Coastal Engineering xxx (2011) xxx–xxx

Contents lists available at ScienceDirect

Coastal Engineering

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

A hybrid efficient method to downscale wave climate to coastal areas

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A R T I C L E I N F O

Article history:
Received 9 December 2010
Received in revised form 20 April 2011
Accepted 2 May 2011
Available online xxxx

Keywords:
Dynamical downscaling
Maximum dissimilarity algorithm
Radial basis function
Reanalysis database
Statistical downscaling
Wave propagation

A B S T R A C T

Long-term time series of sea state parameters are required in different coastal engineering applications. In order to obtain wave data at shallow water and due to the scarcity of instrumental data, ocean wave reanalysis databases ought to be downscaled to increase the spatial resolution and simulate the wave transformation process. In this paper, a hybrid downscaling methodology to transfer wave climate to coastal areas has been developed combining a numerical wave model (dynamical downscaling) with mathematical tools (statistical downscaling). A maximum dissimilarity selection algorithm (MDA) is applied in order to obtain a representative subset of sea states in deep water areas. The reduced number of selected cases spans the marine climate variability, guaranteeing that all possible sea states are represented, capturing even the extreme events. These sea states are propagated using a state-of-the-art wave propagation model. The time series of the propagated sea state parameters at a particular location are reconstructed using a non-linear interpolation technique based on radial basis functions (RBFs), providing excellent results in a high dimensional space with scattered data as occurs in the cases selected with MDA. The numerical validation of the results confirms the ability of the developed methodology to reconstruct sea state time series in shallow water at a particular location and to estimate different spatial wave climate parameters with a considerable reduction in the computational effort.

1. Introduction

A number of engineering coastal applications (e.g. the design of a marine structure, the analysis of equilibrium beach planforms or the assessment of wave energy resources) require long-term time series of sea state parameters (e.g. to define the return level value of significant wave height, the mean wave energy direction) or a long-term database of spatial wave climate parameters (e.g. mean power to characterize the wave energy resources).

Buoy measurements are rarely available in the study area, the nearest buoy is usually located some kilometers from the point of interest, not being representative of the local wave climate. Even when such records are available, they usually are missing data and time series are not sufficiently long in order to correctly define the long-term distribution of different sea state parameters.

In recent years, many multidecadal numerical simulations (reanalysis or hindcasts) of ocean waves have been developed (e.g. Dodet et al., 2010; Pilar et al., 2008; Ratsimandresy et al., 2008; Uppala et al., 2005; Weisse et al., 2002) improving the knowledge of deep water or large-scale wave climate, especially at locations where instrumental data is not available. Although large-scale long-term reanalysis databases have a high spatial and temporal ~~(hourly)~~ resolution, the spatial data resolution is not usually enough for coastal applications, and wave transformation processes nearshore are not accounted for. The information offered by the wave models in an open area must be transferred to shallow water, increasing the spatial resolution (namely downscaling).

Three general approaches have been developed to downscale the large-scale information: A) A dynamical approach consisting of nesting higher resolution models that are able to model wave transformation processes (refraction, bottom friction, shoaling, diffraction, breaking) in shallow water. B) A statistical approach, in which an empirical relationship between an open ocean variable and a nearshore variable affected by the bottom effects is used to obtain reliable small-scale information for coastal environment. C) A hybrid approach which combines dynamical (numerical models) and statistical downscaling (usually an interpolation scheme) in order to reduce the computational effort.

In the dynamical approach (A) the directional spectra are propagated from deep ocean to shallow water by nesting a wave model for coastal areas used for wave transformation in the nearshore (Rusu et al., 2008). Regarding the statistical approach (B), artificial neural networks are widely applied to estimate sea state parameters in shallow water (Browne et al., 2007; Kalra et al., 2005). The common hybrid methodologies (C) are based on a transfer function (statistical downscaling) obtained by means of the numerical propagation of a number of sea state conditions (dynamical downscaling), see for

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0378-3839/$ – see front matter © 2011 Published by Elsevier B.V.
doi:10.1016/j.coastaleng.2011.05.007

instance Groeneweg et al. (2007) and Stansby et al. (2007). A different technique to obtain high resolution nearshore wave statistics is proposed by Galiskova and Weisse (2006). In this work, three different statistical models based on linear regression, canonical correlation analysis and analogs were built approximating the relation between instantaneous medium-scale wave fields from a hindcast database and dynamically obtained wave data in shallow water. Another statistical–dynamical approach is developed by Herman et al. (2009) using a combination of a numerical model, principal component analysis and a neural-network method.

The most accurate solution to solve this problem is the dynamical downscaling approach (A) but the computational time effort is usually impracticable. The statistical downscaling (B) only reproduces the wave parameters, usually the significant wave height, at a specific location in shallow water. Instrumental data is always required to validate the wave transference near the coast, independently of the approach, but in the case of statistical method, this data is necessary in the nearshore location in order to establish the statistical model. The transfer function of some hybrid methods (C) usually requires propagating (dynamical downscaling) a considerable number of sea states in order to represent the climate variability for deep water (Chini et al., 2010) or several years of dynamical downscaling to generate the statistical model and its validation (Galiskova and Weisse, 2006; Herman et al., 2009). On the other hand, these more sophisticated methods are able to reproduce spatial wave statistical parameters.

In this paper, a new hybrid methodology to downscale wave climate to coastal areas is proposed. The methodology is based on a reduced number of cases to be dynamically downscaled, while at the same time representative enough of the wave climate at deep water. The structure of time series of wave parameters at shallow water is reconstructed by the new developed methodology and the spatial wave statistical parameters are estimated with a considerable time reduction. Therefore, the long-term hourly wave reanalysis data at deep water is replaced by a small number of representative wave conditions; these cases are propagated using a state-of-the-art wave propagation model capable of simulating the most important wave transformation processes and finally, the complete offshore time series are transferred by means of an interpolation algorithm.

We describe the proposed methodology and the area of study for an application of the methodology in Section 2. The proposed methodology involves three steps: selection, propagation and time series reconstruction, described in Sections 3, 4 and 5, respectively. The validation of the methodology is detailed in Section 6. Finally, some conclusions are given in Section 7.

2. Proposed methodology

The proposed methodology for transferring wave climate from deep water to shallow water (or to downscale wave climate to coastal areas increasing the spatial resolution) consists of a dynamical downscaling of a representative subset of sea state conditions at deep water or open areas which are obtained using a statistical downscaling procedure. The methodology steps are: (a) definition of wave climate at deep water from historical reanalysis databases; (b) selection of a subset of sea states (open water conditions); (c) deep water-to-shallow water wave transformation of the most representative sea states using a wave propagation model; (d) reconstruction of the time series at shallow water using an interpolation scheme; (e) validation of the results usually using instrumental data; and (f) once the time series are defined in the nearshore points of interest, different statistical models can be applied to characterize the wave climate at shallow waters. A sketch of the methodology is shown in Fig. 1. The steps are explained in the following sections. Note that the proposed methodology can be applied to any area of study with

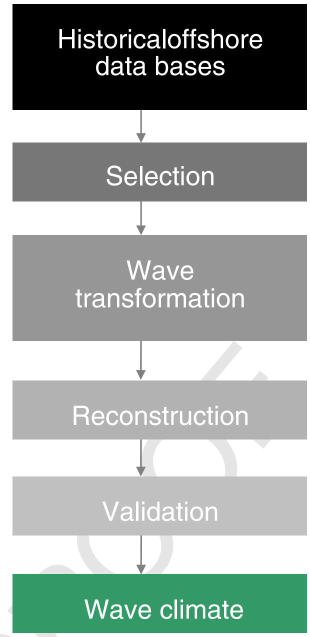

Fig. 1. Scheme of the methodology to transfer wave climate from deep water to shallow water.

different wave climate at deep water and different configurations of the bathymetry and coastal line.

A simple application is considered to show the proposed frame. The study area is located around the west coast of Spain (upper panel of Fig. 2). We use the wave reanalysis database GOW (Global Ocean Waves), developed by IH Cantabria, using WaveWatch III (Tolman, 1999) and forced by 10-m winds from NCEP/NCAR Reanalysis Project (Kalnay et al., 1996), with a spatial resolution of 1.9° and a 6-hourly temporal resolution. The temporal coverage spans 61 years (1948–2008) with an hourly resolution and a spatial resolution of $1° \times 1.5°$ at a global scale, and a resolution of $0.1° \times 0.1°$ along the Spanish coast. We consider one grid node of the GOW database to characterize the wave conditions at deep water, and one grid node of the NCEP/NCAR database to characterize the wind conditions. Each hourly wave data at deep water is defined by five parameters: significant wave height, H_s, peak period, T_p, mean direction, θ_m, wind velocity, W_{10} and wind direction, β_W at point PØ (lower left panel of Fig. 2). The objective of applying this methodology is to obtain the wave time series at shallow water (lower right panel of Fig. 2).

One year (2008) of the hourly time series of the GOW database and its corresponding wind conditions is dynamically downscaled (meaning $N = 8784$ numerical wave propagations) and downscaled by the proposed methodology (meaning M numerical propagations together with the statistical procedure). Several hypotheses are established in order to simplify the application: the wave boundary conditions are considered constant along the computational grid, 5 parameters (H_s, T_p, θ_m, W_{10} and β_w) are considered to define the uniform offshore boundary condition and the local wind-generated waves, a stationary version of the wave propagation model are adopted and a standard parameterization of the directional spectrum is used. Note that the aim of this work is to show the ability of the proposed methodology to reconstruct the time series of sea state parameters propagating only a reduced number of sea states. Therefore, the validation in this example consists of comparing the reconstructed wave time series by the numerical propagation of the selected cases (M) and one complete year of sea states (N) propagated numerically.

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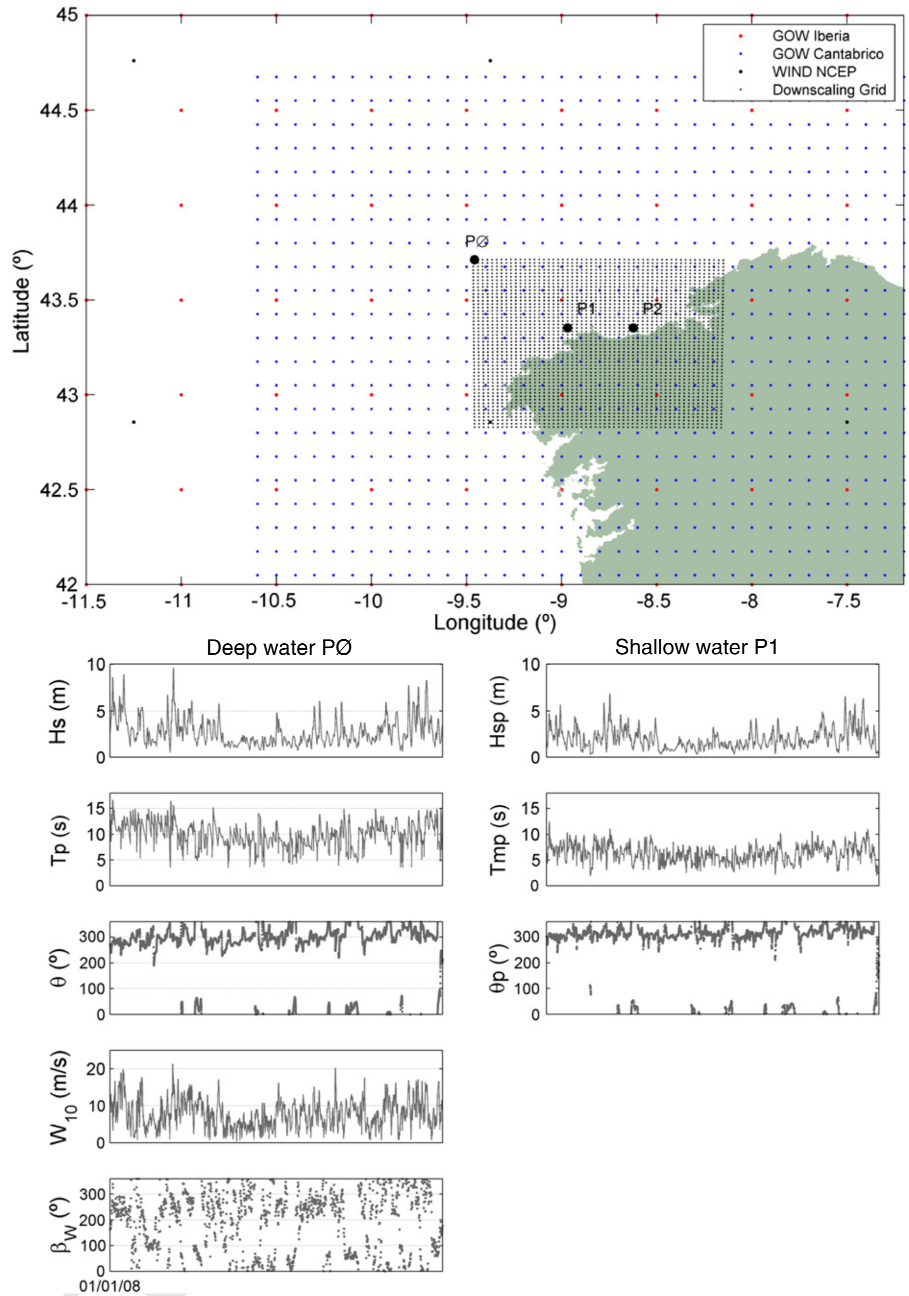

Fig. 2. Study area in the application of the methodology to transfer wave climate from deep water to shallow water.

3. Selection

The aim of the selection process is to extract a subset of wave situations representative of available ocean conditions from the reanalysis database. In the development of computer-based methods to select sets of structurally diverse compounds from chemical databases, dissimilarity-based compound selection has been suggested as an effective method to identify a subset comprising the most dissimilar data in a database (Snarey et al., 1997). The subset selected by the maximum-dissimilarity algorithm (MDA), one subclass of these selection techniques, is distributed fairly evenly across the space with some points selected in the outline of the data space. Therefore, MDA is implemented in the proposed methodology (Camus et al., 2010) to transfer wave climate from deep water to shallow water. In the application considered to describe the methodology, the multivariate data at deep water is defined as: $X^*_i = \{H_{s,i}, T_{p,i}, \theta_{m,i}, W_{10,i}, \beta_{W,i}\}$; $i = 1,\ldots,N$, where $N = 8784$ sea states, corresponding to year 2008. Each data is defined by scalar and directional variables of different magnitudes. On the one hand, vector components must be normalized in order to be equally weighted in the similarity criterion. On the other hand, this criterion is defined by the Euclidean distance. Circular variables entail a problem related with this criterion. The wave direction θ_m is recorded on a continuous scale, with 360° and 0° being identical, while it is adapted to an open linear scale. The problem is solved by implementing the distance in the circle. We define a Euclidean-circular (EC) distance ('E' for the Euclidean distance in scalar parameters and 'C' for the circular distance in directional parameters).

The scalar variables are normalized by scaling the variable values between 0 and 1 with a simple linear transformation which requires the minimum and maximum values of the two scalar variables. For the circular variables, taking into account that the maximum difference

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between two directions in radians over the circle is equal to π and the minimum difference is equal to 0, this variable has been normalized by dividing the direction values between π, therefore rescaling the circular distance between [0,1]. The dimensionless input data is expressed as $X_i=\{H_i, T_i, \theta_i, W_i, \beta_i\}$; $i=1, \ldots, N$, after these transformations.

Therefore, given a data sample $X_i=\{H_i, T_i, \theta_i, W_i, \beta_i\}$; $i=1, \ldots, N$ consisting of N n-dimensional vectors, a subset of M vectors D_j; $j=1, \ldots, M$ representing the diversity of the data is obtained by applying this algorithm. The subset is initialized by transferring one vector from the data sample D_1. The rest of the $M-1$ elements are selected iteratively, calculating the dissimilarity between each remaining data in the database and the elements of the subset, and then transferring the most dissimilar one to the subset. The process finishes when the algorithm reaches M iterations. This algorithm is described in detail in Camus et al. (2010). In this work, the initial data of the subset is considered to be the sea state with the largest value of significant wave height. In the selection process, the dissimilarity between each remaining vector in the database and each vector in the subset is calculated, and a unique dissimilarity between each vector in the database and the subset is established to define the most dissimilar one. In this work, the MaxMin version of the algorithm has been considered.

For example, if the subset is formed by R ($R\leq M$) vectors, the dissimilarity between the vector i of the data sample $N-R$ and the j vectors belonging to the R subset is calculated:

$$d_{ij} = \left\|X_i - D_j\right\|; i = 1, \ldots, N-R; j = 1, \ldots, R \quad (1)$$

where || || stands for the EC distance.

Subsequently, the dissimilarity $d_{i,\ subset}$ between the vector i and the subset R, is calculated as:

$$d_{i,subset} = \min\left\{\left\|X_i - D_j\right\|\right\}; i = 1, \ldots, N-R; j = 1, \ldots, R. \quad (2)$$

Once the $N-R$ dissimilarities are calculated, the next selected data is the one with the largest value of $d_{i,subset}$.

MDA has an expected time complexity of $O(M^2N)$ for M-member subsets from an N-member database. In order to reduce the computational effort, the more efficient algorithm $O(MN)$ developed by Polinsky et al. (1996) has been considered. In this case, the definition of the distance $d_{i,subset}$ does not imply the calculation of the distance between the different vectors d_{ij}. For example, in the selection of the ~~rth~~ vector, the distance $d_{i,subset}$ is defined as the minimum distance between the vector i of the data sample (consisting of $N-(R-1)$ vectors at this cycle) and the last vector transferred to the subset R, and the minimum distance between the vector i and the $R-1$ vectors of the subset determined in the previous cycle:

$$d_{i,subset}^{min} = \min\left[d_{i,R}, d_{i,subset(R-1)}^{min}\right]. \quad (3)$$

The EC distance in the MDA algorithm yields:

$$\left\|X_i - D_j\right\| = \sqrt{\begin{array}{l}\left(H_i - H_j^D\right)^2 + \left(T_i - T_j^D\right)^2 + \left(\min\left(\left|\theta_i - \theta_j^D\right|, 2-\left|\theta_i - \theta_j^D\right|\right)\right)^2 \\ + \left(W_i - W_j^D\right)^2 + \left(\min\left(\left|\beta_i - \beta_j^D\right|, 2-\left|\beta_i - \beta_j^D\right|\right)\right)^2.\end{array}} \quad (4)$$

Finally, applying the opposite transformation of the normalization step, the denormalization of the subset is carried out. The MDA subset is therefore defined by $D_j^*=\{H_{s,\,j}^D, T_{p,\,j}^D, \theta_{m,\,j}^D, W_{10,\,j}^D, \beta_{W,\,j}^D\}$; $j=1, \ldots, M$.

The MDA is applied to the year 2008 hourly time series of the five parameters considered in the definition of wave and wind conditions at deep water. Different sizes of the selected subset have been performed in order to analyze the influence of the number of representative cases in the transfer of wave climate from deep water to shallow water. Fig. 3 shows the time series of the five parameters $\{H_{s,i}, T_{p,i}, \theta_{m,i}, W_{10,i}, \beta_{W,i}\}$ and MDA subsets of different sizes, the first $M=25$ selected data are presented in dark red, the following 75 selected cases to complete a subset of size $M=100$ are shown in red and the following 100 selected data of a subset of size $M=200$ are colored in yellow. The procedure of the MDA algorithm implies that the first R selected data of different subset sizes are the same.

Fig. 4 shows the distribution of the sample data and the selected subset of different sizes using same color scheme as Fig. 3 for the different bidimensional combinations of the analyzed parameters. As seen, the first 25 selected cases span the space of the input data, trying to cover it evenly. The following cases are selected uniformly filling the space of input data. This algorithm adequately covers the outer borders of the domain space (Camus et al., 2010).

4. Deep to shallow water wave transformation

In deep water, wind waves are not affected by the bathymetry. However, in their propagation to the coast, waves are transformed due to the interaction with the bathymetry, inducing variations in the significant wave height and in the mean wave direction. The most important transformation processes are refraction and shoaling by bathymetry or current, diffraction around abrupt bathymetric features and energy loss through dissipation near the bottom. Besides, part of wave energy is reflected back to the deep sea. Continuing their shoreward propagation at a shallower water, the wave profile becomes steeper with increasing wave amplitude and decreasing wavelength, the front face of the wave moves at a slower speed than the wave crest causing the overturning motion of the wave crest. The turbulence associated with breaking waves produces great amounts of energy dissipation.

Wave propagation models simulate the wave transformation processes in their propagation to the coast. There are different wave models depending on the mathematical equations implemented in order to describe wave propagation from deep to shallow waters, which suppose different limitations in the processes they are able to model. Therefore, none of the existing models considers all involved physical processes.

Two basic kinds of numerical wave models can be distinguished: phase-resolving models, which are based on vertically integrated, time-dependent mass and momentum balance equations, and phase-averaged models, which are based on a spectral energy balance equation. The application of phase-resolving models, which require 10–100 time steps for each wave period, is still limited to relatively small areas, O (1–10 km), while phase averaged models can be applied in much larger regions (Losada and Liu, 2002).

The wave energy model SWAN (Booij et al., 1999) with Cartesian coordinates is used due to the size of the propagation domain. Q3 Moreover, a spatial resolution of 2 km is considered, as a certain number of nodes per wave length are not required with this kind of numerical models, and one year of sea state parameters in deep water can be downscaled practically without computational effort. Each hourly wave and wind condition defined by H_s, T_p, θ_m, W_{10}, β_W is propagated by SWAN model. The boundary conditions are defined using constant JONSWAP spectrum along all the borders of the grid characterized by H_s, T_p and θ_m, with a peak enhancement parameter $\gamma=4$ and a directional width expressed in terms of the directional standard deviation $\sigma=25°$. A constant wind field in the computational domain is defined by W_{10} and β_W for each hourly sea state. The stationary SWAN computations imply instantaneous wave propagation across the domain, as well as instantaneous wave response to changes in the wind field. These restrictions are obviously inaccurate

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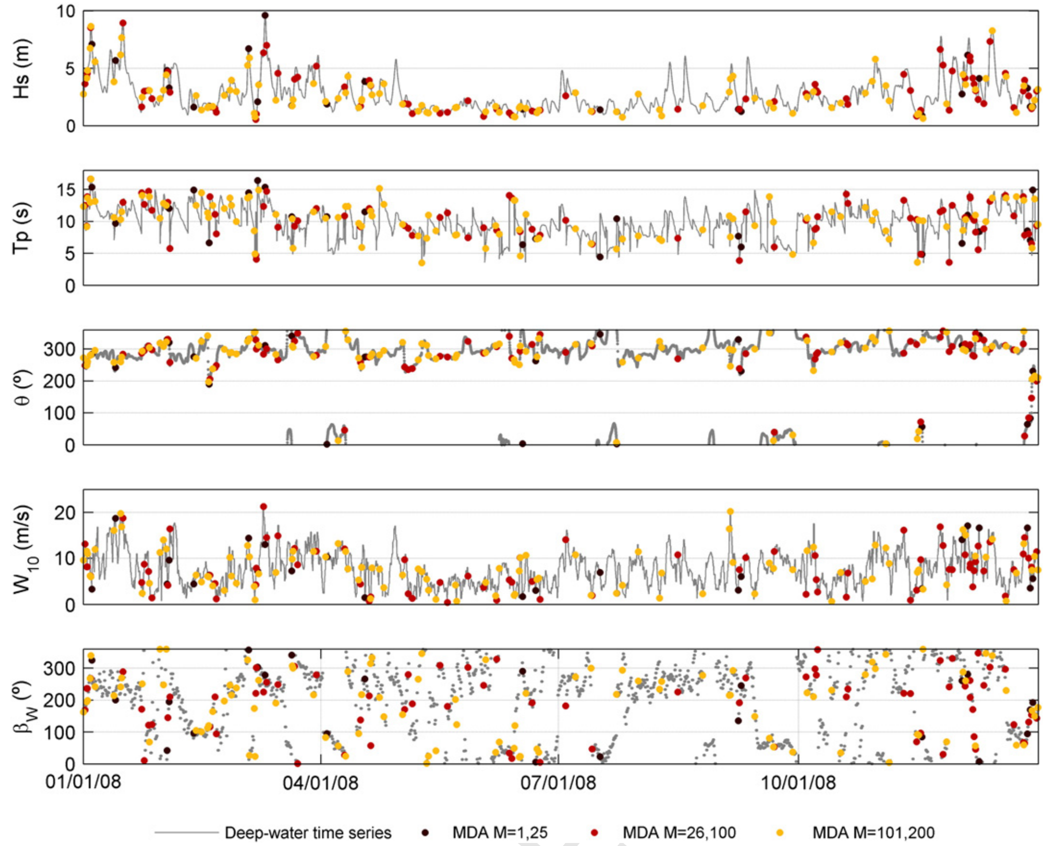

Fig. 3. Time series of H_s, T_m, θ_m, W_{10}, β_W at deep-water (gray line), the selected cases by MDA algorithm, $M=1$–25 black points, $M=26$–100 red points and $M=101$–200 yellow points. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for global or basin-scale models but are reasonable for a smaller domain (Rogers et al., 2007). Furthermore, one of the requirements of the proposed methodology is the assumption of stationary propagations so that the subset of the selected propagation cases can be considered independent.

In the left panel of Fig. 5, the propagation of the most energetic sea state from the SW direction is shown, and corresponds to 13/01/2008, 02:00 defined by $H_s=5.29$ m; $T_p=9.26$ s, $\theta_m=234°$, $W_{10}=18.7$ m/s, $\beta_W=200.66°$. At the two points considered for the reconstruction of the time series, the propagated parameters are $H_{sp}=3.78$ m, $T_{mp}=7.08$ s and $\theta_{mp}=241.92°$ and $H_{sp}=1.37$ m, $T_{mp}=4.26$ s and $\theta_{mp}=254.23°$, for P1 and P2, respectively. In the right panel of Fig. 5, the propagation of the most energetic sea state from the NW direction is shown, which corresponds to 10/03/2008, 14:00, defined by $H_s=9.6$ m; $T_p=15.38$ s, $\theta_m=311°$, $W_{10}=13.04$ m/s, $\beta_W=278.38°$. At the two points considered for the reconstruction of the time series, the propagated parameters are $H_{sp}=8.74$ m, $T_{mp}=11.35$ s and $\theta_{mp}=309.87°$ and $H_{sp}=6.80$ m, $T_{mp}=10.77$ s and $\theta_{mp}=324.46°$, for P1 and P2, respectively.

5. Time series reconstruction

The reconstruction of the time series of wave parameters at the nearshore is carried out by an interpolation technique based on radial basis functions (RBF), a scheme which is very convenient for scattered and multivariate data. The RBF approximation has been applied successfully in many fields, usually with better results than other interpolation methods (Hardy, ~~1971~~). In a comparison of schemes for interpolating scattered two dimensional data, the most accurate results have been obtained by RBF method (Franke, 1982). Q4

Suppose that $f=f(x)$ is the real-valued function that we want to approximate. We are given M scattered data points $\{x_1, \ldots, x_M\}$ of dimension n and the associated real function values $\{f_1, \ldots, f_M\}$, being $f_i=f(x_j)$, $j=1,\ldots,M$. The RBF interpolation method consists of a weighted sum of radially symmetric basic functions located at the data points (see Fig. 6). The approximation function is assumed to be of the form:

$$RBF(x) = p(x) + \sum_{j=1}^{M} a_j \Phi\left(\left\|x-x_j\right\|\right) \quad (5)$$

where Φ is the radial basis function, being $\|\,\|$ the Euclidian norm; $p(x)$ is a monomial basis $\{p_0, p_1, \ldots, p_n\}$, formed of a number of monomials of degree 1 equal to the data dimension (n) and a monomial of degree 0, being $b=\{b_0, b_1, \ldots, b_n\}$ the coefficients of these monomials. The RBF coefficients a_j and the monomial coefficients b are obtained by enforcing the interpolation constraints $RBF(x_i)=f_i$.

There are several expressions for radial basis functions (linear, cubic, Gaussian, multiquadric, …), some of them containing a shape parameter that plays an important role for the accuracy of the interpolation method. Rippa (1999) proposed an algorithm for choosing an optimal value of the shape parameter by minimizing a cost function that imitates the error between the radial interpolant and the unknown function $f(x)$. This cost function collects the errors for a sequence of partial fits to the data: $E=(E_1, \ldots, E_M)^T$, where E_k is defined as the error between the function f_k at the point x_k and the value estimated by the RBF function calculated by removing the point x_k from the original data set. Q5

In the implementation of the RBF interpolation technique in the sea state time series reconstruction, we have M 5-dimensional points $D_j^*=\{H_{s,j}^D, T_{p,j}^D, \theta_{m,j}^D, W_{10,j}^D, \beta_{W,j}^D\}; j=1,\ldots,M$, corresponding to the M cases selected by MDA algorithm and the associated real propagated

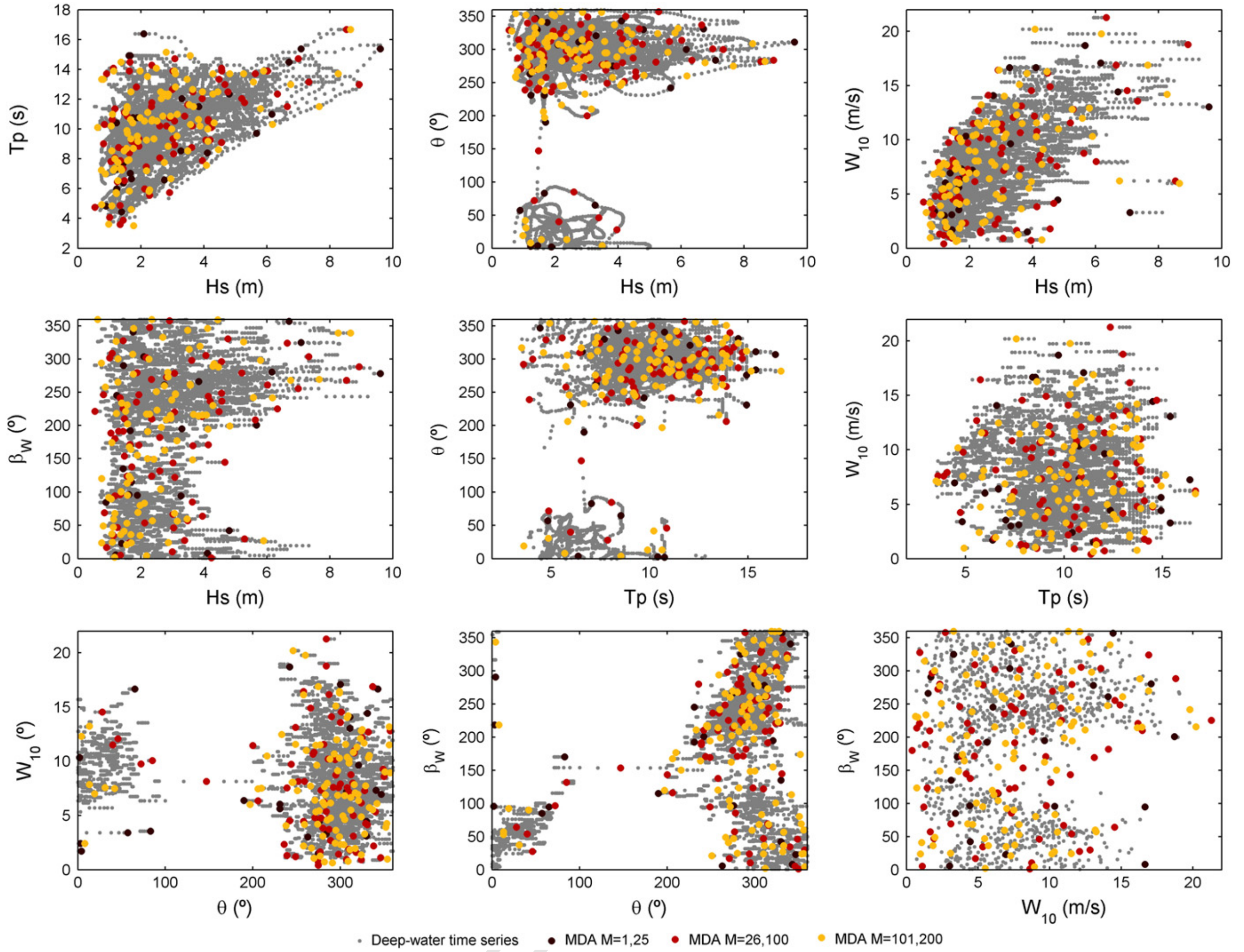

Fig. 4. The distribution of the selected cases by MDA algorithm ($M=1$–25 black points, $M=26$–100 red points and $M=101$–200 yellow points) in the sample time series at deep water (gray points) for different combinations of the five parameters H_s, T_m, θ_m, W_{10}, β_W. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

parameters obtained by the numerical propagation at the shallow water location. These propagated parameters are the propagated significant wave height $\{H^D_{sp,\ j}\}$, the propagated mean period $\{T^D_{mp,\ j}\}$ and the components *x*- and *y*- of the propagated mean direction $\{\theta x^D_{mp,\ j}\theta y^D_{mp,\ j}\}$. The mean wave direction θ_{mp} is reconstructed after the interpolation of the components *x*- and *y*-.

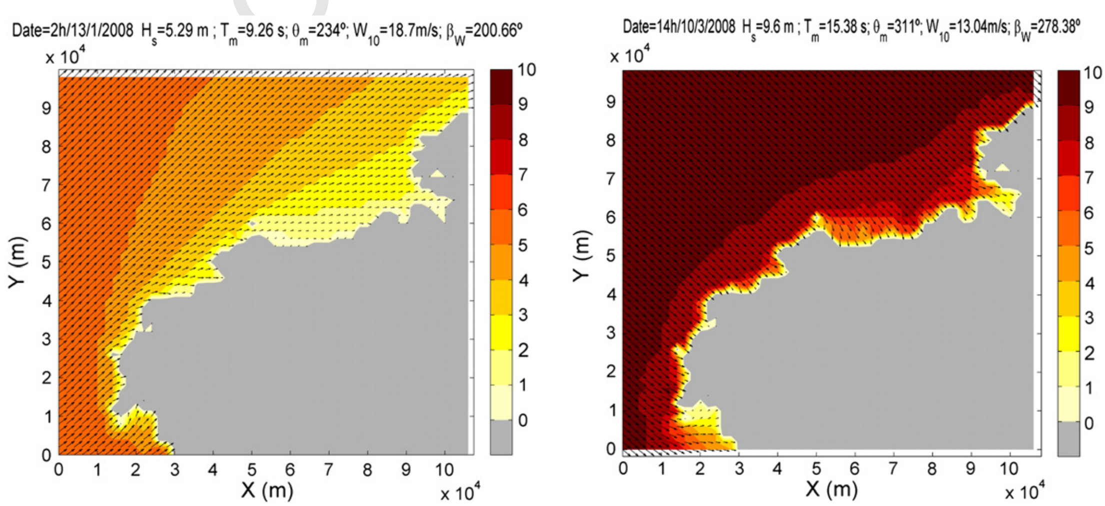

Fig. 5. Significant wave height and mean wave direction for a sea state from SW direction (left panel) and significant wave height and mean direction for a sea state from NW direction (right panel).

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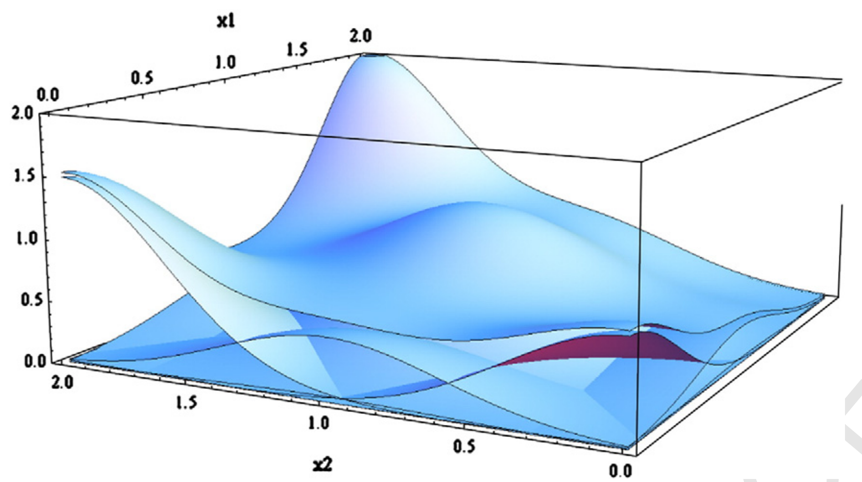

Fig. 6. Sketch of the RBF interpolation methodology for two dimensions. The upper surface is the interpolated RBF.

Therefore, the aim of the RBF application is the evaluation of the interpolation function of the propagated significant wave height RBF_H, the evaluation of the interpolation function of the propagated mean period RBF_T and the evaluation of the interpolation function of the components *x*- and *y*- of the mean wave direction $RBF_{\theta x}$, $RBF_{\theta y}$, respectively.

In order to calculate the interpolation functions, the scalar variables that define the wave and wind conditions at deep water are normalized using a linear transformation which scales the values between 0 and 1. The directional variables are normalized by dividing between π and implementing the circular distance in the norm of RBF method. Therefore each sea state at deep water is defined as $X_i=\{H_i, T_i, \theta_i, W_i, \beta_i\}$; $i=1, \ldots, N$, while each selected case, where the real propagated parameters are available, is expressed as $D_j=\{H_j^D, T_j^D, \theta_j^D, W_j^D, \beta_j^D\}$; $j=1, \ldots, M$.

The interpolation function is calculated by means of this expression:

$$RBF(X_i) = p(X_i) + \sum_{j=1}^{M} a_j \Phi\left(\left\|X_i - D_j\right\|\right) \tag{6}$$

where $p(X_i)=b_0+b_1H_i+b_2T_i+b_3\theta_i+b_4W_i+b_5\beta_i$ and Φ is a Gaussian function with a shape parameter *c*:

$$\Phi\left(\left\|X_i - D_j\right\|\right) = exp\left(-\frac{\left\|X_i - D_j\right\|^2}{2c^2}\right). \tag{7}$$

The Euclidean distance has been replaced by the distance EC as in the MDA algorithm. The optimal shape parameter is estimated using the Rippa (1999) algorithm. The coefficients $b_l=[b_0, b_1, b_2, b_3, b_4, b_5]^T$ of the monomials and the coefficients $a_j=[a_1, \ldots, a_M]^T$ of the radial basis functions are obtained by the interpolation conditions:

$$RBF\left(D_j\right) = f_j\left(D_j\right) = D_{p,j}; \quad j = 1, \ldots, M \tag{8}$$

where the real functions $D_{p,\,j}$ are defined by the propagated parameters $\{H_{sp}\}_j$, $\{T_{mp}\}_j$, $\{\theta_{xp}\}_j$ or $\{\theta_{yp}\}_j$, corresponding to the selected sea states in MDA algorithm D_j.

Therefore, the time series are transferred from deep water to the point of interest at shallow water by means of the RBF functions calculated for each propagated parameter. These functions are defined as:

$$\begin{aligned} H_{sp,i} &= RBF_H\left(\left\{D_j, H_{sp,j}(j=1,\ldots,M)\right\}, X_i\right); i=1,\ldots,N \\ T_{mp,i} &= RBF_T\left(\left\{D_j, T_{mp,j}(j=1,\ldots,M)\right\}, X_i\right); i=1,\ldots,N \\ \theta_{xp,i} &= RBF_{\theta_x}\left(\left\{D_j, \theta_{xp,j}(j=1,\ldots,M)\right\}, X_i\right); i=1,\ldots,N \\ \theta_{yp,i} &= RBF_{\theta_y}\left(\left\{D_j, \theta_{yp,j}(j=1,\ldots,M)\right\}, X_i\right); i=1,\ldots,N. \end{aligned} \tag{9}$$

A general transfer function for a specific location can be defined as:

$$X_{p,i}^{*} = RBF\left(\left\{D_j, D_{p,j}^{*}(j=1,\ldots,M)\right\}, X_i\right); \quad i=1,\ldots,N. \tag{10}$$

And the final result is the reconstructed time series at a specific location in shallow water:

$$X_{p,i}^{*} = \left\{H_{sp,i}, T_{mp,i}, \theta_{mp,i}\right\}; \quad i=1,\ldots,N. \tag{11}$$

As an example, the interpolation function for the propagated significant wave height at P1, considering a subset of size $M=10$ selected by MDA algorithm is expressed as the following:

$$\begin{aligned} H_{sp,i} = RBF_H(X_i) &= b_0 + b_1H_i + b_2T_i + b_3\theta_i + b_4W_i + b_5\beta_i \\ &+ \sum_{j=1}^{10} a_j \Phi\left(\left\|X_i - D_j\right\|\right) \end{aligned}$$

where the coefficients are: $b_0=-0.133$; $b_1=8{,}466$; $b_2=-0.631$; $b_3=0.251$; $b_4=-1.172$; $b_5=0.055$; $a_1=0.064$; $a_2=-0.165$; $a_3=0.636$; $a_4=0.734$; $a_5=0.979$; $a_6=-0.577$; $a_7=-0.651$; $a_8=0.644$; $a_9=-1.012$ and $a_{10}=-0.653$. For this particular case the value of the shape parameter is $c=0.37687452$.

6. Validation of the methodology

6.1. Time series

The proposed methodology is applied to transfer wave climate from deep water to P1 and P2 located near the coast (see Fig. 2). The time series of the propagated parameters H_{sp}, T_{mp} and θ_{mp} are reconstructed considering a different number of cases selected by MDA algorithm ($M=25$, $M=100$ and $M=1000$) and compared with the time series obtained from the numerical wave propagation of the complete year of hourly sea states ($N=8784$).

The scatter plots of the propagated time series and the reconstructed time series of the H_{sp}, T_{mp} and θ_{mp} are shown in Fig. 7. The root mean square error (rmse) and the scatter index (SI) were computed for the significant wave height, mean period and mean direction. Those statistics are given in Table 1. As we can see in the scatter plots and Table 1, the differences between the propagated time series and the reconstructed ones are relatively small even for a number of cases $M=25$ (around 0.3 m, 0.8 s and 13° for H_s, T_m and θ_m, respectively). The quality of the reproduced parameters, in terms of the rmse, is especially satisfactory for H_s and T_m but worse for the wave directions. The reconstruction at the two points improves with

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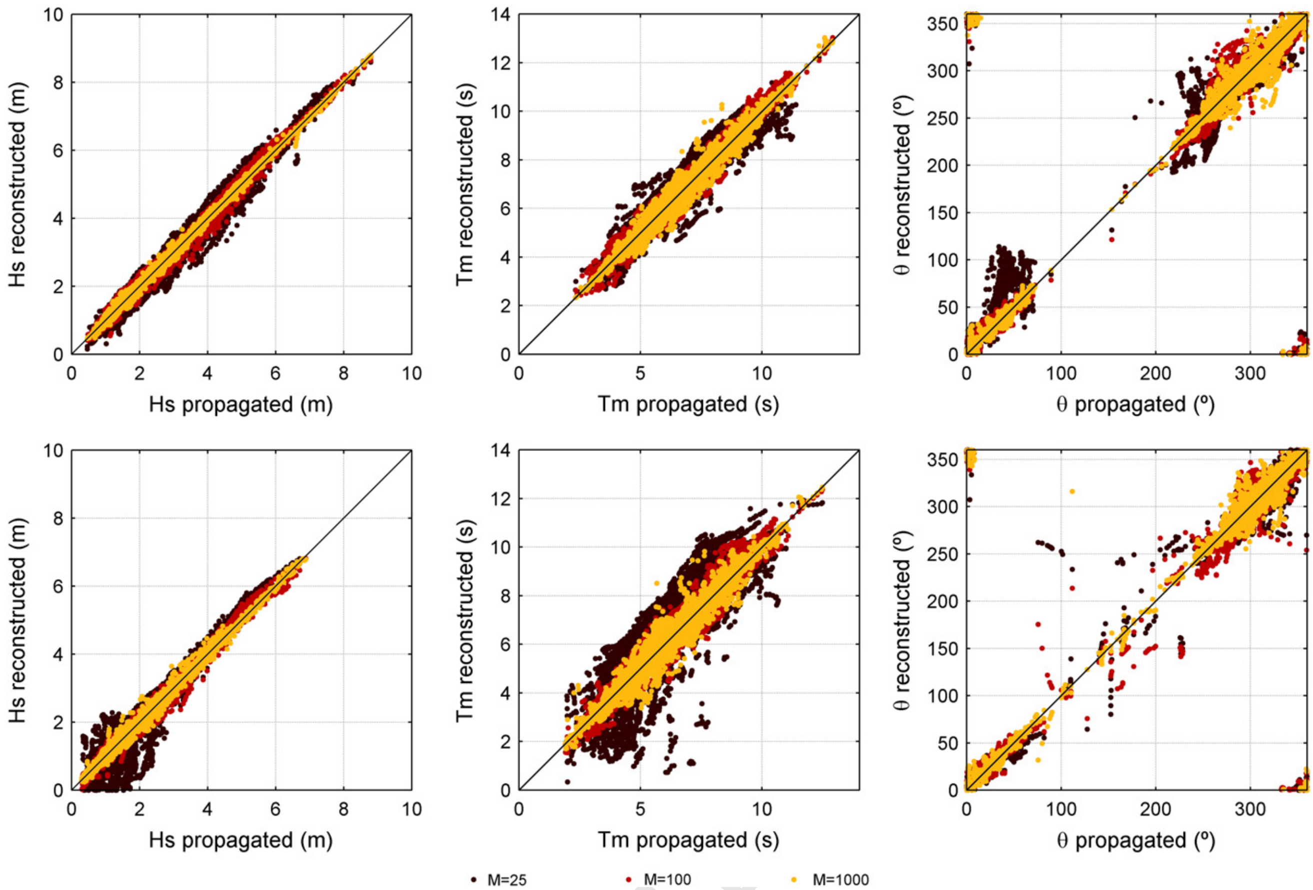

Q1 **Fig. 7.** Scatter of the time series propagated against reconstruction of H_s, T_m and θ_m at P1 and P2 (indicated in Fig. 1), considering $M=25$ (in black), $M=100$ (in red) and $M=1000$ (in yellow) in the methodology to transfer wave climate from deep water to shallow water. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the increase of M. The rmse using $M=100$ cases is around 50% smaller than using $M=25$ cases for the three variables considered. However, the increase in the quality of reconstruction is not as important when using $M=100$ or $M=1000$ cases. The reconstruction of the significant wave height and mean period is worse at P2, especially for the lowest significant wave heights. The rmse of H_s and T_m using $M=25$ cases is double than at P1. However, the increase of the quality using $M=100$ cases is higher than at P1; being rmse of H_s and T_m similar at both points although SI is higher at P2. The results of the mean direction are slightly better at P2 due to the narrower range of the propagated directions caused by the higher refraction at a smaller depth. In the case of the significant wave height and the mean period, the smaller depth at P2 supposes less linearity with regard to significant wave height at deep water. More cases are therefore needed to represent the diversity of waves at nearshore and to reconstruct the time series. The reconstructed time series of H_{sp}, T_{mp} and θ_{mp} by $M=25$ cases (in dark red) and $M=100$ cases (in red) and the real time series (in gray) at P2 are shown in Fig. 8.

Table 1
The mean square error (RMSE) and the scatter index (SI) for H_s, T_m and θ_m.

	H_s (m)			T_m RMSE (s)			θ_m RMSE (°)		
	25	100	1000	25	100	1000	25	100	1000
P1	0.207	0.120	0.062	0.573	0.300	0.223	14.708	7.554	5.809
P2	0.375	0.124	0.086	1.147	0.405	0.310	12.472	8.444	6.008
	H_s SI			T_m SI			θ_m SI		
P1	0.081	0.047	0.024	0.0845	0.044	0.033	0.0478	0.024	0.019
P2	0.189	0.062	0.043	0.185	0.065	0.050	0.038	0.026	0.019

The accuracy of the reconstruction of the time series depends on the number (M) of cases selected and propagated. We have analyzed the error obtained in the wave climate reconstruction at coastal areas using the proposed methodology with different numbers of selected cases. Fig. 9 shows the root mean square error in the reproduction of the parameters H_s, T_m and θ_m at the two points considered near the coast (P1 and P2). We can observe that with a number of selected cases $M=100$, the errors are stabilized and are quite similar for the two points at shallow water. The $M=100$ selected cases span the wave climate variability at deep water properly and the results are hardly influenced by the non linearity of the wave propagation. Therefore, in this application of the proposed methodology on the west coast of Spain, a number of cases $M=100$ are enough for a good transformation of wave climate from deep water to shallow water. If we analyze more in detail the error of the 90th and 99th of H_s, T_m (not shown), we observe how the decrease of the error is almost insignificant with a number of cases $M \geq 200$. The small errors confirm the excellent representation of the selected sea states by MDA in order to reproduce the extreme wave statistical parameters with great accuracy. Although this result of the optimal number of cases (M) is not generalizable, our tests for this kind of problems reveal that M–100–200 is an adequate number of propagations to cover the diversity of sea states. Further research is still required to generalize the selection of parameter M depending on the number of degrees of freedom and the complexity of the bathymetry and local boundaries.

6.2. Spatial fields

The subset of the M propagated cases selected by MDA algorithm defines a library of M hourly wave parameters: significant wave

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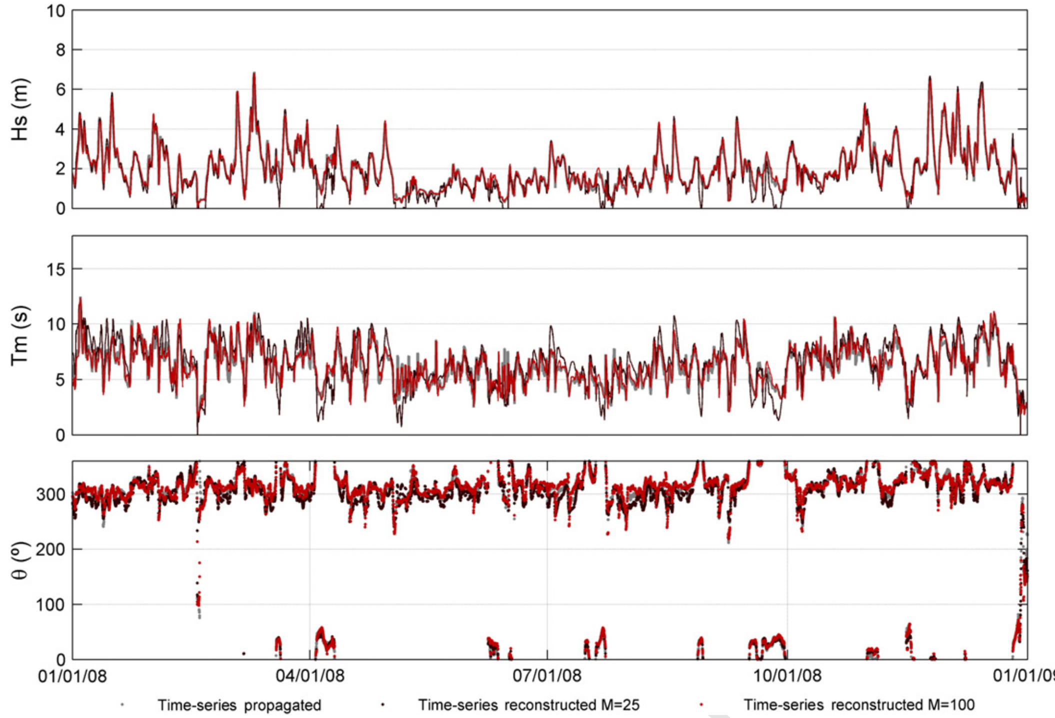

Fig. 8. Time series propagated (in gray) and reconstructed considering $M = 25$ (in black) and $M = 100$ cases (in red) of the parameters H_s, T_m and θ_m at point 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

height (H_{sp}), mean period (T_{mp}) and mean direction (θ_{mp}) at the nodes of the computational grid, corresponding to the associated deep water conditions. Although MDA algorithm is not a clustering technique, we can consider that each data is represented by the closest vector of the selected subset (see Camus et al., 2010). Therefore, each selected case has an associated probability, a function of the number of similar deep

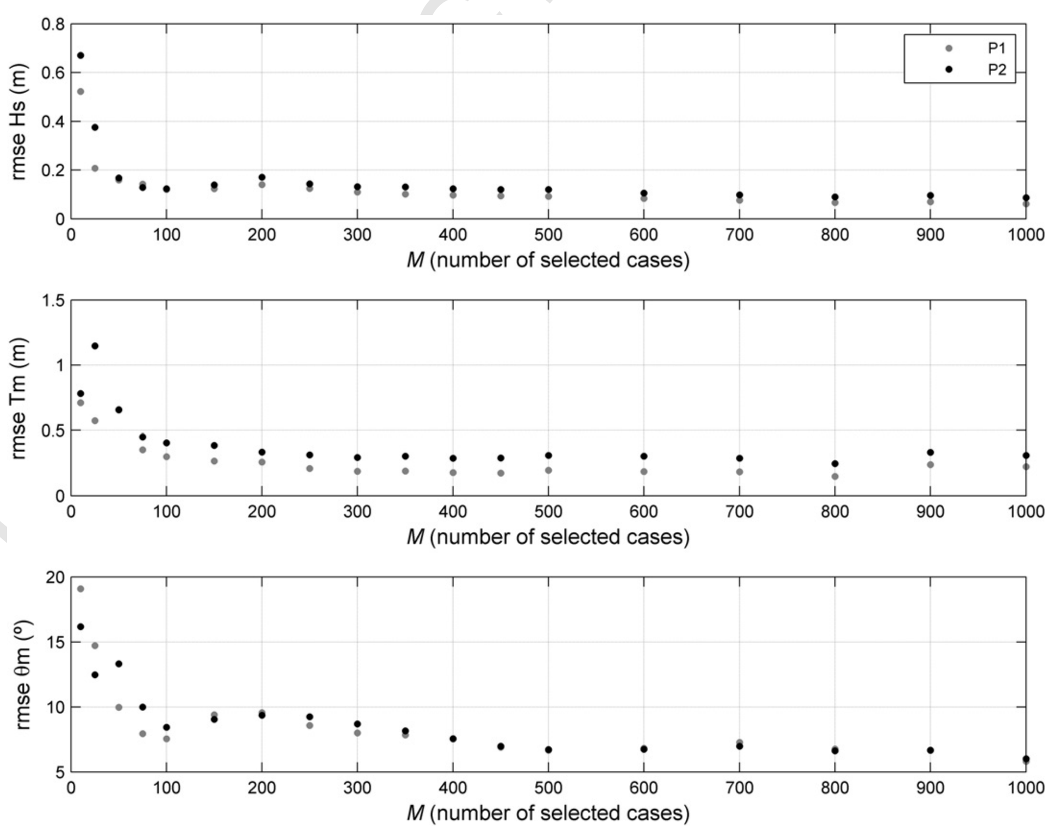

Fig. 9. The root mean square error (rmse) of H_s, T_m and θ_m obtained by the proposed methodology for different numbers of selected cases (M) and the dynamical downscaling at P1 and P2.

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water conditions represented by each one. An easy spatial definition of wave climate statistics is possible by means of the results of the propagation of the M cases and the corresponding probability without applying the most time consuming RBF interpolation scheme.

For example, the M values of the significant wave height $H_{sp}=\{H_{sp1}, H_{sp2}, \ldots, H_{spM}\}$ and its corresponding probability $p=\{p_1, p_2, \ldots, p_M\}$ are available at each node of the computational grid. The mean significant wave height can be calculated by means of the following expression:

$$\overline{H}_{sp} = \sum_{j=1}^{M} H_{spj} \cdot p_j.$$

On the other hand, a given percentile of the significant wave height can be calculated applying the following steps:

- The $H_{sp,\,j}$ values are sorted in ascending order:

$$Y = \left\{H_{sp(1)}, H_{sp(2)}, \ldots, H_{sp(M)}\right\}.$$

- The associated cumulative probabilities are calculated:

$$X = \left\{p_{(1)}, p_{(1)} + p_{(2)}, \ldots, \sum_{i=1}^{M} p_{(j)} = 1\right\}.$$

- Interpolation to find the qth percentile $Y_q = H_{sq}$, the value of the underlying function Y for the non-exceedance probability at the point $P_q = q/100$.

Fig. 10 shows the mean significant wave height at the area of study (upper left panel) and the error in % between the mean significant wave height calculated using the $N=8784$ propagations and the approximated significant wave height calculated by $M=25$ cases selected by MDA algorithm and the corresponding probability (upper right panel), by means of $M=100$ cases (lower left panel) and $M=200$ cases (lower right panel). As seen, the mean errors Q6 considering $M=25$ cases are around 1–2% at deep water while the errors are around 5–6% at shallow water. In the case of $M=100$, the errors are around 2% practically for the whole computational grid. The errors are lower than 0.63% considering $M=200$ cases, showing the ability of this approach to evaluate spatial wave climate parameters.

The 95th percentile of the significant wave height and the errors (%) considering $M=25$, 100 and 200 cases are shown in Fig. 11. The errors are around 8% at deep water and around 15–20% at shallow water for $M=25$ cases. In the case of $M=100$ cases, the errors are lower than 2% at deep water and around 7% at shallow water. In the case of $M=200$ cases, the errors are lower than 2%, reinforcing the methodology proposed in this work.

7. Conclusions

A hybrid methodology to transfer wave climate from deep water to shallow water (or to downscale wave climate increasing the spatial resolution) has been developed. The methodology is based on a selection of M sea states representative of wave climate at deep water by MDA algorithm, the dynamical propagation of these selected cases

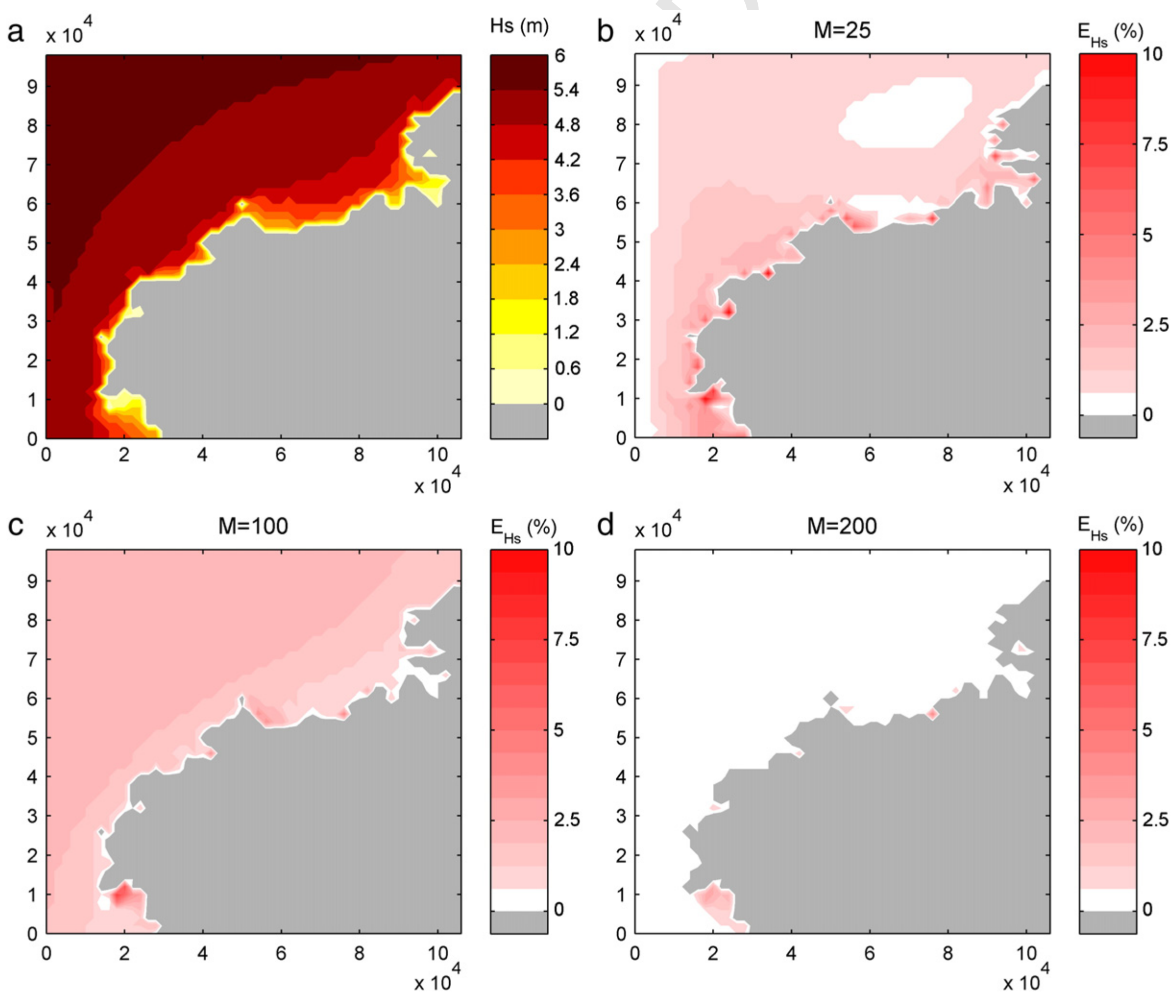

Fig. 10. a) Mean significant wave height; b) differences in % between the annual mean significant wave height field and the approximation by the $M=25$ cases selected by MDA and their corresponding probability; c) the differences in the case of the approximation by $M=100$ cases and d) the differences in the case of the approximation by $M=200$ cases.

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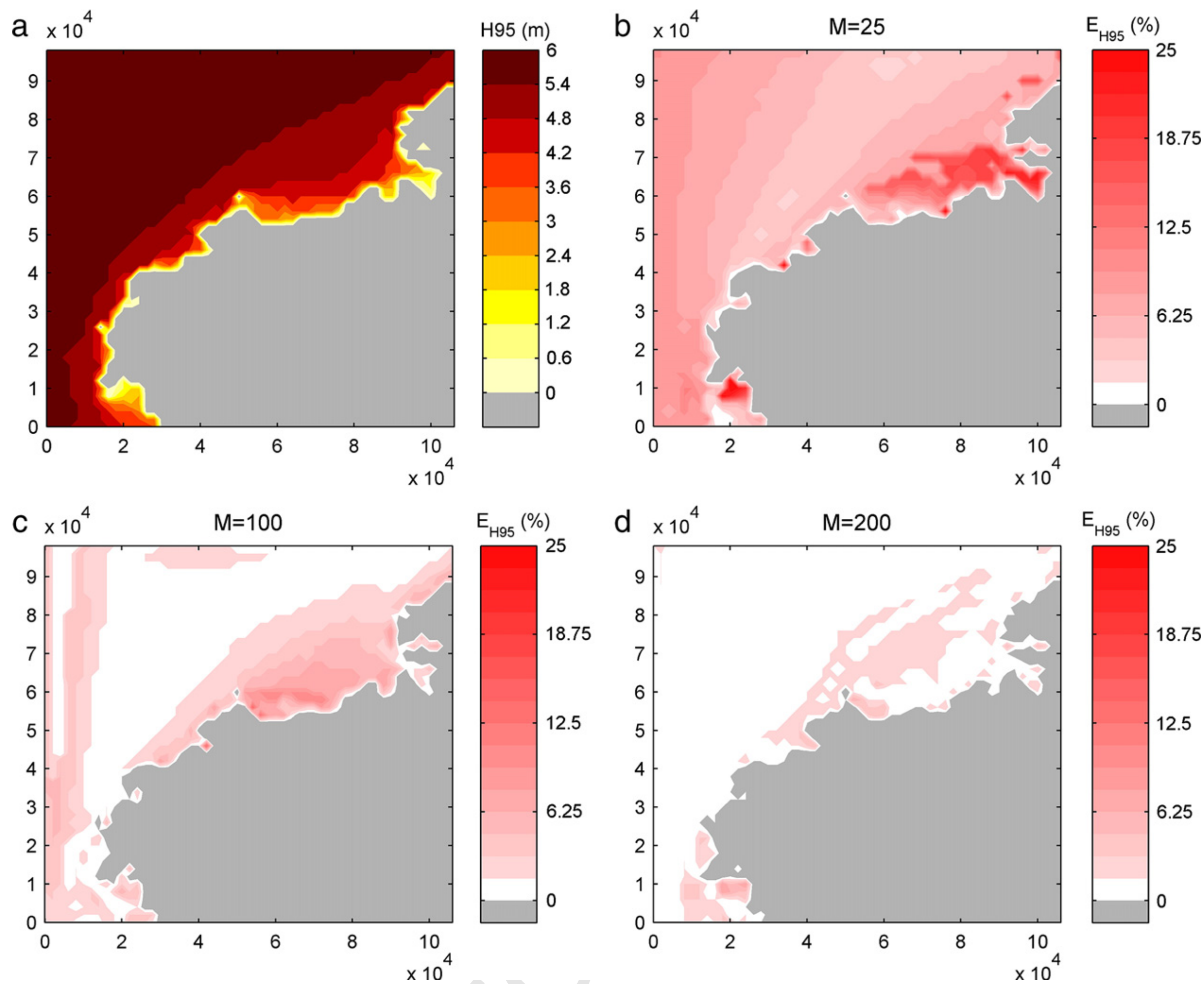

Fig. 11. a) 95th percentile of the significant wave height; b) differences in % between the 95th percentile of the annual significant wave height field and the approximation by the $M = 25$ cases selected by MDA and their corresponding probability; c) differences in the case of the approximation by $M = 100$ cases and d) differences in the case of the approximation by $M = 200$ cases.

and a multidimensional RBF interpolation to reconstruct the time series of wave parameters at shallow water.

The proposed methodology has been applied to wave data around the west coast of Spain with the objective to analyze its ability to reproduce the dynamical downscaling, the most accurate approach to transfer wave climate to coastal areas. One year of hourly time series has been considered to represent the variability of wave climate at the study area and has been propagated both dynamically and with the proposed methodology using different sizes of subsets of sea states selected by MDA. The validation of results confirms that the proposed methodology is able to reproduce the time series of wave parameters at coastal areas. The good performance of the methodology is due to the good behavior of MDA selection and RBF interpolation. The MDA automatically selects M multivariate sea states uniformly distributed over data, covering the edges and ~~samples of~~ the variability of deep water wave climate, which is very convenient in the RBF interpolation. The RBF technique, improved by the Rippa (1999) algorithm, has proved to be a powerful technique to reconstruct time series of sea state parameters being, in this example, each sea state at deep water defined by five parameters. The very good representativeness of wave climate at deep water by the selected cases using MDA can be observed in the reproduction of the extreme sea state statistical parameters.

The accuracy of the methodology to reconstruct sea state time series at shallow water depends on the number (M) of cases selected and propagated. In the example used to explain the methodology, the errors in the estimation of wave parameters at shallow water are almost negligible with only $M = 100$ cases. We observe from the analysis of the estimation of some wave statistical parameters considering different numbers of selected cases that the error of these parameters tends to stabilize. There is a threshold in the number of cases which entails a small decrease in the errors of the sea state parameters. Therefore, the analysis of the error evolution informs about an appropriate number of cases in the proposed methodology for each case of study.

Besides, another different approach is possible by means of the library of M propagations and its corresponding probabilities. Although this approach is less accurate than the RBF reconstruction, it supposes an efficient and easy method to estimate high resolution of spatial wave climate statistics. The selected cases by MDA are so representative of the wave climate that the reconstruction of the extreme values of the statistical parameters is correctly achieved.

Although this methodology is presented assuming a number of simplifications, we believe that this method opens the possibility to be applied to more complex sea state definitions (spatial variability in the boundaries, directional spectra) helping to transfer wave climate to coastal areas with a small computational effort. Moreover, although our test in this work is restricted just to one year it is clear that the method can be applied to transfer long-term series (>20 years) to coastal areas.

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Acknowledgments

The work was partially funded by projects “GRACCIE” (CSD2007-00067, CONSOLIDER-INGENIO 2010) from the Spanish Ministry of Science and Technology, “MARUCA” (200800050084091) from the Spanish Ministry of Public Works, “C3E” (E17/08) from the Spanish Ministry of Environment, Rural and Marine Affairs and “Modeling the morphodynamic evolution of beaches at medium-term time scale” from the Spanish Ministry of Science and Technology (CTM2008-06640).

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