Statistical post processes for the improvement of the results of numerical wave prediction models. A combination of Kolmogorov-Zurbenko and Kalman filters

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A new mathematical technique for adaptation of the results of numerical wave prediction models to local conditions is proposed. The main aim is to reduce the systematic part of the prediction error in the direct model outputs by taking advantage of the availability of local measurements in the area of interest. The methodology is based on a combination of two different statistical tools: Kolmogorov-Zurbenko (KZ) and Kalman filters. The first smoothes the observation time series as well as that of model direct outputs in order to be comparable via a Kalman filter. This is not the case in general, since forecasted values are smoothed spatially and temporarily by the model itself while observations are point records where no smoothing procedure is applied. The direct application of a Kalman filter to such qualitatively different series may lead to serious instabilities of the method and discontinuities in the results. The proper utilisation of KZ-filters turn the two series into a compatible mode and, therefore, makes possible the exploitation of Kalman filters for the identification and subtraction of systematic errors. The proposed method was tested in an open sea area for significant wave height forecasts using the wave model WAM and six buoys as observational stations.

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INTRODUCTION

The need for accurate local wave predictions has seriously increased during the last few years due to several affected activities, such as ship traffic, tourism, offshore exploration, etc. The most reliable tools today used for such forecasts are numerical wave predictions models. A large number of operational and research centres worldwide base their predictions on global or regional

wave models with rather successful results concerning the general sea state forecast. However, if one focuses on specific locations and tries to obtain accurate local wave information, serious and systematic divergences are usually revealed. These divergences are mainly due to the fact that wave model outputs are strongly dependent on local characteristics, initial conditions, as well as the corresponding atmospheric data used as input. On the other hand, numerical models cannot simulate successfully sub-grid scale phenomena. Similar drawbacks have been also pointed out in numerical forecasting of atmospheric parameters.

In order to reduce the impact of the abovementioned problems to the final outputs of the forecasting systems, a variety of approaches have been employed. One possible way out is to increase the model resolution. This may lead to some improvement in the representation of smaller scale wave characteristics. However, such a change would also demand the corresponding increase of the resolution of the atmospheric model that is used to provide the necessary wind input; this is imposed by the fact that all wave models used today are wind driven with the wind input being the most crucial component. On the other hand, it remains an open question whether the use of higher resolution models improves forecast skill or whether potential improvement compensates for the increase in computational resources required.[1]

An alternative option for the improvement of the local forecasts in numerical (wave or atmospheric) forecasting is also provided by statistical methods aimed at local adaptation of the direct model outputs. Many of them are derived from Model Output Statistics (MOS), which are able to account for local effects and seasonal changes. However, discrepancies have been found in such applications in cases of short time local weather changes or updates of the numerical model in use.[2,3]

An interesting approach with excellent results in many previous studies for different forecasted parameters is the use of Kalman filtering.[4–11] The Kalman filter consists of a set of mathematical equations that provides an efficient computational solution of the least square method. Observations are recursively combined with recent forecasts using weights that minimise the corresponding biases.

The main advantage of Kalman filters is the easy adaptation to any alteration of the observations as well as the fact that only short series of background information are needed. However, even by the use of this more dynamic methodology a number of problems remain unsolved leading to serious divergences. The main reason is that the two time series used as input to Kalman filters, the model forecasts and the corresponding observed values, are of different qualitative characteristics. Model outputs are always smoothed in time and space having, therefore, a continuous and mild evolution. On the other hand, observations are point measurements recorded at discrete times without smoothing and are therefore discontinuous and highly variable (see Fig 3). As a result, the direct utilisation of such time series by a Kalman filter may lead to serious instabilities. Such a case is discussed later and has been visualised in Fig 4.

In this work a new methodology is proposed that responds quite successfully to the above mentioned difficulties and leads to a considerable improvement of the local wave forecast. It consists of a combination of Kolmogorov-Zurbenko (KZ) fil-

ters[12,13] with Kalman algorithms. The former is applied to the initial recorded observations and to model direct outputs, smoothing any possible high variability and reducing noisy intervals. The percentage of the removed variability can be controlled by an appropriate choice of filter parameters. In this way, the above mentioned different quality characteristics of the time series in study are eased. On the other hand, possible systematic deviations are clearly revealed. In a second step, the KZ-filtered results are input to a Kalman filter, which can be applied smoothly with no instabilities, leading to a very satisfactory adaptation of the forecasts to local area's characteristics.

MODEL DESCRIPTION

The wave model used in this paper is WAM cycle 4[2,14,15,16,17] developed in the European Centre for Medium-Range Weather Forecasts (ECMWF). WAM is a third generation wave model which solves the wave transport equation explicitly without any assumptions on the shape of the wave spectrum. It represents the physics of wave evolution in accordance with today's knowledge for the full set of degrees of freedom of a two-dimensional wave spectrum.

The first statistical tool employed is a Kolmogorov-Zurbenko (KZ) filter. (A detailed presentation of the philosophy and the way of using such type of filters can be found in[12,13]). It is based on iterative moving averages and is able to remove high frequency variations from the initial data. To be more precise, if the initial values of a series is denoted by $(x_i^0)_i$, the first iteration of the filter smoothes them as follows:

$$x_i^1 = \frac{1}{2q+1} \sum_{j=-q}^{q} x_{i+j}^0 \qquad (1)$$

where parameter q designates the length of the filter window which is $m = 2q + 1$.

In the next step, these values $(x_i^1)_i$ become the input for the second iteration $x_i^2 = \frac{1}{2q+1} \sum_{j=-q}^{q} x_{i+j}^1$, and so on.

The parameter m and the number of iterations (n) control the portion of the variability that wants to be excluded. In particular, the desired separating frequency is[12,13]:

$$\omega_o \cong \frac{\sqrt{6}}{\pi} \sqrt{\frac{1-(\frac{1}{2})^{1/2n}}{m^2-(\frac{1}{2})^{1/2n}}} \ .$$

It is worth noting that, in the present work, the KZ-filter is not utilised within the forecasting period. It is only applied to past observations and model results in order to ease possible qualitative differences and transform them to a comparable mode.

The KZ-smoothed time series form the initial data for Kalman filtering. In order to make this paper as self-contained as possible, a detailed description of the general form of the Kalman filter algorithm, based on the unified notation proposed in[18] follows.

Kalman filters simulate the evolution in time of an unknown process (state vector), whose 'true' value at time t_i is denoted here by $x^t(t_i)$. This is combined with a corresponding known array (observations) y_i^O which refers to the same time. The change of x in time is governed by the system equation:

$$x^t(t_i) = M_{i-1}[x^t(t_{i-1})] + \eta(t_{i-1}) \qquad (2)$$

The observation equation describes the relation between the observation vector and the unknown one:

$$y_i^O = H_i[x^t(t_i)] + \varepsilon_i . \qquad (3)$$

The matrices M_i (system operator), H_i (observation operator) as well as the covariance matrices $Q(t_i)$, $R(t_i)$ of the Gaussian (by assumption) and independent random vectors $\eta(t_i)$, ε_i, respectively, have to be determined before the application of the filter.

The first forecast step of the state vector x and its error covariance matrix P is given by:

$$x^f(t_i) = M_{i-1}[x^a(t_{i-1})], \qquad (4a)$$

$$P^f(t_i) = M_{i-1}P^a(t_{i-1})M_{i-1}^T + Q(t_{i-1}) \qquad (4b)$$

This is followed up by an update (analysis) step in which the observation available at time t_i is combined with the previous information:

$$x^a(t_i) = x^f(t_i) + K_i(y_i^O - H_i[x^f(t_i)]), \qquad (5a)$$

$$P^a(t_i) = (I - K_iH_i)P^f(t_i) \qquad (5b)$$

Here

$$K_i = P^f(t_i)H_i^T[H_iP^f(t_i)H_i^T + R_i]^{-1} \qquad (6)$$

is the Kalman gain that arranges how easily the filter adjusts to possible new conditions. The superscripts o, t, f, a denote observations, true, forecast and analysis value correspondingly. Moreover, T and -1 stand for the transpose and the inverse matrices, respectively, while I is the unitary matrix. Equations (2)–(6) update the Kalman algorithm from time t_{i-1} to t_i.

THE CASE STUDIED

For the present work, a global version of the WAM model was utilised. The wave spectrum was descritised in bands of 30 frequencies and 24 directions. The first integration

Buoy Label	Lat	Lon
A	N 34.88	W 120.87
B	N 33.65	W 120.2
C	N 33.75	W 119.08
D	N 33.22	W 119.88
E	N 32.43	W 119.53
F	N 32.5	W 118

Table 1: Buoys' coordinates

frequency was determined at 0.0417Hz and the propagation time step to 300 seconds. The model ran in a deepwater mode with no refraction. WAM was driven by NCEP/GFS model wind data with a horizontal grid resolution of 1.0 x 1.0 deg.

The area of study was that of the southwest coast of the USA as presented in Fig 1. In the same map, the location of the buoys used as observational sources are indicated. All of them belong to the NOAA/National Data Buoy Center network and their exact positions in Lat-Lon coordinates are declared in Table 1. It should be noted that, since these locations do not coincide with WAM grid points, the corresponding forecasts have been interpolated to them.

A KZ (m=5, n=5) filter was employed, which is equivalent to a cut-off frequency of 0.0411, or 24.3 time steps (see the corresponding criterion presented in the previous section and relevant references[12,13]).

Concerning the Kalman filter used, a brief description follows: A single forecasted parameter in time was utilised: the significant wave height (swh). The corresponding bias is estimated as a polynomial of the forecasting model direct output. This choice has been already used in previous applications of Kalman filtering for other meteorological parameters (temperature[6], wind speed[7]) resulting in the considerable reduction of the systematic error. To be more precise, let swh_i denote the direct output of the model at time t_i. Then, the corresponding bias y_i^O is estimated by means of swh_i in a linear form:

$$y_i^O = a_{0,i} + a_{1,i} \cdot swh_i + \varepsilon_i \qquad (7)$$

The coefficients $(a_{0,i}, a_{1,i})$ are the parameters that have to be estimated by the filter, while ε_i is the Gaussian, non systematic, error of the procedure.

In this way, the state vector of the filter becomes $x(t_i) = [a_{0,i}, a_{1,i}]^T$, the observation is the (scalar) bias y_i^O, the observation matrix takes the form $H_i = [1 \; swh_i]$ and as system matrix the identity I_2 is used. Therefore, the system and observation equations take the following form:
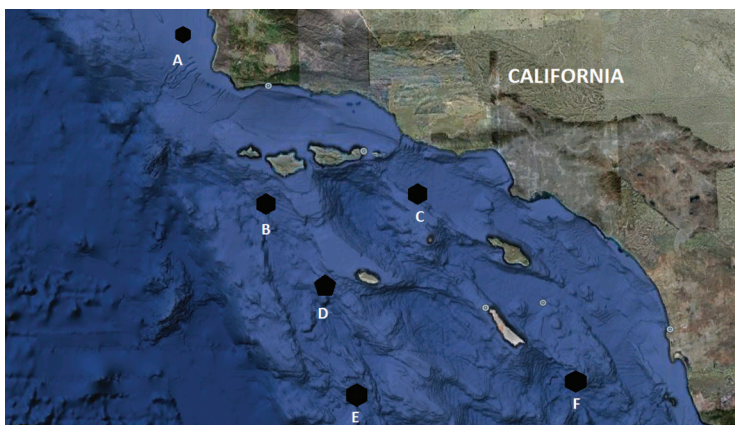

Fig 1: The area of interest and the locations of buoys used (A–F)

$$x^t(t_{i+1}) = x^t(t_i) + \boldsymbol{\eta}(t_i), \quad y_i^O = H_i[x^t(t_i)] + \boldsymbol{\varepsilon}_i \qquad (8)$$

The initial value of the state vector x is zero, assuming, in this way, that the initial bias of the forecasting model is non-systematic: $y_0^O = \varepsilon_0$ (equations (7), (8)). The covariance matrix P (equation (4b)) is considered initially diagonal, indicating no correlations between different coordinates of the state vector x. The diagonal elements have an initially relatively large value, here we propose $P(t_0) = \begin{pmatrix} 4 & 0 \\ 0 & 4 \end{pmatrix}$, that declares low credibility of the first guess.

The initial values of the variances $Q(t_i)$, $R(t_i)$ (equations (4b), (6)) are $Q(t_0) = I_2$, $R(t_0) = 6$ (a sufficiently large estimation leading to quick independence from initial conditions). The selection of the above values leads also to an initial Kalman gain that contributes to the fast adaptability of the filter to possible new conditions (equation (6)).

The subsequent values of $Q(t_i)$ and $R(t_i)$ are based on the sample of the last seven values of $\eta(t_i) = x^t(t_{i+1}) - x^t(t_i)$ and $\varepsilon_i = y_i^O - H_i[x^t(t_i)]$ respectively:

$$Q(t_i) \equiv \frac{1}{6} \cdot \sum_{i=0}^{6} (((x^t(t_{i+1}) - x^t(t_i)) - (\frac{\sum_{i=0}^{6}(x^t(t_{i+1}) - x^t(t_i))}{7})))^2, \quad (9)$$

$$R(t_i) \equiv \frac{1}{6} \cdot \sum_{i=0}^{6} (((y_i^O - H_i[x^t(t_i)]) - (\frac{\sum_{i=0}^{6}(y_i^O - H_i[x^t(t_i)])}{7})))^2. \quad (10)$$

These are objective estimators of $Q(t_i)$, $R(t_i)$ respectively due to the fact that the variables $\eta(t_i)$ and ε_i, denote the non-systematic part of errors in equations (8) and follow the normal distribution.

The time period of seven time steps was chosen after a sensitivity analysis that was made for different meteorological parameters and led to the conclusion that this short time interval is adequate to obtain significantly improved forecasts with the application of the filter (for the relevant tests see[7]). On the other hand, this choice allows fast adaptability to possible data alternations and does not create needs for extended data storage.
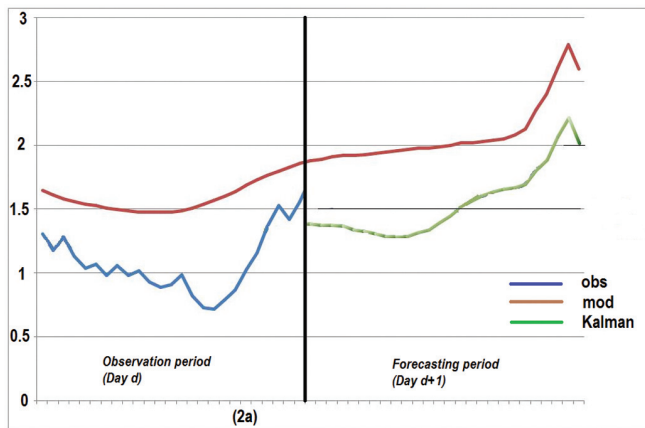
It is worth also noting that this study was based on an operational run. More specifically, all the models were used iteratively and the observations of each day d were combined with model forecasts for the same day d and the next one $d+1$ so to achieve a Kalman-filter forecast for day $d+1$ (Fig 2a). These new forecasts were evaluated against the observations of the new day $d+1$ when these were available (Fig 2b). In this way, it was ensured that the evaluation data were not mixed with those used for forecasting.

The statistical analysis was based on the following parameters:

● Bias of forecasted (filtered or not) values:

$$Bias = \frac{1}{k} \cdot \sum_{i=1}^{k} \left(for(i) - obs(i) \right) \qquad (11)$$

where $obs(i)$ denotes the recorded (observed) value at time i, $for(i)$ the respective forecast (direct model output or improved forecast via the proposed filter) and k the size of the sample. Bias is the most crucial parameter for any type of filtering procedure since they all aim at eliminating the standard error.

● Mean Average Percentage Error:

$$MAPE = \frac{1}{k} \cdot \sum_{i=1}^{k} \left| \frac{for(i) - obs(i)}{obs(i)} \right| \qquad (12)$$

where $|\,\,|$ stands for the absolute value. This parameter measures the bias of the forecasts as a proportion of the observations.

● Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{k} \cdot \sum_{i=1}^{k} \left(for(i) - obs(i) \right)^2} \qquad (13)$$

a classical and widely used divergence measure.

RESULTS

As already discussed in the previous sections, one of the main problems in numerical wave forecasting is the difficulty in
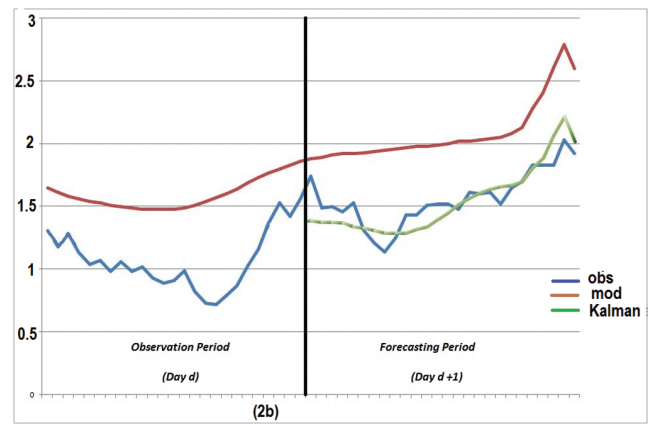

Fig 2: The operational run; (a) Available observations and WAM forecasts are combined by the filters to reach a new improved forecast for the next day; (b) The direct model outputs as well as the filtered forecasts are evaluated against next day observations
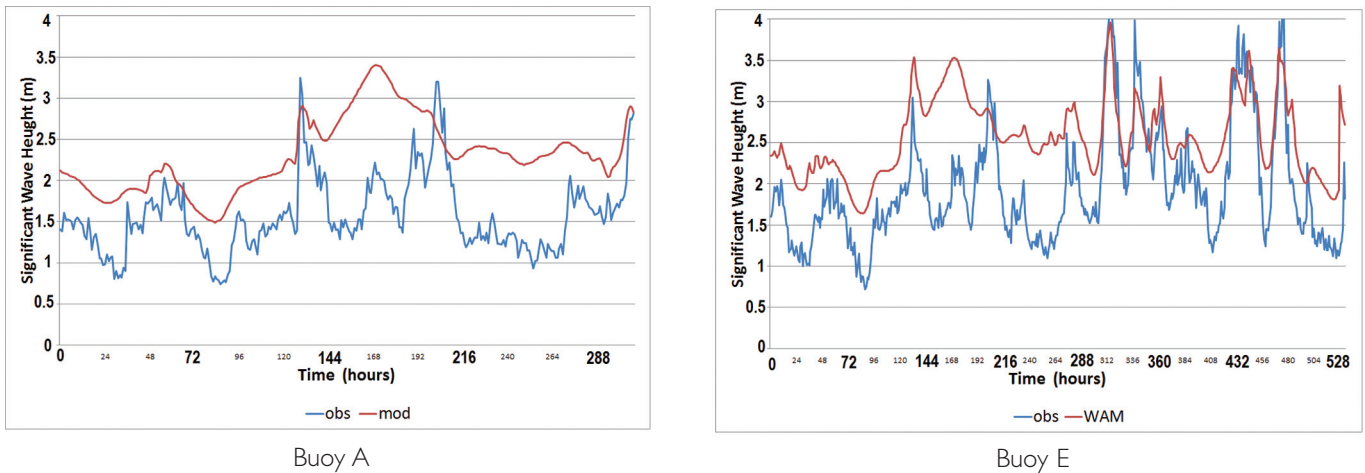
Buoy A

Buoy E

Fig 3: Direct model outputs and observations from buoys (A) and (E)

providing accurate local predictions which are crucial for several applications. A main and popular tool to encounter this issue is the Kalman filter, which provides fast and accurate adaptation to local conditions by recursively combining direct model outputs with recent corresponding observations. However, an aspect that should be seriously taken into account when using Kalman filter post-processing is the prerequisite demanding the time series employed be of the same qualitative characteristics. Kalman filters may detect and subtract possible systematic error that emerges between model and observation time series no matter its magnitude or type (underestimation or overestimation). However, both series used have to follow a 'similar', qualitatively speaking, evolution in time. Filtering a smooth and continuous time series by using a corresponding noisy one with increased variability and discontinuities is risky and may lead to serious instabilities in the corresponding results. A relevant example is presented in Fig 3.

The time series of significant wave height values as fore-casted by WAM and the corresponding buoy A and E records are plotted. It is obvious in both cases that, although the model follows the general pattern of the observations, the two time series are of totally different qualitative characteristics. The prediction model outputs are much smoother and contin-uous than the observations; something expected since WAM forecasts, as with any numerical prediction model results, are

smoothed in time and space. On the other hand, the buoy time series are point records with no smoothing procedure applied. Therefore, although a systematic error is almost obvious, if one tries to pass these time series through a Kalman filter (the latter being unable to compare them in an appropriate way) produces filtered values with serious instabilities, setting under question its validity. In Figs 4a and 4b a relevant exam-ple is presented.

Two time series of different qualitative characteristics (Fig 4a) are filtered by a linear Kalman algorithm. Several moderate or major instabilities emerge (Fig 4b).

In order to further clarify this argument, a variability index is presented in Table 2 for both model forecasts and observations. This index measures the 'distance' of the initial values $(x(i))_{i=1,2,...,n}$ from their corresponding KZ-filter counter-parts $(y(i))_{i=1,2,...,n}$ and is calculated as follows:

$$Var(x) = \sqrt{\sum_{i=1}^{n} \frac{1}{n}(x(i) - y(i))^2} \qquad (14)$$

It is a rather similar index to the well known Root Mean Square Error measuring the divergence of the time series in study from the corresponding KZ-filtered values instead of their mean.

In all cases the variability of the observations are on aver-age more than double the corresponding model predictions. It is important to underline that this is not a strange or extreme
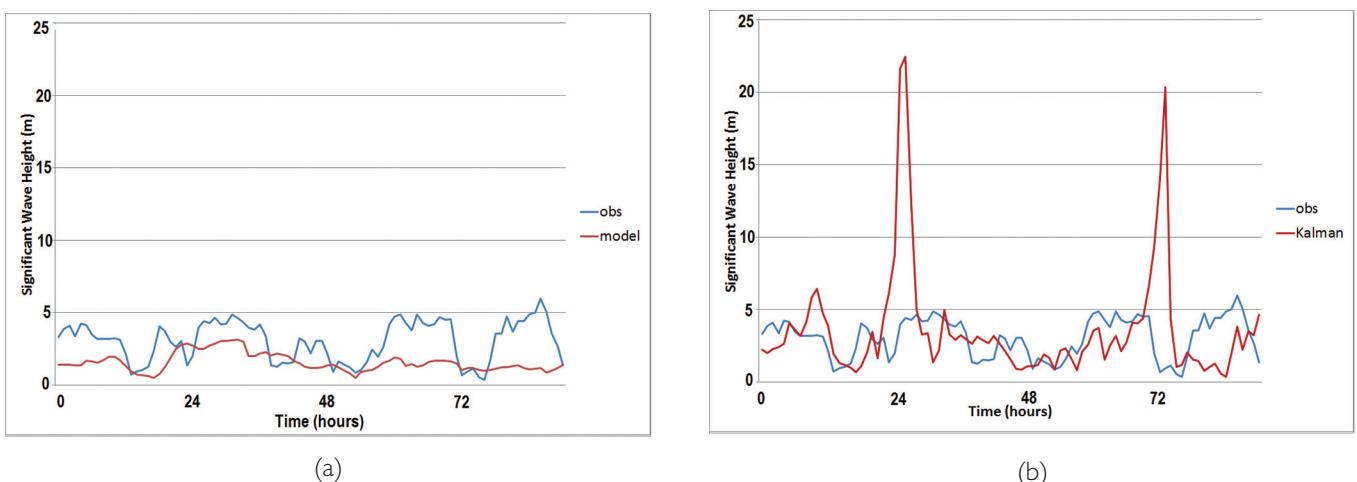

(a)

(b)

Fig 4: (a) Direct model output and observations. The time series are of different characteristics. (b) Instabilities are produced by the direct application of a Kalman filter

	Buoy A		Buoy B		Buoy C			
	Model	Obs	Model	Obs	Model	Obs		
Var Index	0.07	0.22	0.17	0.29	0.13	0.18		
	Buoy D		Buoy E		Buoy F		Average	
	Model	Obs	Model	Obs	Model	Obs	Model	Obs
Var Index	0.16	0.24	0.17	0.31	0.14	0.18	0.14	0.24

Table 2: Variability Index for the forecasted and observed values
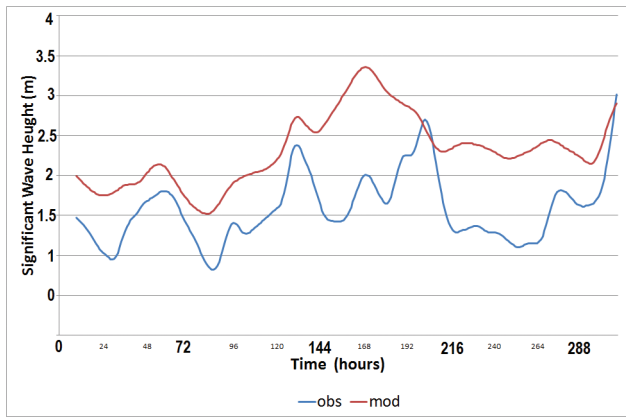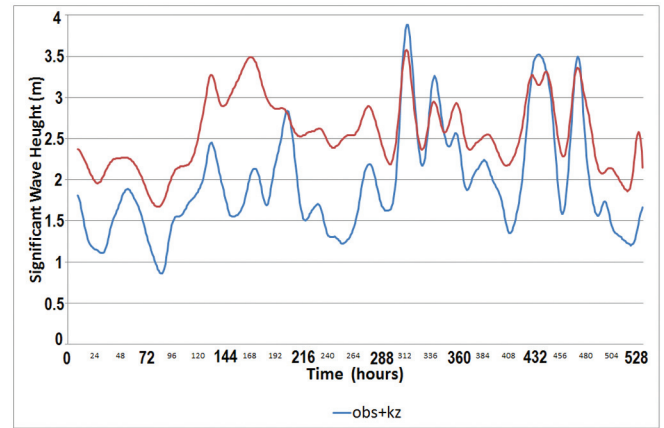
Buoy A   Buoy E

Fig 5: WAM forecasts and observations from buoys (A) and (E) after passing a (5,5)–KZ filter

situation. However, it is a serious problem if one wants to filter these time series through a Kalman process in order to extract possible systematic error.

A way out of the above difficulties can be given by the use of Kolmogorov-Zurbenko (KZ) filters presented earlier. If the two time series of interest, WAM predictions and the corresponding observation records, pass through such a filter, then the high frequencies and the undesired variances are subtracted. In Fig 5, the time series of Fig 3 are presented after the application of a KZ-filter.

It is obvious that the resulting time series have much more similar qualitative characteristics while the existing systematic divergence between forecasts and observations becomes more evident. Therefore, these time series are more appropriate to be utilised by a Kalman filter.

It is worth noticing here that, given the smoothness procedure used by numerical prediction models, one could avoid KZ filtering the forecasts, restricting this only to observations. However, it is the author's belief that, by filtering both time

series, their compatibility is further ensured. Note also that for both filters the corresponding parameters are those defined in the previous section where the details of the tests are presented. The corresponding training period has been restricted to a seven day interval, exploiting the ability of Kalman filters to easily adopt possible new conditions as well as their limited need for background information. The above described procedure was applied to the six available buoys. The filters performed well in all cases, eliminating the major part of the systematic error, despite its type, and leading to more accurate local forecasts. In Table 3 some statistical results for the area of interest before and after the filters application are presented.

In all cases, the bias has almost vanished, fulfilling the main goal of any Kalman type filter. On the other hand, RMSE is significantly decreased and the MAPE, which gives the discrepancies of the forecasts as a percentage of the observations, is reduced to less than the half of its initial value. It is worth noting that such improvements have not been achieved when using only Kalman filters.[6,7,19] The stride has

	Buoy A		Buoy B		Buoy C			
	Model	Model + Filters	Model	Model + Filters	Model	Model + Filters		
Bias	0.51	−0.08	0.13	−0.03	0.99	0.03		
RMSE	0.74	0.63	0.74	0.72	1.12	0.44		
MAPE	0.42	0.26	0.31	0.25	1.05	0.30		
	Buoy A		Buoy B		Buoy C		Average	
	Model	Model + Filters	Model	Model + Filters	Model	Model + Filters	Model	Model + Filters
Bias	0.56	0.002	0.36	−0.02	0.70	0.01	0.54	−0.01
RMSE	0.84	0.61	0.82	0.69	0.89	0.49	0.86	0.60
MAPE	0.43	0.21	0.38	0.23	0.63	0.23	0.54	0.25

Table 3: Statistics for all buoy locations before and after the use of the filters referring to all study period
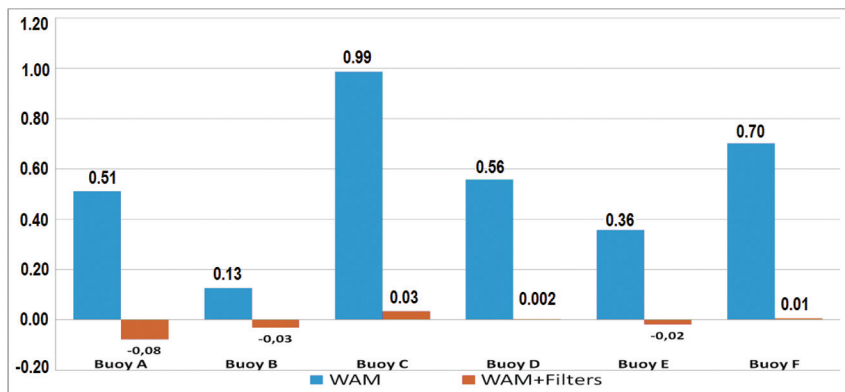
Fig 6: Bias of WAM direct outputs and WAM+Filters

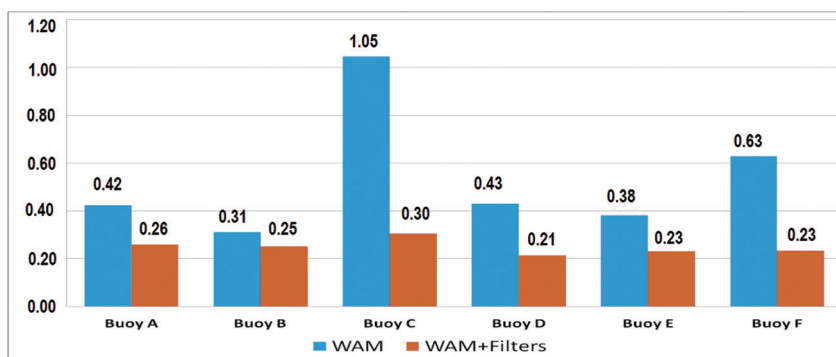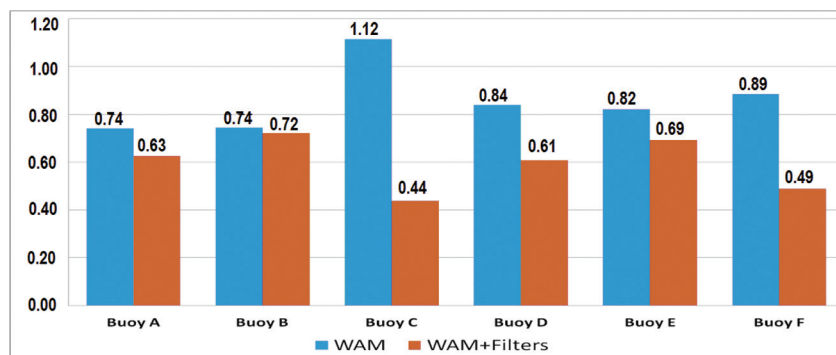Fig 7: Root Mean Square Error of WAM direct outputs and WAM+Filters

Fig 8: Mean Average Percentage Error of WAM direct outputs and WAM+Filters

been taken due to the combined used of Kalman with KZ-filters that ensure the best adaptability of the time series in use to the Kalman algorithm. The statistical results are graphically represented in Figs 6–8. In order to further support the above arguments, the time series of three different cases (buoys C, D, F) are presented in Figs 9–11. The improvement of the initial forecast by the elimination of the systematic error is obvious.

In Fig 12, the added value obtained from the combined use of KZ and Kalman filters is clarified. The instabilities produced by the use of Kalman filter only (circled) are eased by the prior utilisation of a KZ(5, 5) smoothing filter.

CONCLUSIONS

A new methodology is proposed for adapting the results of numerical wave prediction models to local wave conditions. It is based on the combination of two independent statistical techniques: the Kolmogorov-Zurbenko and Kalman filters. The first transforms the time series used – model direct outputs and corresponding observations – into a comparable mode. Comparability is achieved by subtracting high variability which is normally present only in the observations since the forecasts are already smoothed spatially and temporally by the model itself. In a second step, the KZ-smoothed series are elaborated by a Kalman filter which may identify and subtract possible existing systematic errors.

The proposed methodology was applied to an open sea area and has been evaluated by means of six buoys. In all cases, a considerable reduction of the systematic error was achieved no matter what its form (under- or over-estimation). The corresponding biases practically disappeared while variability indexes (Root Mean Square Error and Mean Average Percentage Error) were also noticeably decreased.

It is worth noticing that a substantial part of the success of the methodology presented is due to the presence of KZ filters. Without the latter the Kalman algorithm may produce serious instabilities due to the different qualitative characteristics of the initial time series. It is the author's belief that the proposed techniques may also give similar satisfactory results if applied to other atmospheric or wave parameters, like temperature, wind speed, mean wave period, etc, contributing to the improvement of local meteorological predictions.
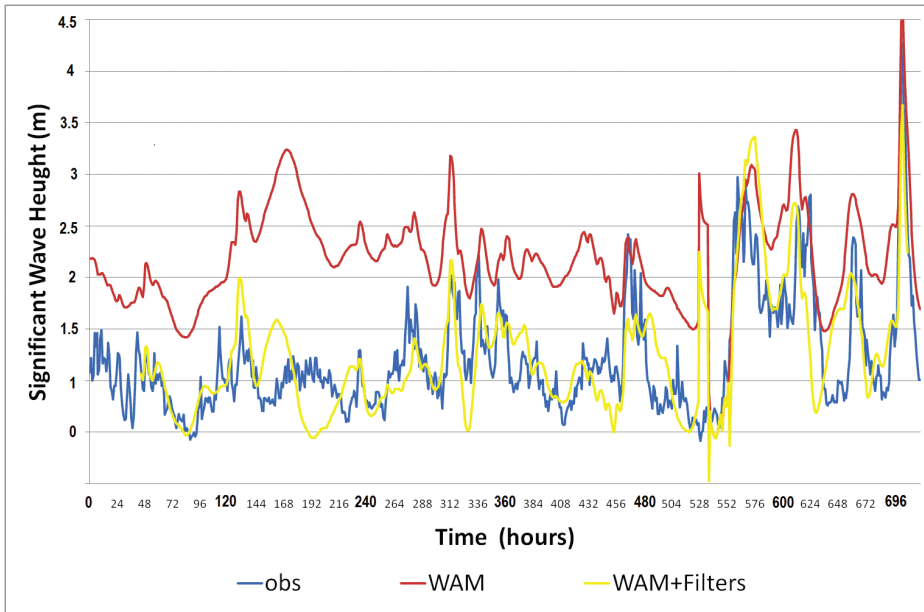
Fig 9: WAM direct outputs, KZ+Kalman improved forecasts and the corresponding observations from buoy C

Fig 10: WAM direct outputs, KZ+Kalman improved forecasts and the corresponding observations from buoy D
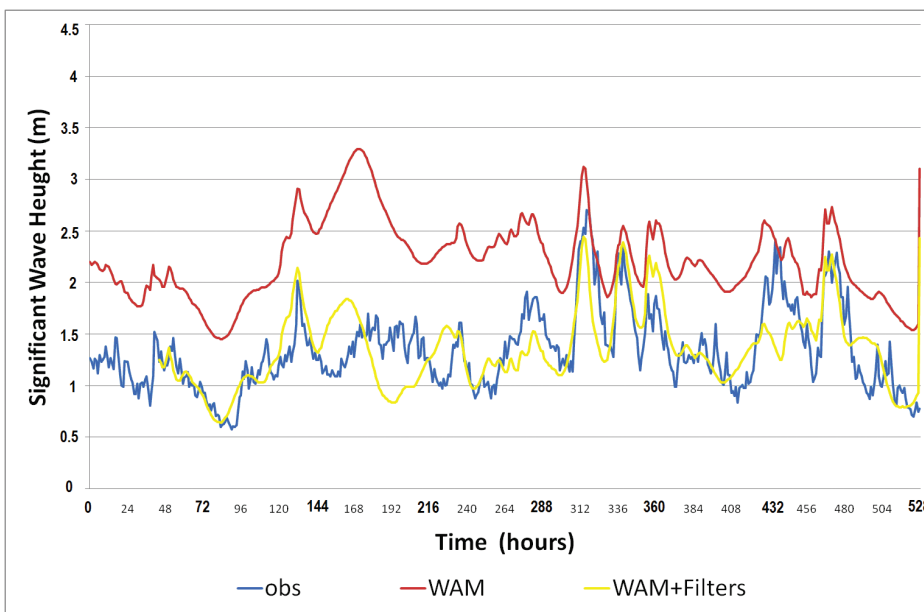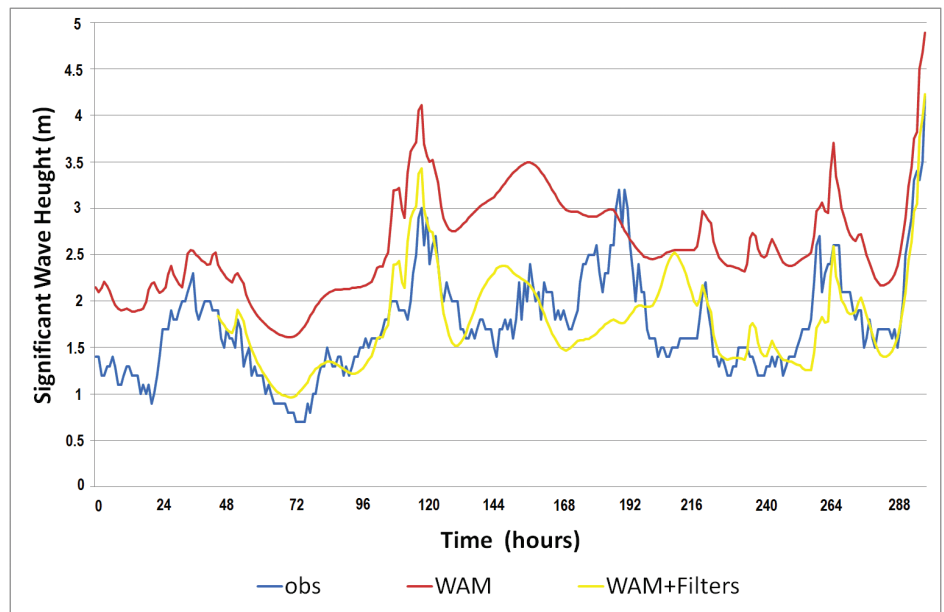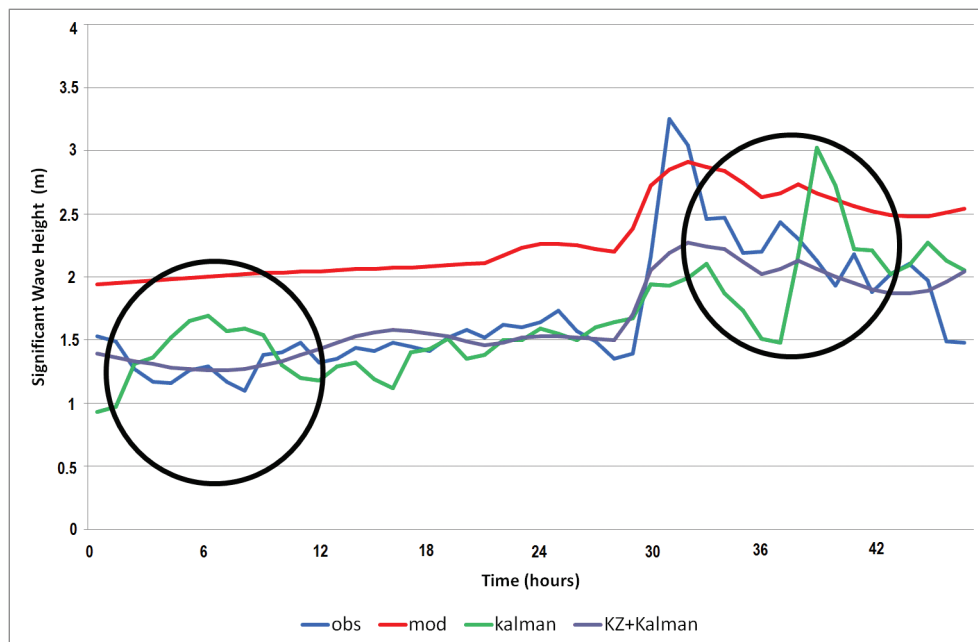

Fig 11: WAM direct outputs, KZ+Kalman improved forecasts and the corresponding observations from buoy F

Fig 12: WAM direct outputs (red line), Kalman filtered forecast (green line) and KZ+Kalman filtered forecasts (purple line) against the corresponding observations (blue line) from buoy A

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