However, this may also be a reflection of model tuning.

As discussed in section 2, modern wave model source terms, though physically based to an extent, have undergone significant tuning. In the context of a review of the capability of modern wave models to properly reproduce the conditions during and at the peak of severe and extreme storms, Cavaleri (2009) make the point that model tuning, in general, is completed on the bulk of the data, with error minimization during the most common conditions the inevitable product. Historically, buoy data have been obtained from the major North American and European buoy networks, potentially biasing this tuning to conditions in the Northern Hemisphere.

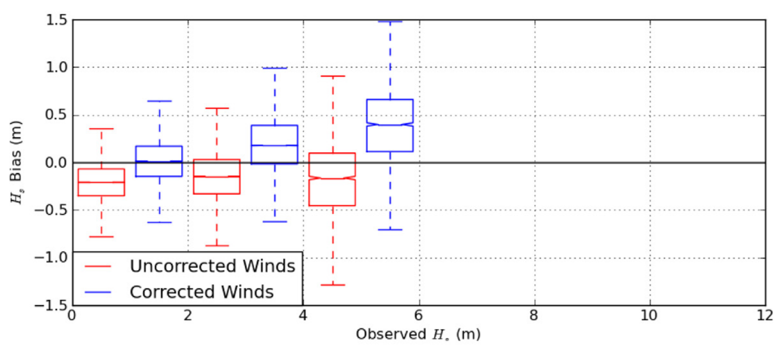
Similarly, consideration must be given to the fact that the tuning of these terms has been done under imperfect winds. Global tuning of the BJA source terms has been performed under ECMWF winds, while TC96 terms have been tuned primarily under NCEP GFS winds, and the default tunings may reflect, to some degree, the bias characteristics of these models. Several studies have suggested ECMWF winds have been historically negatively biased (e.g. Chelton and Freilich, 2005; Ardhuin et al., 2007), though perhaps not as strongly as the uncorrected ACCESS winds (and it should be noted that this negative bias in ECMWF winds has been greatly reduced in the latest system (Bidlot, personal communication, September 2012)). The work presented here has shown that unbiased winds produce a positive bias in the Southern Ocean using BJA source terms, which may reflect this tuning. NCEP GFS winds reportedly show less negative bias than the ECMWF winds (e.g. Bidlot et al., 2002; Chelton and Freilich, 2005). This is seemingly at odds with the large positive H_s bias seen here in the Southern Ocean using TC96 terms. However, this high bias in the Southern Ocean is an issue that is common to the operational NCEP WW3 model. The existence of this bias in the NCEP WW3 model is discussed in the recent validations of Chawla et al. (2009), in which it is suggested that this may be due to changes in the operational winds since the last time the model was tuned (2000–2001). Specifically, since 2005, an upward shift is noted in higher wind speeds in the Southern Hemisphere, a trend that is absent in the Northern Hemisphere, manifesting in a positive H_s bias in the former.



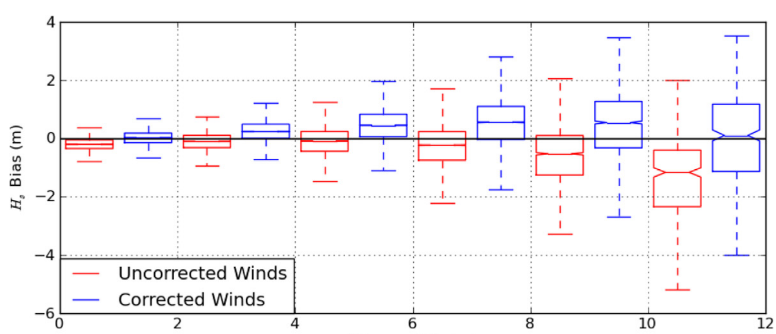
(a) Global



(b) Northern Extratropics



(c) Tropics



(d) Southern Extraptropics

Fig. 8. As Fig. 4 for TC96 source terms.

In general, H_s has been shown here to be highly sensitive to changes in U_{10}. As such, it is unrealistic to expect a wave model to perform well under different forcing, without undertaking some re-tuning of the model. Given that such tuning of the model is necessary, the question could be asked, why not just tune to the negatively biased winds in this case? Error characteristics in the forcing winds are expected to vary with time, due to factors such as seasonal changes, long-lived atmospheric modes of variation, and with physical changes in the model, as illustrated in the case of the NCEP GFS winds above. By tuning the wave model to the corrected winds, the problem of maintaining this tuned state is reduced, as the automatically evolving wind corrections make future wave model retuning somewhat redundant. The ability to account for spatial variation in the systematic wind error is also something that is not easily accounted for by simple wave model tuning alone. This is demonstrated in Durrant (2011).

7. Conclusions

In this work, the spatial biases in the wave field resulting from three different wind fields with known spatial biases have been compared. With respect to the questions posed in Section 2, the following answers can be provided for wave model runs performed using BJA source terms:

- To what extent can the large-scale systematic biases in the waves be attributed to the forcing winds?

For wave model runs forced with uncorrected ACCESS winds, the majority of the negative bias in H_s can be attributed to a negative bias in the forcing. This result emphasizes the importance of analyzing the two in parallel. The reduction of systematic wind biases does not result in universal improvement in modelled H_s. In some situations, internal wave model error is compensated for by error in the forcing winds. In a general sense, it is clear that spatial bias in the wave fields is highly sensitive to that of the forcing wind fields. This applies not only to the overall bias, but its spatial variation.

- Do statistical adjustments to remove these winds biases lead to better wave forecasts?

The improvement in the wind bias as a result of corrections is not matched in the modelled H_s results overall. Large regional variation is, however, apparent. Results in the Northern extratropics indicate strong improvements (approximately 17% in terms of RMSE), while in general, results have been degraded in the Southern extratropics. The Tropics too show degradation, due primarily to excess swell on the eastern boundaries of the major ocean basins. Small-scale features such as coastal biases show improvement.

- What are the residual wave biases?

A positive bias is present in the Southern extratropics due primarily to an overestimation of high H_s values in the Southern Ocean storm tracks. A positive bias is present in the east Pacific and east Indian Ocean. This is due both to the over-prediction of waves in the Southern Ocean and the inherent lack of swell attenuation in the BJA source terms. Smaller scale features are apparent, such as a positive bias off the Cape of Good Hope, and a negative bias off Cape Horn. The origin of these features is unclear. Current effects that are not included in the wave model are a possible explanation. The effect of currents on the wind correction methods applied may also be a factor.

For TC96 source terms, conclusions are generally similar. TC96 terms appear to respond well to spatially varying wind corrections in the Northern extratropics, similar to the BJA results. On the large scale, spatial bias is greatly reduced when forced with spatially unbiased winds, and RMSE is reduced by almost 20%. Results are degraded in the Southern extratropics, even more than the BJA terms. Where low and moderate waves appear well captured in the case of BJA, they are overestimated by TC96 terms, while TC96 produces better values at high wave heights likely due to a capping of the drag coefficient.

8. Further work and closing remarks

The work presented here has focused on large scale, time averaged, systematic bias, as determined by comparison with altimeter data for the modelled H_s. The advantages of the spatial coverage of altimeter data have been made clear, both in this and other work, however, *in situ* buoy measurements maintain a number of advantages over the altimeter data; consistent, frequent (often hourly) observations in a single location, as well as the ability to measure the frequency and direction of waves. Further analysis using buoy data would be a valuable addition to the results presented here.

The signature of ocean surface current effects can be seen in the modelled wave results presented in this work. In hindsight, the neglect of currents adds some uncertainty to the results, both in terms of the proposed correction methodology and their contribution to wave biases on global scales. The increasing skill of operational ocean modelling and the availability of modelled ocean current forecasts in real time (e.g. Brassington et al., 2007) provides the opportunity for them to be explicitly accounted for. Further examination of the effect of ocean currents on the wind methodology, as well as the influence of currents on global scales (i.e. extending the work of Hersbach and Bidlot (2008)), is warranted.

Finally, this study has been performed on a limited period, covering the Southern Hemisphere winter months. Conclusions drawn have greatly differed for the Northern and Southern Hemispheres. In general, it is unclear whether these differences are specific to these respective hemispheres, or whether they are simply a result of seasonal differences. This could be addressed by performing a similar analysis for the Northern Hemisphere winter months.

A number of deficiencies in the wave model have been highlighted when forced with corrected winds. It is worth noting here however, the current work occurring under the NOPP project, a NOAA/U.S. Navy/United States Army Corps of Engineers (USACE) collaboration funded over four years beginning in 2010 (Tolman et al., 2011). This project has the broad aims of, among other things, developing new spectral source terms within WW3 incorporating recent advances in theoretical knowledge of wind input and in particular, wave breaking and dissipation. In this circumstance, the source terms of BJA and TC96 may be unlikely to receive significant additional attention.

In the context of wave model development, the need to assess the spatial wind bias has been made clear. In general, regions where the wave model has degraded as a result of correcting the winds has highlighted problems in the wave model itself, which, in many cases, were masked by compensating systematic errors in the forcing winds. Overall, it is clear that by performing the spatially and temporally varying wind corrections applied in this work, the contribution of the systematic wind error to the H_s bias is significantly reduced, allowing inherent wave model error to be more effectively isolated and addressed.

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