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Super-ensemble techniques applied to wave forecast: performance and limitations

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Abstract

Nowadays, several operational forecasts of surface gravity waves are available for a same region through different forecasting systems. However, their results may considerably diverge, and choosing one single forecasting system among them is not an easy task. A recently developed approach consists in merging different forecasts and past observations into a single multi-model prediction system, called the super-ensemble. First implemented in meteorology, the method has also already been tested with success in oceanography for determining temperature, acoustic properties or surface drift. During the DART06 campaigns organized by the NURC, four wave forecasting systems were simultaneously run in the Adriatic Sea, while significant wave height was measured at six stations and along the tracks of two remote sensors, hence offering an opportunity to evaluate the skills of the super-ensemble techniques. The improvement shown during both the learning and testing periods was essentially due to a bias reduction, though the correlation was also increased. The possibility of extrapolating locally obtained results in the whole domain of interest was assessed against satellite observations. Though definitive conclusions can not be drawn from these experiments, the results open the door for further investigations.

1 Introduction

Wave models have come to a mature stage in the last decades. Although there are still debated issues – e.g. wave generation by wind, hypothesis of linearity, numerical implementation of non-linear wave-wave interactions, dissipation by whitecapping, etc., see The WISE Group (2007) for a review – the performance of such models has greatly improved. Part of this improvement is directly associated to the better representation of the forcing wind fields. However, inclusion of new physical features and refinement of others also play an important role. Thus, according to its atmospheric forcings and to the implemented physics, each wave forecasting system has its own strength and weakness. Therefore, a combination of several models outputs may be expected to yield better results. This is the underlying idea of the super-ensemble (SE)

techniques, which aim at improving forecasts by optimally combining different models, making use of past data.

SE techniques were first applied in meteorology to improve weather and seasonal climate forecasts (Krishnamurti et al., 2000b). Then tropical precipitation forecasts (Krishnamurti et al., 2000a) and tracking of tropical cyclones in the Pacific (Kumar et al., 2003) also benefited from the SE. Along the last few years, the method has been further investigated with dynamical linear models, from the Kalman Filter (Shin and Krishnamurti, 2003a) to probabilistic approaches (Shin and Krishnamurti, 2003b) for short- to medium-range precipitation forecasts using satellite products. In oceanography, it has been shown that the prediction of temperature (Logutov and Robinson, 2005; Rixen et al., 2009) or acoustic properties (Rixen and Ferreira-Coelho, 2006) in the water column could also be improved by using multi-model statistics. More recently, Rixen and Ferreira-Coelho (2007) introduced the hyper-ensemble, a SE combining models of different nature, to improve surface drift prediction; a method also tested in Vandenbulcke et al. (2009).

Operational wave forecasting systems are now spreading worldwide. In general, wave forecasts are required for the monitoring and the prevention of storm surges and coastal hazards, for offshore industry purposes, for the optimization of shipping routes, for tourism, surfers, etc. Wave modeling is crucial for the description of near-shore dynamics, and it is also increasingly advised for a coherent description of the upper ocean hydrodynamics (Ardhuin et al., 2005). This proliferation of forecasting systems gives the formidable chance to have several of them running over the same region with prompt availability, providing the necessary set of outputs to be used in SE techniques.

The Adriatic Sea is a semi-enclosed basin surrounded by a complex topography, which plays a major role when interacting with the atmospheric boundary layer. It results, for instance, in wind deflection due to mountain blockage or generation of downslope winds (i.e. the northeasterly Bora wind). For this reason, accurate representation of the orography is required. Indeed, the performance of the models mostly relies on the correctness of the wind forcing. Signell et al. (2005) have shown that the use of regional atmospheric models with a very high horizontal resolution (less than 10 km) can improve the performance of the induced wave field, reducing the

amplitude response error by a factor of two or more, compared to the case of wind provided by coarse resolution models. Dykes et al. (2009) also have shown that using higher-resolution orography allows to decrease the underestimation bias of the 10-m wind field, but not to decrease correspondingly the underestimation bias of the significant wave height (SWH). While this is mostly true for the northern part of the sea, Pasarić et al. (2007, 2009) have observed that the horizontal resolution of the atmospheric model also affects the resulting modeled wind field in the southern Adriatic Sea, and thus possibly the wave field.

The purpose of the present study is to examine the SE forecasting skills of the SWH at six different locations in the Adriatic Sea during two sea trials. Though posterior to the cruises, this work has been realized with the operational context kept in mind, i.e. working only with models available in real time and reducing to the minimum the computational cost.

The paper is organized as follows: in Sect. 2 we present the data and the four forecasting systems SWAN ARPA, SWAN NRL, WAM ATHENS and WAM ISMAR. The SE theoretical background is introduced in Sect. 3 with an overview of each scheme used in this paper: the Ensemble Mean, the Linear Combination and the Kalman Filter, as well as their respective unbiased versions. The application to wave forecast is described in Sect. 4, and conclusions are drawn in Sect. 5.

2 Data and forecasting systems

The *Dynamics of the Adriatic in Real-Time 2006* (DART06) campaigns, which took place during Spring and Summer, were coordinated by the NATO Undersea Research Centre (NURC) and generally dedicated to rapid environmental assessment capability. A considerable amount of resources and people were involved in the deployment of numerous instruments, in the real-time forecast of meteorological, hydrodynamical and wave models, in the coordination of communications, in the treatment of satellite imagery, etc. However, we confine ourselves in presenting data and modeling systems relevant to our application of the SE techniques to wave forecast.

2.1 Data

Wave characteristics can be measured in situ or via satellite-borne remote-sensors (Stewart, 1980; Hwang et al., 1998). The instruments used in the first approach include pressure gauges, accelerometers and bottom mounted acoustic Doppler current profilers (ADCP). The second approach includes high-frequency radar altimetry, synthetic aperture radar, scatterometry and photography.

During and in between both DART06 campaigns, ADCP, which were installed by the Naval Research Laboratory (NRL), combined measurements of orbital velocities of waves, acoustic tracking of the sea surface, and pressure fluctuations in order to produce estimates of the surface gravity wave parameters and spectra (Strong et al., 2000). Since pressure measurement quality becomes questionable as depth increases (D. W. Wang, personal communication, 2007), only measurements from three stations in shallow waters were used for this work. Moorings located at GS1 (41°58.21' N, 15°54.54' E), GS2 (42°0.95' N; 15°55.15' E) and A20 (41°46.20' N; 16°16.80' E) provided us with time series ($\Delta T = 6$ h or 8 h) of the SWH. In addition, high temporal resolution data ($\Delta T = 30$ min) from three stations of the Rete Ondametrica Nazionale (RON), located at Ancona (43°49.78' N, 13°42.85' E), Monopoli (40°58.50' N, 17°22.60' E) and Ortona (42°24.90' N, 14°30.33' E), were also available. These data are courtesy of the Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA).

In order to test the spatial extension of our methods over the whole Adriatic basin, we also consider satellite-borne altimetry data from ENVISAT of the European Space Agency, and JASON-1 of the National Aeronautics and Space Administration (NASA) and the Centre Nationale d'Études Spatiales (CNES). The location of the six stations and both satellites tracks over the region are shown in Fig. 1.

2.2 Wave forecasting systems

In early wave models based on the action balance equation, physical processes were not properly represented. First generation wave models assumed that wave components suddenly stopped growing as soon as they reached an assumed universal upper limit of the spectral density. These

models did not include a non-linear transfer term. Second generation wave models tried to remedy this situation by parameterizing the non-linear transfer of wave energy through the redistribution of energy over frequencies, according to a reference spectrum. Yet, these models were still unable to properly simulate waves generated by rapidly changing wind fields, such as hurricanes or intense cyclones. Present wave models belong to the third generation: they calculate the evolution of the wave field on a purely physical basis, without any parameterization or a priori assumption on the shape of the wave spectrum. Two well known examples of third generation wave models are employed by the forecasting systems used in this work: WAM (WAVE Model by WAMDI Group, 1988) and SWAN (Simulating WAVes Nearshore by Booij et al., 1999).

In the particular case of the DART06 campaigns, two implementations of WAM were run, one at the University of Athens (Greece) and the other at the Institute of Marine Sciences of the Italian National Research Council (Italy), as well as two implementations of SWAN, one at the Servizio Idro-Meteo-Clima ARPA-SIMC of the Emilia Romagna region (Italy), and the other at the NRL in Stennis Space Center (USA). The details regarding the implementation of the wave forecast systems correspond to the specific products used for this study, their present characteristics may differ.

2.3 WAM

The WAVE Model was originally designed for modeling waves in the deep ocean or in intermediate depth water. However, in the course of time it has been adapted for simulations in shallow water by the use of a shallow-water phase speed in the expressions of wind input, a depth dependent scaling of the quadruplet wave-wave interactions, a reformulation of whitecapping in terms of wave number rather than frequency and the addition of bottom dissipation. WAM was the first wave model to use the discrete interaction approximation to calculate non-linear transfers of energy by quadruplet wave-wave interactions. Besides, it accounts for the effects of shoaling and refraction due to spatial variations in bottom and current and can also simulate blocking and reflection when waves propagate against the current. Still, WAM cannot be realistically applied to coastal regions with water depths less than 20-30 m. Regarding the numerics, WAM uses a

different discretization scheme for the integration of the source functions and the calculation of the advective terms of the action balance equation: the source functions are computed with a fully implicit scheme, while two alternative explicit propagation schemes are implemented to calculate the advection terms, a first-order upwind scheme or a second-order leapfrog scheme.

WAM ATHENS (WA)

This Adriatic Sea wave forecast system¹ uses a modified version of WAM (cycle 4) to get a more reliable wave forecast in coastal areas by taking into account, among other processes, depth induced wave breaking. The model is forced by the SKIRON weather forecast system², which runs twice a day and provides a 72-h forecast with hourly output over a computational grid of $1/10^\circ$. The Adriatic Sea wave model is nested into a Mediterranean and Black Sea wave model, which provides it with wave spectra at its open boundary. It covers the geographical area between $12\text{--}21^\circ$ E and $39\text{--}46^\circ$ N with a spatial resolution of $1/20^\circ$. The wave forecast system issues a 2.5-day forecast of significant wave height and mean wave direction at a time interval of 3 h.

WAM ISMAR (WI)

This Adriatic Sea wave forecast system³ uses as forcings the wind analysis and forecast fields from the European Centre for Medium-range Weather Forecast (ECMWF⁴). Because the resolution of this global model is relatively coarse (about 39 km), the wind speeds are enhanced by coefficients previously deduced by long-term comparison between model outputs and scatterometer wind speeds, and also on the base of the wave model results compared to altimeter and buoy data (Cavaleri and Bertotti, 1997; Cavaleri and Sclavo, 2006). The wave model covers the geographical area between $12\text{--}20^\circ$ E and $40\text{--}46^\circ$ N with a spatial resolution of $1/12^\circ$. The

¹<http://forecast.uoa.gr/waminfo.php>

²<http://forecast.uoa.gr/forecastnewinfo.php>

³http://ricerca.ismar.cnr.it/MODELLI/ONDE_MED_ITALIA/page-html/nettuno/NE

⁴<http://www.ecmwf.int/research/ifsdocs/CY31r1/WAVES/IFSPart7.pdf>

standard output time interval is 3 h. Daily, a 1-day analysis and a 3-day forecast of the wave field are released.

2.4 SWAN

The Simulating WAVes Nearshore model was developed to compute short crested waves in coastal regions with shallow water and ambient currents. Two rather important processes in coastal environment were added with respect to WAM: depth induced wave breaking and triad wave-wave interactions. Similarly to WAM, SWAN incorporates the effects of shoaling, refraction, blocking and reflection due to currents and variations in bathymetry. Concerning its numerical implementation, SWAN uses an implicit propagation scheme based on finite differences, which is unconditionally stable and more suited for small-scale, shallow-water and high-resolution computations. This scheme allows a relatively large time steps because it is only limited by accuracy. The drawback of this implicit scheme is that it is fairly diffusive for long propagation distances (oceanic scales).

SWAN ARPA (SA)

This operational implementation of SWAN⁵ in the Adriatic Sea is driven by wind fields provided by COSMO-I7⁶, a 7-km resolution non-hydrostatic numerical weather prediction model based on Lokal Modell (Steppeler et al., 2003). The wave forecast system covers the area between 12–20° E and 40–46° N, with a spatial resolution of 1/12°. The output time interval is 3 h. Each simulation starts with a *hotstart field*, an initial wave field derived from a previous run, and is run twice a day, respectively at 00:00 and at 12:00 UTC, with a forecast range of 48 hours (Valentini et al., 2007).

⁵<http://www.arpa.emr.it/sim/?mare&idlivello=72>

⁶<http://www.cosmo-model.org>

SWAN NRL (SN)

This operational version of SWAN in the Adriatic Sea is forced by wind fields from the Aire Limitée Adaptation Dynamique INitialisation (ALADIN) model⁷, a limited area, non-hydrostatic, numerical weather prediction model nested in Action de Recherche Petite Échelle Grande Échelle (ARPEGE) from Météo France. The atmospheric model was run by the Croatian Meteorological and Hydrological Service and provided a 48-h forecast of the wind field. The wave forecast system covers the geographical area between 11–20° E and 40–47° N with a spatial resolution of $1/20^\circ$. It is run twice a day with a 48-h forecast range and an output time interval of 1 h.

In Table 1 we summarize the systems configuration used for this study. In Figs. 2 and 3, we present snapshots of the wave fields produced by the four forecasting systems for 23 March 2006 at 00:00 UTC and 2 August 2006 at 18:00 UTC, in respectively strong- and weak-wind situations. Though the simulations present some similar patterns, discrepancies also exist, leaving room for the application of multi-model methods.

3 Methods

The general procedure of the SE techniques consists of two steps: the learning and the testing periods. The first one aims to determine the weighting of the models by using past information, this is the training phase. At its end, the evaluated weights are frozen and the second one starts. From this moment on, no additional observation is considered and the forecasting phase simply consists in linearly combining the models outputs.

We present the SE techniques used in this work by increasing complexity order. Notation conventions are the following: subscript i denotes the model index and j the time index, M the number of models, N_l the number of time steps during the learning period and N_t the number of time steps during the testing period. The data are represented by y and the model values at the same location by x . The prediction produced by the method during the learning

⁷<http://www.meteo.hr/>

period is the hindcast, denoted by h , whereas the one produced during the testing period is the forecast, denoted by f . Acronym of the techniques are written as superscripts, hence the hindcast produced thanks to the Kalman filter is denoted by h^{KF} .

Ensemble mean (EM)

This very simple method consists in taking, at each time step, the average value of the models for both the hindcast (Eq. 1) and the forecast (Eq. 2).

$$h_j^{\text{EM}} = \frac{1}{M} \sum_{i=1}^M x_{j,i}, \quad j = 1, \dots, N_l \quad (1)$$

$$f_j^{\text{EM}} = \frac{1}{M} \sum_{i=1}^M x_{j,i}, \quad j = N_l + 1, \dots, N_l + N_t \quad (2)$$

In opposition to the EM, the four following techniques all use the data during the learning period to improve the model outputs.

Unbiased ensemble mean (UEM)

This slightly more elaborated method has the advantage of removing the hindcast bias and, as a consequence, potentially reducing the forecast bias. The unbiased hindcast is obtained by adding the models anomalies $x'_{j,i}$, with respect to the time-averaged models outputs during the learning period \bar{x}_i , to the time-averaged observations during the same period \bar{y} (Eq. 3). The forecast is computed in the same way (Eq. 4).

$$h_j^{\text{UEM}} = \bar{y} + \frac{1}{M} \sum_{i=1}^M x'_{j,i}, \quad j = 1, \dots, N_l \quad (3)$$

$$f_j^{\text{UEM}} = \bar{y} + \frac{1}{M} \sum_{i=1}^M x'_{j,i}, \quad j = N_l + 1, \dots, N_l + N_t \quad (4)$$

where $\bar{y} = \frac{1}{N_l} \sum_{j=1}^{N_l} y_j$ and $x'_{j,i} = x_{j,i} - \bar{x}_i$ with $\bar{x}_i = \frac{1}{N_l} \sum_{j=1}^{N_l} x_{j,i}$.

Linear combination (LC)

This method illustrates particularly well the SE concept and can be seen as an improved version of the EM, with weights w_i depending on the performance of the models over the learning period. These are determined by minimizing Eq. (5) in the least-square sense and then used to compute both the hindcast (Eq. 6) and the forecast (Eq. 7).

$$\begin{bmatrix} x_{1,1} & \cdots & x_{1,M} \\ \vdots & x_{j,i} & \vdots \\ x_{N_l,1} & \cdots & x_{N_l,M} \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_M \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_{N_l} \end{bmatrix} \quad (5)$$

$$h_j^{\text{LC}} = \sum_{i=1}^M x_{j,i} w_i, \quad j = 1, \dots, N_l \quad (6)$$

$$f_j^{\text{LC}} = \sum_{i=1}^M x_{j,i} w_i, \quad j = N_l + 1, \dots, N_l + N_t \quad (7)$$

Please note that there is no restrictive hypothesis about weights, i.e. they can be negative, in case there are colinearities between the model forecasts, and their sum does not have to be equal to one. It is also worth mentioning that a too short training period, i.e. if there are less measurements than the number of models, leads to an under-determined system of equations to be solved.

Unbiased linear combination (ULC)

This method differs from the previous one by the use of an additional pseudo-model, which gives a constant output. This independent term allows the hindcast to be unbiased in the least-square sense. The equation to minimize is then

$$\begin{bmatrix} x_{1,1} & \cdots & x_{1,M} & 1 \\ \vdots & x_{j,i} & \vdots & \vdots \\ x_{N_l,1} & \cdots & x_{N_l,M} & 1 \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_{M+1} \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_{N_l} \end{bmatrix}. \quad (8)$$

Hindcast and forecast equations are similar to the LC equations, except that the linear combination includes one more term. This technique may also be used with only one model, and in this case it corresponds to a simple, but usually very beneficial, bias correction.

Kalman filter (KF)

The Kalman filter uses the same approach as the LC but propagates dynamically the weights and their covariance matrix during the learning period, which allows a better consideration of the most recent observations. As the way weights should evolve in time is not known a priori, and as the persistence of the best fit seems to be the best possible guess, the identity matrix is chosen as model operator. During the learning period, forecast is performed as follows:

$$\mathbf{w}_j^f = \mathbf{I}\mathbf{w}_{j-1}^a, \quad j = 1, \dots, N_l, \quad (9)$$

$$\mathbf{P}_j^f = \mathbf{I}\mathbf{P}_{j-1}^a\mathbf{I}^T + \mathbf{Q}_{j-1}, \quad j = 1, \dots, N_l. \quad (10)$$

Superscript f denotes the forecast, or propagation, of the weights during the learning period, \mathbf{I} is the identity matrix ($M \times M$), \mathbf{w}_j the vector of the weights at time j ($M \times 1$), \mathbf{P}_j the weight error covariance matrix at time j ($M \times M$), and \mathbf{Q}_j the model error covariance matrix ($M \times M$). Initially \mathbf{P} and \mathbf{Q} are both diagonal, but then some out diagonal elements can develop in the first, whereas the second remains diagonal all along the process. At the analysis step, the state vector and the state covariance matrix are *corrected* by adding to their prediction a component that

takes into account the uncertainties on the model and on the observation, as shown in Eqs. (11) and (12).

$$\mathbf{w}_j^a = \mathbf{w}_j^f + \mathbf{K}_j(y_j - \mathbf{x}_j \mathbf{w}_j^f), \quad j = 1, \dots, N_l, \quad (11)$$

$$\mathbf{P}_j^a = \mathbf{P}_j^f + \mathbf{K}_j \mathbf{x}_j \mathbf{P}_j^f, \quad j = 1, \dots, N_l. \quad (12)$$

Superscript a denotes the analysis, or correction, of the weights once new data are assimilated, \mathbf{x}_j is the equivalent of the observation operator ($1 \times M$) of the KF classical theory and can be interpreted as the operator that maps the weight space to the observation space, \mathbf{R}_j is the observation covariance matrix at time j , a scalar, and $\mathbf{K}_j = \mathbf{P}_j^f \mathbf{x}_j^T (\mathbf{x}_j \mathbf{P}_j^f \mathbf{x}_j^T + \mathbf{R}_j)^{-1}$ is the Kalman gain matrix at time j ($M \times 1$). Finally, hindcast and forecast are computed as usual

$$h_j^{KF} = \sum_{i=1}^M x_{j,i} w_i, \quad j = 1, \dots, N_l, \quad (13)$$

$$f_j^{KF} = \sum_{i=1}^M x_{j,i} w_i, \quad j = N_l + 1, \dots, N_l + N_t. \quad (14)$$

Unbiased Kalman filter (UKF)

Similarly to the LC, we can add a pseudo-model predicting a constant value in order to reduce a possible bias. Equations are similar to those presented above.

4 Results

The SE techniques have been applied to the data set and model outputs collected during both DART06 campaigns, i.e. from 15 to 31 March 2006 and from 1 August to 15 September 2006. Though this work has been realized afterwards, we decided to place ourselves in *operational*

conditions, and thus we only considered model outputs available during the cruises: the absence of a model during either the entire or a part of the learning period or during the testing period, naturally prevents its use by the SE techniques. In order to compare model outputs with observations, we performed spatial (inverse distance) and temporal (linear) interpolations. The time series of the concatenated daily first 24-h of forecast of each model are presented in Figs. 4 and 5.

In order to test and validate the methods, the following procedure is applied: at each station and for each campaign, we consider the time series for which the four forecasting systems outputs are available. Then, we split them into overlapping bins of 2-day every 6 h, in order to virtually increase our dataset. The first half of each bin constitutes the learning period, the second half constitutes the testing period. Since three models provide a forecast starting at midnight of each day, while the 4th one provides a forecast starting at noon of each day, a 12-h time-shift exists in the forecast range between them. Hence, in our experiments, at midnight of a hypothetical day 4, the 24-h learning period consists of the 0-24 h forecast of day 3 for SA, SN and WA, while for WI it consists of the second 12-h range of forecast of day 2 followed by the first 12 h of forecast of day 3. The corresponding 24-h testing period consists of the 0-24 h forecast of day 4 for SA, SN and WA, while for WI it consists of the second 12-h range of forecast of day 3, followed by the first 12 h of forecast of day 4. For both the learning and testing periods the bias, the linear correlation coefficient and the root-mean-square difference (RMSD) of the forecasting systems outputs, as well as of the SE techniques outputs, are computed. The different acronyms used for the tested schemes are recalled in Table 2 and Fig. 6 presents the average of the statistics over all stations and both campaigns.

Let us first take a look at the bias. We observe that the four forecasting systems (the first four blue bars) have a similar bias at hindcast and forecast, which indicates that if we are able to get rid of the bias during the hindcast, we should reduce it during the forecast too. We also note that the UEM and the ULC present no bias at hindcast, whereas the UKF does. This is due to the fact that the initial vector of weights in the KF and UKF approaches is set to $1/M$ (respectively $1/(M + 1)$) and that a 24-h learning period is not necessarily long enough for the adjustment of the filter, especially at the GS1 and GS2 stations where we only have 3 or 4 measurements

per day. At forecast, the KF presents the lowest bias. Regarding the correlation, the similitude between the KF and the observations is no worse than the one between the forecasting systems and the data. As for the RMSD, though the LC and the ULC reduce it more at hindcast, at forecast we see that the dynamical methods perform better. This is due to the higher importance of the most recent observations.

Due to the small number of measurements during a 1-day learning period, at least at the GS1, GS2 and A20 stations, previous conclusions are somewhat biased. Though they should not be discarded, in order to improve the understanding of the general behavior of our methods, we also present the results relative to a 2-day learning period and a 2-day testing period at Ortona. For this experiment the learning period consists of two successive one day learning periods, as presented previously, whereas the testing period consists of the 48-h forecast of the considered day for SA, SN and WA, and of the second 12-h range of forecast of the previous day followed by the first 36 h of forecast of the considered day for WI. As for the bias, we clearly see in Fig. 7 the benefit of all SE techniques except in the case of the EM. They reduce or remove the bias at hindcast, and also improve the performance at forecast, in the case of the dynamical methods. Similar conclusions can be drawn for the correlation at hindcast, but at forecast the SE techniques perform neither better nor worse than the forecasting systems. Finally, the RMSD also decreased at hindcast along with the method's complexity, but at forecast only the one corresponding to the KF is slightly lower than the one of the best forecasting system.

Without surprise, results differ from one station to another and also depend on the duration of the learning and testing periods. Nevertheless, our numerous experiments generally confirmed the conclusion that the SE based on the KF outperforms, or at least equally performs as, any of the forecasting systems at forecast.

Even if the SE techniques performance is promising, limitations quickly appear:

- an abrupt change in the time series of the models outputs, e.g. due to a model re-initialization, can obviously yield very poor results;
- without constraint on the weights, negative values of significant wave height could be predicted, yet, with a long enough training period and a short enough testing period we should avoid these unfortunate forecasts;

- as the performance of models can vary in space, their optimal combination may change as well, which means that the spatial extrapolation is conceivable but not direct.

In order to illustrate this last point, we present in Fig. 8 the results obtained at the Ortona buoy by using weights computed at the Monopoli buoy. We can see that the relative importance of each model in both stations is rather similar: the largest weight is given to WAM ISMAR, a negative one to WAM ATHENS and positive but lower ones to SWAN NRL and SWAN ARPA. Both forecasts present a similar pattern, but the one from the locally trained filter is closer to the observations, especially during the first 24 h.

Figure 9 shows the results obtained with weights computed at the Monopoli, A20 and GS1 stations, along the most southern JASON-1 track shown in Fig. 1. For this test case and for clarity's sake, we only use two models for the combination. We notice that the forecast computed with a filter trained at Monopoli, which is the closest station to the western part of the JASON-1 track, almost sticks to the forecast of one of the models and only slightly reduces the RMSD with respect to this model. The forecast computed from A20, which is the station just at north of the track, decreases the RMSD, especially on the western side of the Adriatic Sea; on the eastern part predictions and actual values are anti-correlated. The forecast computed from GS1 fails entirely at representing the significant wave height values. Finally, similar conclusions were drawn from experiments along different other tracks.

5 Conclusions

In the framework of the DART06 campaigns, super-ensemble techniques have been implemented and successfully applied to wave forecasting. We have shown that (i) at hindcast several of these methods perform better than any single forecasting system and (ii) at forecast the super-ensemble technique based on the Kalman filter is the most suitable one. In an operational context, the method has proven to be appropriate for local improvements.

We have also tested the ability of one SE technique to be extended spatially by using weights determined through a training of the filter at one station, at another or several others. Experiments discourage the extrapolation of local results to the whole domain of interest. However,

we think that a more elaborated strategy involving a larger set of observation sites could lead to a global improvement of the forecast.

Eventually, we wish to develop a SE technique with an increased number of weights per model, which would allow an automatic selection of the best features represented by the available models, and would combine their outputs to create a physically-consistent forecast field presenting a lower RMS error than any individual model. In order to reach this goal the addition of a priori and a posteriori constraints is essential and will require some more effort.

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This is MARE contribution 187.

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Table 1. Main specificities of the forecasting systems.

Wave forecasting systems				
Name	Abbreviation	$\Delta x = \Delta y$	Forcing system	Output time interval
SWAN ARPA	SA	1/12°	COSMO-I7	3 h
SWAN NRL	SN	1/20°	ALADIN	1 h
WAM ATHENS	WA	1/20°	SKIRON	3 h
WAM ISMAR	WI	1/12°	ECMWF	3 h

Table 2. Acronyms of the used SE techniques.

Tested SE schemes	
EM	Ensemble Mean
UEM	Unbiased Ensemble Mean
ELC	Ensemble Linear Combination
UELC	Unbiased Ensemble Linear Combination
KF	Kalman Filter
UKF	Unbiased Kalman Filter

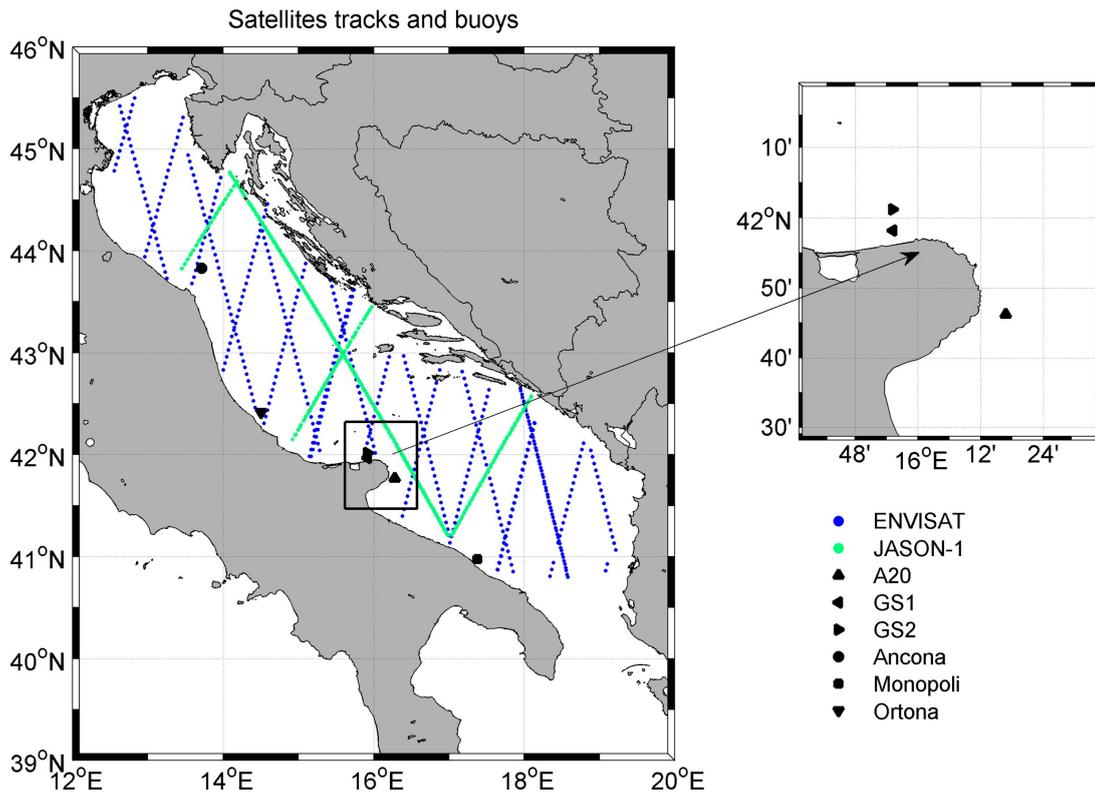


Fig. 1. Location of the buoys and satellite tracks available during the DART06 campaigns.

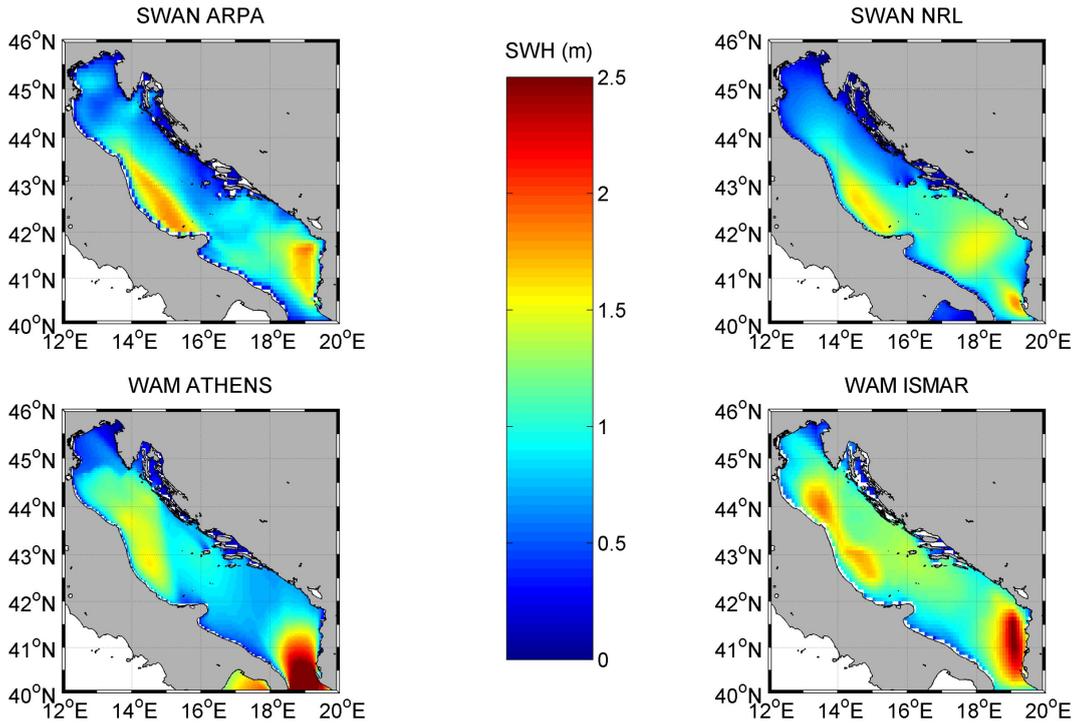


Fig. 2. Wave forecasts for 23 March 2006 at 00:00 UTC in the Adriatic Sea.

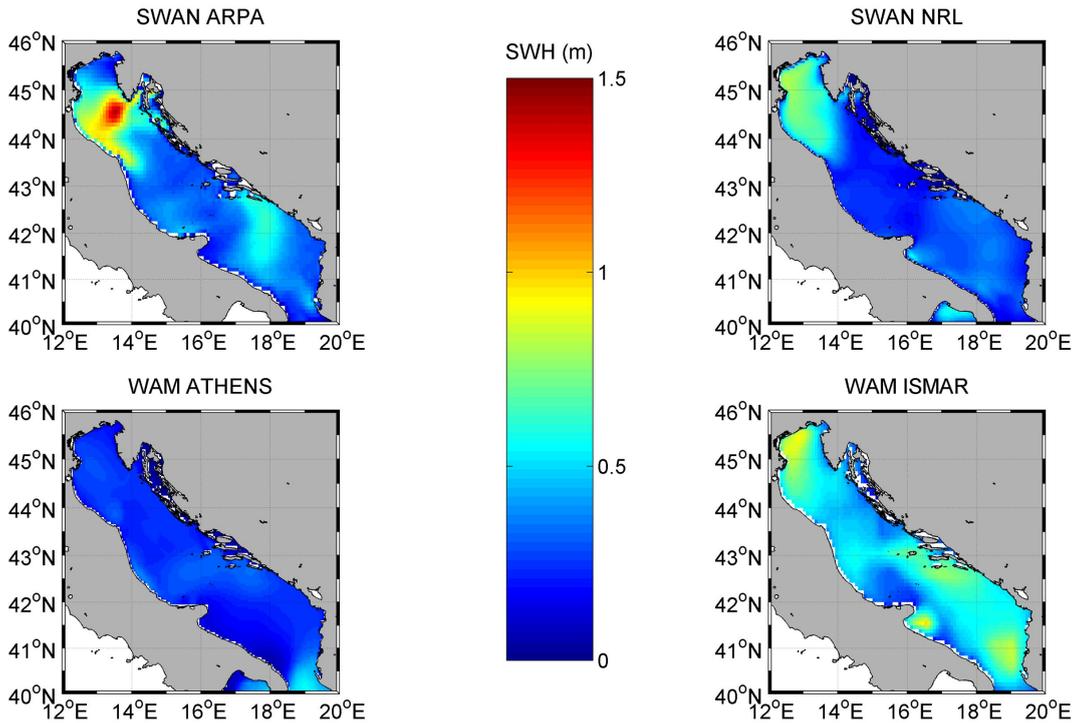


Fig. 3. Wave forecasts for 2 August 2006 at 18:00 UTC in the Adriatic Sea.

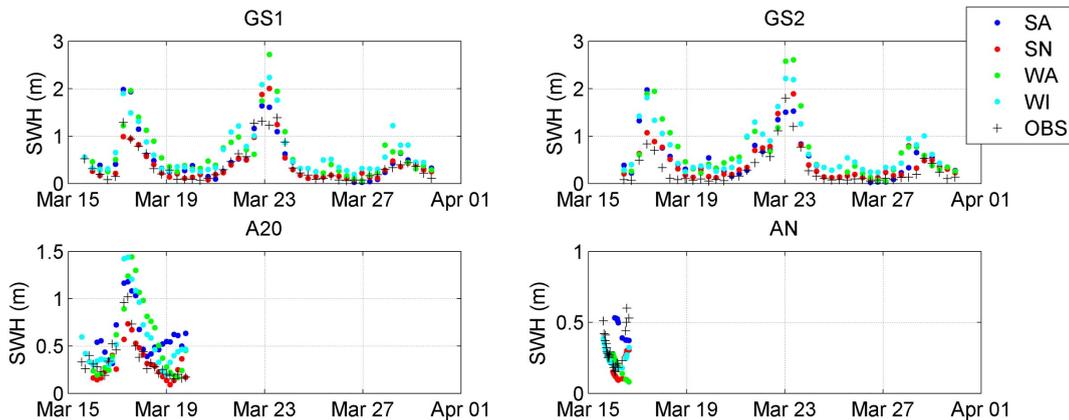


Fig. 4. Data at the survey stations and interpolated models outputs during DART06A.

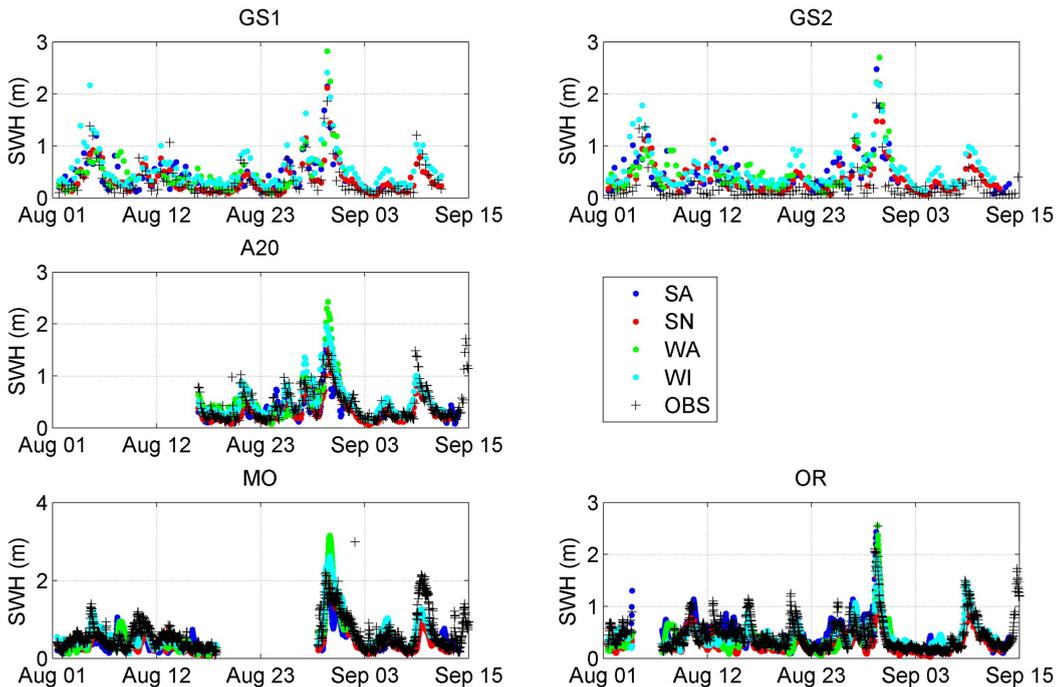


Fig. 5. Data at the survey stations and interpolated models outputs during DART06B.

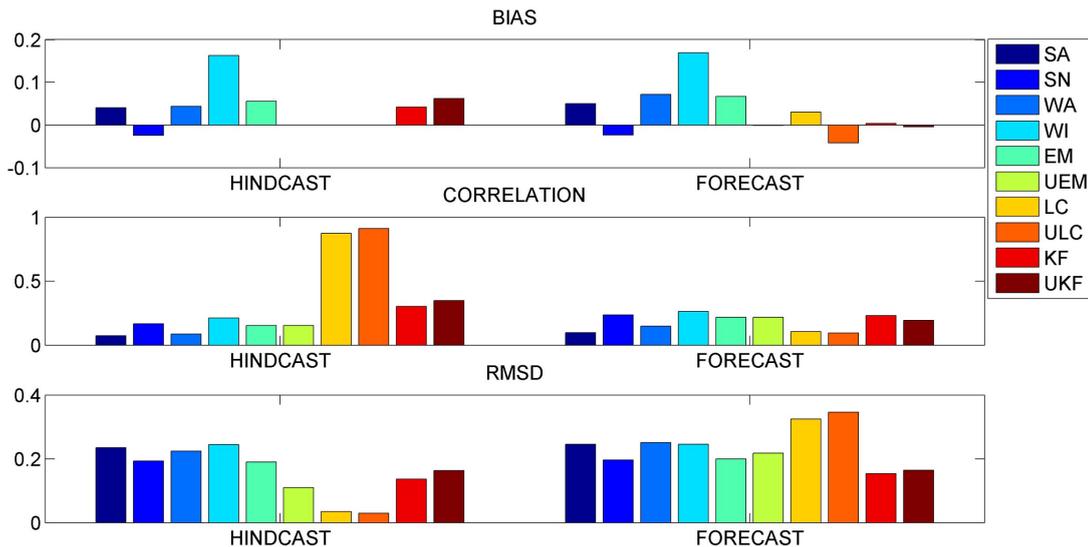


Fig. 6. Hindcast and forecast statistics of the different forecast systems and the tested SE techniques, averaged over the two campaigns and all stations, using a 1-day learning period and a 1-day testing period.

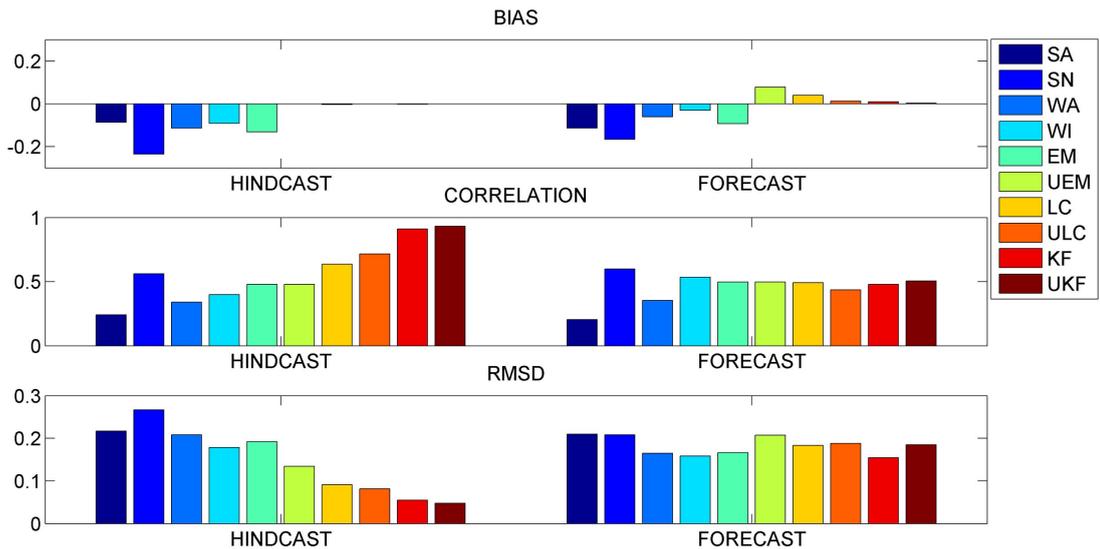


Fig. 7. Hindcast and forecast statistics of the different forecasting systems and the tested SE techniques, averaged over a 1-week period at the Ortona station, using a 2-day learning period and a 2-day testing period.

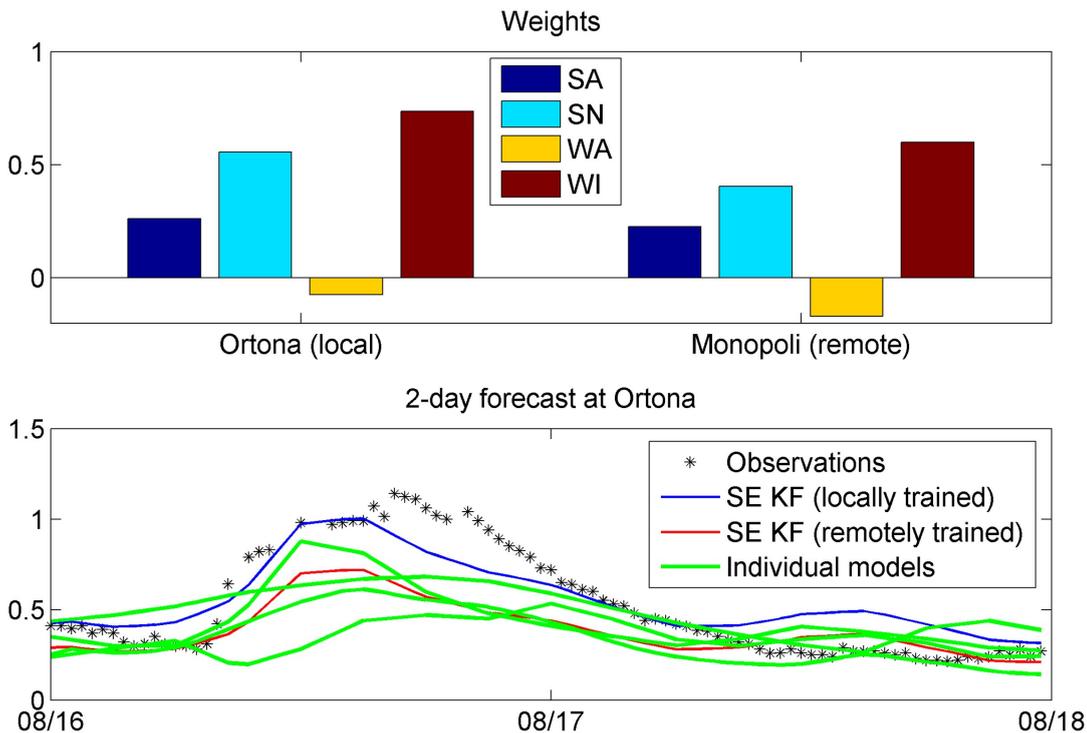


Fig. 8. Weights value computed at Monopoli and Ortona at the end of a 2-day hindcast (top panel) – Forecast of the individual models and the SE at Ortona with weights computed locally or remotely, i.e. at Monopoli (bottom panel).

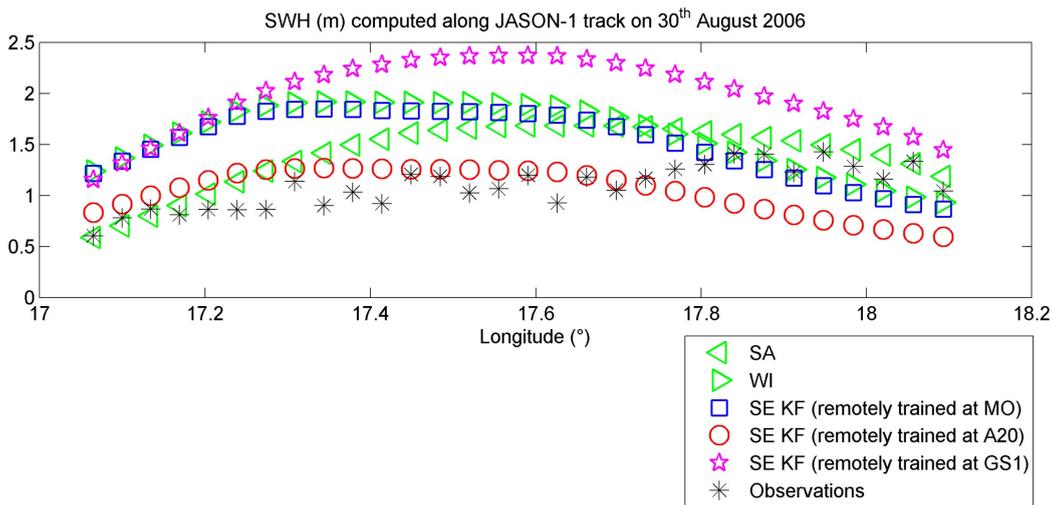


Fig. 9. Individual models and SE forecasts along a JASON-1 track during a strong-wind event.