ON THE NON-PARAMETRIC CORRECTION OF WAVE FIELDS

Sofia Caires
Meteorological Service of Canada and Royal Netherlands Meteorological Institute
P.O. Box 201, NL-3730 AE De Bilt, Netherlands
email: caires@knmi.nl

Val Swail
Meteorological Service of Canada, Toronto, Ontario, Canada

1. INTRODUCTION

Two global data sets of 6-hourly fields of significant wave height data covering more than 4 decades are presently available:

- The American National Center for Atmospheric Research and the National Centers for Environmental Prediction (NCEP/NCAR) have produced a global reanalysis of the surface winds from 1958-1997 which continues to be extended (Kalnay et al., 1996). Cox and Swail (2001) used these winds to force the second generation ODGP2 spectral ocean wave model (see Cox and Swail, 2001) and produced the first 40-year wave reanalysis covering the whole globe, hereafter named the Cox&Swail data set.
- The European Centre for Medium-Range Weather Forecasts (ECMWF) produced the ERA-40 data set (Uppala, 2001), a reanalysis of global variables from 1957 to 2002. It used ECMWF's Integrated Forecasting System, a coupled atmosphere-wave model with variational data assimilation, which is a state-of-the-art model very similar to the one used operationally, but with lower resolution. A distinguishing feature of ECMWF's model is its coupling, through the wave height dependent Charnock parameter (see Janssen et al., 2002), to a third generation wave model, the well-known WAM (Komen et al., 1994), and so wave data is a natural output of ERA-40.

The availability of these data sets makes it possible to carry out detailed global studies of the wave climate and its variability, which until recently could only be made from sparsely located, though high quality, buoy data covering about 20 years (e.g. Gower (2002)), from global but subsampled altimeter data or visual ship observations (e.g. Gulev et al. (2003)), or from wave analysis or hindcasts with limited spatial coverage or duration (e.g. Gűnter et al. (1998), Young (1999)).

There are, however, still some deficiencies associated with reanalysis data sets. Although the reanalysis ensures, by using the same numerical model throughout, that no inhomogeneities due to different analysis techniques exist, there remain inhomogeneities due to differences in availability and coverage of the observations used. Also, in order to obtain such long data sets, compromises must be reached in terms of resolution. Although reanalysis data sets are produced by state-of-the-art models, the resolution is lower than those used operationally and, therefore, the quality of their wind fields, and consequently of their wave fields, is lower.

Limitations in the Cox&Swail data set motivated a kinematical improvement of the NCEP/NCAR reanalysis wind fields for the North Atlantic, which involved a reported 10,000 meteorologist hours of effort (Swail and Cox, 2000). The corrected wind field was then used to force a third generation wave model, the OWI 3-G wave model (see Swail and Cox (2000) and references therein), producing a very high quality wave data set, hereafter named the Swail&Cox data set.

Validation of the Swail&Cox data set, the ERA-40 data set, and the Cox&Swail data set against buoy and altimeter observations has shown that the ERA-40 data set, although severely underestimating high sea states, compares better with observations in terms of root mean square error and scatter index than the Cox&Swail data set, and that the Swail&Cox data set is the best in describing wave data in the North Atlantic (see Caires et al. (2004)).

Limitations in the ERA-40 significant wave height data set, which besides the underestimation mentioned above also includes inhomogeneities due to the assimilation of ERS-1 and ERS-2 altimeter wave heights for the period 1992-2001, also motivated their correction by Caires and Sterl (2005). These authors corrected the data through a non-parametric regression method that predicts the bias between significant wave height ERA-40 data and Topex altimeter measurements. This technique, which is much cheaper than kinematically improving the wind fields, also produced a very high quality data set - and in this case a global one. The corrected ERA-40 data set is hereafter referred to as the C-ERA40 data set.

Although kinematically improving the wind fields seems to be quite effective in producing better significant wave height fields, the high cost involved restricted the study of Swail and Cox (2000) to the North Atlantic. Also, errors in the forcing wind fields explain only some of the deficiencies in predicted wave fields; other sources of deficiencies are wave model inadequacies and resolution. In this article we will use a non-parametric method to correct the Cox&Swail data set and investigate whether the method is as effective as the kinematic improvement of wind fields. We will concentrate just on two years, 1994 and 1997, for which we have Cox&Swail, Swail&Cox, ERA-40, C-ERA40 and Topex data simultaneously available.

Specifically, we shall use the Cox&Swail and Topex data of 1994 as a 'learning data set' to correct the Cox&Swail data of 1997, and use the Cox&Swail and Topex data of 1997 to correct the Cox&Swail data of 1994. The resulting corrected data set will be referred to as the C-Cox&Swail data set. The reanalysis data, Topex and buoy measurements will be used to assess the quality of the C-Cox&Swail data set.

This paper is organized as follows: We start by describing the data sets that will be used in the data correction and validation. Next we describe briefly the basis and the present application of the non-parametric correction method, then summarize and discuss the results, and finally state our main conclusions.

2. DATA DESCRIPTION

2.1 REANALYSIS DATA

We consider four significant wave height (H_s) data sets: Cox&Swail, Swail&Cox, ERA-40 and C-ERA40. These were already introduced, so here we just add information on their coverage and resolution.

All data sets consist of 6-hourly fields. The Cox&Swail data set is the one with lower resolution, with the data on a global 1.25º x 2.5º latitude/longitude grid. The Swail&Cox data set is the one with the smaller spatial coverage, but with the highest resolution, with data on a 0.625º x 0.833º latitude/longitude grid covering the North Atlantic. Both the ERA-40 and the C-ERA40 data sets are global and the data is on a 1.5º x 1.5º latitude/longitude grid.

2.2 OBSERVATIONS

We will take recourse to both buoy and altimeter Topex H_s observations to validate the reanalysis data sets. The Topex data will also be used in the creation of the C-Cox&Swail data set. Since data from 1994 will be used in the creation of data from 1997, and vice versa, the 1994 and 1997 Topex data sets are independent for the validation of C-Cox&Swail data for the respective period.

Buoy observations are the most reliable wave observations, but they are limited in space and time. Most buoys are located along the coast in the Northern Hemisphere, and are available only after 1978. We use measurements from the American National Data Buoy Center (NDBC-NOAA), which are freely available at http://www.nodc.noaa.gov/BUOY/buoy.html.

The buoys are situated along the coasts of North America. From the available NDBC-NOAA buoy locations 16 have been selected for the validations: 4 around the Hawaiian Islands (buoys 51001, 51002, 51003 and 51004), 3 in the Gulf of Mexico (42001, 42002 and 42003), 4 in the Northwest Atlantic (41001, 41002, 41010 and 44004), 2 off the coast of Alaska (46001 and 46003), and 3 in the Northeast Pacific (46002, 46005 and 46006).

Selection criteria were the distance from the coast and the water depth. Only deep water locations can be taken into account since no shallow water effects are accounted for in the wave models, and the buoys should not be too close to the coast in order for the corresponding grid points to be located at sea. The buoy H_s measurements are available hourly from 20-minute long records. Although these measurements have gone through some quality control they are processed further using a procedure similar to the one used at ECMWF (Bidlot et al. 2002) and described in Caires and Sterl (2003). In order to compare the reanalysis with the observations, time and space scales must be made compatible. The reanalysis results are available at synoptic times (every 6 hours) and each value is an estimate of the average condition in a grid cell, while the buoy measurements are local. Since the ERA-40 resolution is in-between the resolution of the other reanalysis products, we will use the resolution of the ERA-40 data as a reference. Therefore, the reanalysis data are compared with 3-hour averages of buoy observations, 3 hours being the approximate time a long wave would take to cross the diagonal of a 1.5º x 1.5º grid cell at mid latitude. To get reanalysis data at the buoy location, the reanalysis data at the appropriate synoptic time is interpolated bilinearly to the buoy location.

While buoys provide high-quality continuous measurements at fixed points, satellite-born altimeters provide near-global coverage, but every point is sampled only once in several (typically 10) days. We use along-track quality checked deep water altimeter measurements of H_s from TOPEX, obtained from the Southampton Oceanography Centre (SOC) GAPS interface (http://www.soc.soton.ac.uk/ALTIMETER; Snaith, 2000). The drift observed in TOPEX wave heights during 1997 is corrected according to Challenor and Cotton (1999), and in order to make the TOPEX observations compatible with the buoy observations the relationship $H_{sbuoy} = 1.05 H_{stopex} - 0.07$ (Caires and Sterl, 2003) is used.

The satellite measurements are performed about every second with a spacing of about 5.8 km. *Super observations* are formed by first grouping together consecutive measurements crossing a 1.5º x 1.5º region, i.e., observations that are at most 30 seconds or $1.5\sqrt{2}$ º apart. The satellite observation is then taken as the mean of these grouped data points. A quality control similar to the one applied to the buoy data is done. The reanalysis data is linearly interpolated in space and time to the mean location and the mean time of the altimeter observation.

3. NON-PARAMETRIC CORRECTION

Results about the consistency of non-parametric regression estimators of the conditional distribution function, estimators of conditional quantiles, and estimators of conditional means for sequences of certain conditionally stationary processes to which wave data seems to conform approximately have been proved in the statistical literature (see Caires and Ferreira (2005)). Caires and Sterl (2005) used these results as a theoretical foundation for the use of non-parametric estimators for the correction of wave model data; they provided a detailed motivation for the use of non-parametric regression in correcting wave model results and proposed a correction method. Here we will briefly reproduce the motivation and method for the sake of completeness; the reader is, however, directed to their work for details.

Wave hindcasts often suffer from over- and underestimation of particular storms. Since the occurrence of misestimates is, to a certain extent, random, the problem they present cannot be solved by simply applying a parametric correction to the data. A solution to the problem would be to somehow learn or understand how the error process works in a range of situations, and then use this knowledge to predict the error that would result in partly new situations, which consequently would enable an appropriate correction. A natural way to learn – to estimate, really – how misestimates take place is to gather a large amount of observed and predicted data and quantify the statistical behaviour of the corresponding errors according to the particular context in which they occurred. In statistical terms, our problem can thus be translated into that of predicting the value of one variable (an appropriate correction) *conditionally* on the information provided by other variables (the values of certain wind- and wave-related variables conditionally upon which the need for the correction arose), and hence to the problem of *regression*. The apparently difficult aspect of the proposed solution lies in two facts: first, the data we are interested in are dependent and non-stationary; secondly, it seems difficult to come up with a parametric function which would fit and explain the data in all situations (linear regression, for instance, would appear as unrealistic at the outset). The statistical tool tailored to deal precisely with this problem is non-parametric regression estimators (see e.g. Caires and Ferreira (2005) and references therein).

The prediction method consists of predicting the required correction of an H_s model value, H_s^M, at a certain time, given *m* consecutive H_s^M values, in terms of the conditional distribution and conditional mean of the correction as estimated from a “learning data set”, i.e., a data set containing both model data and measurements, and hence also corrections. More specifically, let us denote by V the correction to be applied to an H_s^M value at a particular time and location, and by U a vector of dimension *m* containing the H_s^M value at that time and the *m*-1 previous H_s^M values (all at the particular location). In order to predict V on the basis of the knowledge that $U = u$ we need to know the conditional mean of V given $U = u$,

$R(u) = E(V \mid U = u)$,

and the conditional distribution function of V given $U = u$,

$F(v \mid u) = P(V \le v \mid U = u)$.

Although these items are unknown, we can estimate them using a sample of pairs (U_i, V_i), $i = 1,...,n$, the 'learning data set', where U_i and V_i are analogous to the above U and V variables. This sample of pairs can be obtained from model data and buoy/altimeter measurements whenever the two are available at the same time and location, so that the corrections are also available.

Write $S(u,h) = \{u' \in \Re^m : |u_j - u'_j| < h,\ j = 1,...,m\}$ for $h > 0$, and let $h_n > 0$ be a given number depending on the sample size n. Then the estimator of $R(u)$ is called *the empirical regression function* and is defined by

$$R_n(u) = \frac{\sum_{i=1}^{n} V_i 1_{[U_i \in S(u,h_n)]}}{\sum_{i=1}^{n} 1_{[U_i \in S(u,h_n)]}},$$

and the estimator of $F(v \mid u)$ is called *the empirical conditional distribution function* and is defined by

$$F_n(v \mid u) = \frac{\sum_{i=1}^{n} 1_{[V_i \le u,\, U_i \in S(u,h_n)]}}{\sum_{i=1}^{n} 1_{[U_i \in S(u,h_n)]}}$$

Here, the notation 1_A, where A is an event, means 1 if A occurs, and 0 otherwise. Thus, each value of both $R_n(u)$ and $F_n(v \mid u)$ is an average whose terms include only those values of V_i for which $U_i \in S(u,h_n)$. The motivation for using these estimators is that they both converge (as n grows) in some sense and in certain conditions to their theoretical counterparts, $R(u)$ and $F(v \mid u)$.

Once $R_n(u)$ is available, one can estimate an unknown value of V on the basis of U by $\hat{V} := R_n(U)$. Similarly, using $F_n(v \mid u)$ one can estimate the probability that the unknown value of V falls in a particular interval (a,b) on the basis of U by $F_n(b \mid U) - F_n(a \mid U)$, and consequently find a prediction interval for V with a specified approximate probability of containing it.

Besides the choice of m, the application of the method now outlined requires the specification of h_n, which is called the smoothing parameter. In theory, h_n should tend to 0 as n tends to infinity, and in most applications one may suppose that (see Caires and Ferreira (2005))

$$h_n = (cn^{\alpha-1} \log n^2)^{1/m},$$

where c and α are constants which, just like m, have to be determined empirically.

4. RESULTS

We started by trying to correct the Cox&Swail data using exactly the same settings used to correct the ERA-40 data:

- $m = 3$: U consists of sequences of 3 model values;
- V is given by the error between the last value in the sequence and the corresponding Topex measurement, used to estimate the conditional mean and distribution functions;
- $c = \dfrac{0.3^m}{700^{\alpha-1} \log 700^2}$, allows two sequences to be considered as analogues if the maximum absolute difference between them is of at most 30 cm, when the sample size of possible analogues is $n = 700$;
- $\alpha = 0.2$;
- at each location the learning data set is composed of sequences that are within a 10º circle centred at the location for which the values are being corrected.

The resulting C-Cox&Swail data set compared only slightly better with observations than the original Cox&Swail data set. We did some sensitivity studies as to what the best choice of the learning data set and settings would be and found that slightly better results could be obtained after making the following modifications:

- Only data from October to March was used to correct October to March and only data from April to September was used to correct April to September. The error characteristics seem to have a seasonal behavior.
- The parameter c was increased to $c = \dfrac{0.5^m}{700^{\alpha-1} \log 700^2}$, which being less restrictive allows more data to be used in the estimation of the corrections.

We now proceed with the validation of the C-Cox&Swail data obtained with these improved settings.

We will validate the reanalysis data sets against Topex observations for the North Atlantic and buoy data both in the North Atlantic and the North Pacific. The buoy data validation also includes the North Pacific because the number of NDBC-NOAA buoys in the North Atlantic is small. Naturally, the quality of the C-Cox&Swail data set in the North Pacific cannot be compared with that of the Swail&Cox data set since the latter is restricted to the North Atlantic.

The differences between the reanalyses products and the observations were qualitatively assessed by looking at quantile plots, and quantified through some standard statistics such as the bias, ($\bar{y}-\bar{x}$), the root-mean-square error,

$$Rmse = \sqrt{n^{-1}\sum(y_i - x_i)^2} ,$$

the scatter-index,

$$SI = \sqrt{n^{-1}\sum[(y_i - \bar{y}) - (x_i - \bar{x})]^2} \,/\, \bar{x} ,$$

and the correlation coefficient,

$$\rho = \sum(x_i - \bar{x})(y_i - \bar{y}) \Big/ \sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2} .$$

In all these formulae the x_i's represent the altimeter or buoy observations, the y_i's represent the reanalysis products, n the number of observations, and a bar over a variable represents its average.

Tables 1 and 2 present statistics of different reanalysis products versus Topex measurements in the North Atlantic for 1994 and 1997, respectively.

Table 1. Statistics of significant wave height (m) data for 1994 from different reanalysis products versus Topex measurements in the North Atlantic. The number of measurements is 49,478 and their average is 2.44 m.

	Bias	RMSE	SI	P
ERA-40	-0.32	0.50	0.16	0.97
C-ERA40	0.00	0.32	0.13	0.97
Cox&Swail	0.04	0.47	0.19	0.94
Swail&Cox	0.03	0.43	0.17	0.95
C-Cox&Swail	0.04	0.44	0.18	0.94

Figures 1 and 2 contain graphs comparing the 1%-99% quantiles of Topex observations for 1994 in the North Atlantic against those of the C-Cox&Swail, Cox&Swail and Swail&Cox data, and against those of the C-ERA40, ERA-40, and Swail&Cox data, respectively. Figures 3 and 4 present the same information as figures 1 and 2 but for 1997.

Table 2. Statistics of significant wave height (m) data for 1997 from different reanalysis products versus Topex measurements in the North Atlantic. The number of measurements is 48,054 and their average is 2.45 m.

	Bias	RMSE	SI	ρ
ERA-40	-0.22	0.49	0.18	0.96
C-ERA40	0.00	0.34	0.14	0.97
Cox&Swail	0.00	0.50	0.20	0.93
Swail&Cox	-0.03	0.44	0.18	0.95
C-Cox&Swail	-0.05	0.48	0.19	0.93

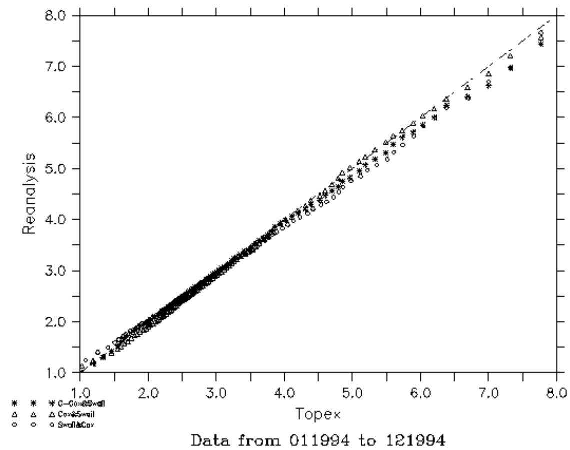

Figure 1. Graphs comparing the 1%-99% quantiles of Topex observations for 1994 in the North Atlantic against those of the C-Cox&Swail (*), Cox&Swail (Δ) and Swail&Cox data sets (O).

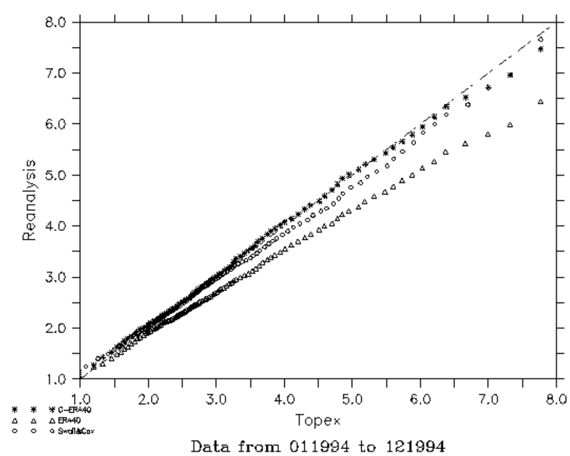

Figure 2. Graphs comparing the 1%-99% quantiles of Topex observations for 1994 in the North Atlantic against those of C-ERA40 (*), ERA-40 (Δ) and Swail&Cox data sets (O).

Table 3. Statistics of significant wave height (m) from different reanalysis products versus buoy measurements in different ocean basins; data for 1994.

Region	n	$\bar{x}$	Reanalysis	bias	Rmse	SI	ρ
Hawaiian Islands	4570	2.55	ERA-40	-0.38	0.51	0.13	0.90
			C-ERA40	-0.12	0.34	0.12	0.90
			Cox&Swail	-0.46	0.62	0.17	0.81
			C-Cox&Swail	-0.23	0.48	0.16	0.82
Gulf of Mexico	3884	1.09	ERA-40	-0.18	0.33	0.25	0.93
			C-ERA40	0.05	0.26	0.23	0.93
			Cox&Swail	0.32	0.45	0.30	0.89
			C-Cox&Swail	0.04	0.32	0.29	0.89
Northwest Atlantic	5213	1.87	ERA-40	-0.31	0.52	0.22	0.95
			C-ERA40	-0.04	0.34	0.18	0.95
			Cox&Swail	-0.02	0.47	0.25	0.91
			Swail&Cox	0.06	0.35	0.19	0.95
			C-Cox&Swail	-0.09	0.47	0.25	0.90
Alaska	3783	2.91	ERA-40	-0.37	0.60	0.16	0.97
			C-ERA40	-0.07	0.40	0.14	0.97
			Cox&Swail	0.20	0.59	0.19	0.94
			C-Cox&Swail	0.08	0.52	0.18	0.94
Northeast Pacific	2910	2.88	ERA-40	-0.38	0.60	0.16	0.96
			C-ERA40	-0.07	0.40	0.14	0.96
			Cox&Swail	0.02	0.54	0.19	0.93
			C-Cox&Swail	-0.03	0.52	0.18	0.93

Table 4. Statistics of significant wave height (m) from different reanalysis products versus buoy measurements in different ocean basins; data for 1997.

Region	n	$\bar{x}$	Reanalysis	bias	Rmse	SI	ρ
Hawaiian Islands	5569	2.37	ERA-40	-0.16	0.35	0.13	0.90
			C-ERA40	-0.08	0.30	0.12	0.91
			Cox&Swail	-0.31	0.48	0.15	0.85
			C-Cox&Swail	-0.04	0.37	0.15	0.84
Gulf of Mexico	3671	1.09	ERA-40	-0.09	0.31	0.27	0.92
			C-ERA40	-0.01	0.26	0.24	0.92
			Cox&Swail	0.27	0.41	0.29	0.90
			C-Cox&Swail	-0.01	0.29	0.27	0.91
Northwest Atlantic	4774	1.74	ERA-40	-0.15	0.42	0.23	0.94
			C-ERA40	-0.03	0.35	0.20	0.93
			Cox&Swail	-0.01	0.47	0.27	0.88
			SwailCox	0.05	0.37	0.21	0.92
			C-Cox&Swail	-0.05	0.47	0.27	0.88
Alaska	3788	2.87	ERA-40	-0.21	0.50	0.16	0.96
			C-ERA40	0.00	0.41	0.14	0.96
			Cox&Swail	0.20	0.65	0.22	0.92
			C-Cox&Swail	0.01	0.56	0.20	0.92
Northeast Pacific	1911	2.89	ERA-40	-0.14	0.45	0.15	0.95
			C-ERA40	0.08	0.42	0.14	0.95
			Cox&Swail	0.19	0.60	0.20	0.92
			C-Cox&Swail	0.09	0.53	0.18	0.92

Tables 3 and 4 present statistics of different reanalysis products versus buoy measurements in different ocean basins for 1994 and 1997, respectively.

We will not analyse in detail the differences between the ERA-40, Cox&Swail and Swail&Cox data sets or between the C-ERA40 and the ERA-40 data sets; extensive comparisons of these are available in Caires et al. (2004) and Caires and Sterl (2005), respectively. We will concentrate on the comparisons between the C-Cox&Swail data set and the other data sets, and on the comparison between the C-ERA-40 data set and the Cox&Swail and Swail&Cox data sets, since they are obtained here for the first time.

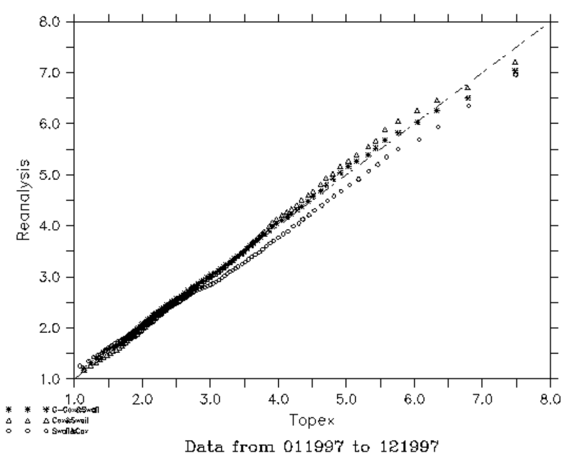

Fig. 3. Graphs comparing the 1%-99% quantiles of Topex observations for 1997 in the North Atlantic against those of the C-Cox&Swail (*), Cox&Swail (Δ) and Swail&Cox data sets (O).

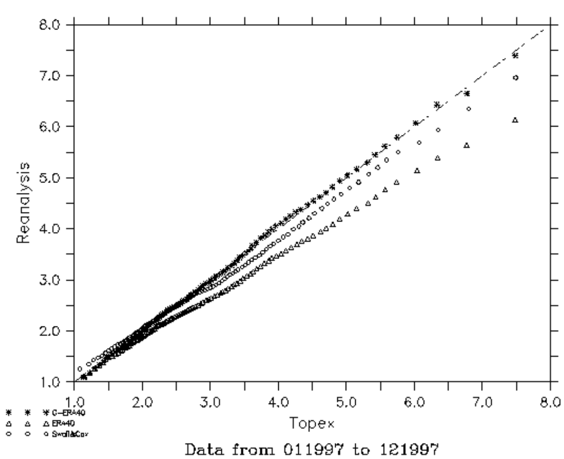

Fig. 4. Graphs comparing the 1%-99% quantiles of Topex observations for 1994 in the North Atlantic against those of the C-ERA40 (*), ERA-40 (Δ) and Swail&Cox data sets (O).

The analysis of the above tables and figures leads to the following statements:

- The C-Cox&Swail data set compares better with the Topex data than the Cox&Swail data set. The improvements are, however, small: a decrease of about 3 cm in the root-mean-square-error and of 0.01 in scatter-index.
- The Swail&Cox data set compares better with the Topex observations than the C-Cox&Swail data set, although only marginally.
- The C-ERA40 data set compares much better with the Topex observations than all the other data sets. Its root-mean-square-error is at least 10 cm lower than that of the others, its scatter-index is the lowest, and its correlation with the observations is the highest.
- If we were to rank the different reanalysis data sets based on the statistics presented in tables 1 and 2, then the order by decreasing quality would be: C-ERA-40, Swail&Cox, C-Cox&Swail and, ex aequo, ERA-40 and Cox&Swail.
- The 1%-99% quantile plots show that the non-parametric correction of the Cox&Swail data was effective in improving the quantiles of the data at least up to the 90% quantile, the improvements being greater in 1997 than in 1994. On the other hand, the quantiles of the Cox&Swail data set already compare so well with the observations that improvements have little impact; clearly, the non-parametric correction has much less impact here than in the case of the ERA-40 data set. The C-ERA40 data set is the data set with the quantiles closer to the observations.
- The comparisons with buoy data show that the non-parametric correction has almost no impact in the Cox&Swail data in the Northwest Atlantic buoy locations. The impact in the data for the North Pacific buoy locations is, however, quite visible, with decreases in the root-mean-square-error of about 10 cm. The C-ERA-40 is, as in the comparisons with Topex data, the one that compares better with observations, having the lowest root-mean-square error and scatter-index and the highest correlation with the observations.

5. CONCLUSIONS

We have tried to obtain an improved Cox&Swail data set by using the non-parametric technique used to successfully improve the ERA-40 significant wave height data set. The results of the present attempt are, however, less far reaching than those of the ERA-40.

In short, our comparisons show that the Cox&Swail data set can be improved non-parametrically, but the improved data set was still of lower quality than the Swail&Cox data set, especially at the buoy locations. The improvements of ERA-40 data obtained by the non-parametric correction were much more substantial that those obtained for the Cox&Swail data.

One of the reasons for the success of the non-parametric correction of the ERA-40 data was the high correlation between the ERA-40 data and the observations. We suspect that the correction of the Cox&Swail data set was less successful because the correlation between the Cox&Swail data and the observations is smaller than in the case of ERA-40. The monthly correlation between the Cox&Swail data and the Topex observations varies in 1994 from 0.81 to 0.95 and in 1997 from 0.86 to 0.94. For the ERA-40 data the correlations are between 0.91 and 0.97 in both years.

The non-parametric correction will not introduce missing storms, remove fake features nor displace storms, and therefore it is important that even if errors are gross that the correlation between the data sets is high. This type of errors can, on the other hand, be corrected kinematically, and indeed the Swail and Cox (2000) kinematically improved winds show a correlation with the observations that is up to 0.15 higher than the one of the NCEP/NCAR reanalysis winds (see Caires et al. (2004)); consequently, the Swail&Cox data set also correlates better with observations than the Cox&Swail data set.

The results of the non-parametric correction could probably be further improved by extending the learning data set or by adding the wind speed in the conditional setting, but the results will most definitely fall short of the quality of the C-ERA-40 data set.

Acknowledgements. We are thankful to Helen Snaith of the Southampton Oceanography Centre for the altimeter data, to the American National Oceanographic Data Center for the available buoy data, to ECMWF and NCEP/NCAR for the available reanalysis data. The plotting was done with the free Ferret software developed by NOAA/PMEL/TMAP .

REFERENCES

Bidlot, J.-R., D. J. Holmes,. P. A. Wittmann, R. Lalbeharry, and H. S. Chen, 2002: Intercomparison of the performance of operational wave forecasting systems with buoy data. *Weather and Forecasting*, **17**, 287-310.

Caires, S. and J. A. Ferreira, 2005: On the non-parametric prediction of conditionally stationary sequences. *Statistical Inference for Stochastic Processes*, **8** (in press).

Caires, S. and A. Sterl, 2003: Validation of ocean wind and wave data using triple collocation. *J. Geophys. Res.*, **108**(C3), 3098, doi:10.1029/2002JC001491.

Caires, S., A. Sterl., J.-R. Bidlot, N. Graham, and V. Swail, 2004: Intercomparison of different wind wave reanalyses. *J. Climate*, **17**, 1893-1913.

Caires, S. and A. Sterl, 2005: A new non-parametric method to correct model data: Application to significant wave height from the ERA-40 reanalysis. *J. Atmos. Oceanic Tech*. (accepted).

Cox, A. T. and V. R. Swail, 2001: A global wave hindcast over the period 1958-1997: Validation and climate assessment. *J. Geophys. Res.*, **106**, 2313-2329.

Gower, J. F. R., 2002: Temperature, wind, and wave climatologies, and trends from marine meteorological buoys in the Northeast Pacific. *J. Clim.*, **15**, 3709-3718.

Gulev, S. K., V. Grigorieva, A. Sterl and D. Woolf, 2003: Assessment of the reliability of wave observations from voluntary observing ships: Insights from the validation of a global wind wave climatology based on voluntary observing ship data. *J. Geophys. Res.*, **108**, 3236, doi:10.1029/2002JC001437.

Gűnter, H., W. Rosenthal, M. Stawarz, J. C. Carretero, M. Gomez, I. Lozano, O. Serrano, and M. Reistad, 1998: The wave climate of the Northeast Atlantic over de period 1955-1994: The WASA wave hindcast. *The Global Atmosphere and Ocean System*, **6**, 121-163.

Janssen, P.A.E.M., D. Doyle, J. Bidlot, B. Hansen, L. Isaksen and P. Viterbo, 2002: Impact and feedback of ocean waves on the atmosphere. *Advances in Fluid Mechanics*, *Atmosphere-Ocean Interactions*, **I**, WIT press, Ed. W. Perrie. 155-197.

Kalnay, E., M. Kanamitsu, R. Kistler, W. Collins, D. Deaven, L. Gandin, M. Iredell, S. Saha, G. White, J. Woolen, Y. Zhu, M. Chelliah, W. Ebisuzaki, W. Higgins, J. Janowiak, K.C. Mo, C. Ropelewski, J. Wang, A. Leetmaa, R. Reynolds, R. Jenne and D. Joseph, 1996: The NCEP/NCAR 40-year reanalysis project. *Bull. Amer. Meteorol. Soc.*, **77**, 437-471.

Komen, G. J., L. Cavaleri, M. Donelan, K. Hasselmann, S. Hasselmann and P. A. E. M. Janssen, 1994:Dynamics and Modelling of Ocean Waves. Cambridge Univ. Press.

Swail, V. R. and A. T. Cox, 2000: On the use of NCEP-NCAR reanalysis surfce marine wind fields for a long-term North Atlantic wave hindcast. *J. Atmos. Oceanic Technol.*, **17**, 532-545.

Uppala, S., 2001: ECMWF ReAnalysis, 1957-2001. Proc. of the ECMWF workshop on re-analysis, ERA-40 Project Report Series, No.3, pp. 1-10, Reading, 5-9 November 2001.

Young, I. R., 1999: Seasonal variability of the global ocean wind and wave climate. *International Journal of Climatology*, **19**, 931-950.