

A new methodology to evaluate wave energy resources in intermediate depths. Application to the Asturias coast (North Spain)

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Abstract

In EWTEC2007 [1] a methodology was presented to evaluate the wave energy resource in coastal waters based on wave data obtained from numerical reanalysis of meteorological data. The proposed methodology had the following steps: (a) calibration of deep water wave reanalysis data; (b) sea states classification; (c) deep to shallow water propagation of the most representative sea states; (d) propagation of the complete series of sea states using an interpolation scheme; and (e) statistical characterization of the wave energy resources in the objective points.

In the new approach presented in this paper, some improvements to the different steps of the methodology have been incorporated. A maximum-dissimilarity algorithm has been applied to select a reduced number of sea states which are more appropriate for transferring the reanalysis database from deep water to shallow water.

Besides, wind energy generation has also been considered to improve the definition of local wave energy resources by incorporating wind data in the propagation of each sea state. Finally, a scattered data interpolation based on Radial Basic Function has been used to propagate the wave climate.

The proposed methodology has been calibrated and validated using satellite and buoy wave data for the wave resource analysis of the Asturias coast (North Spain). Some results of that analysis are finally presented.

Keywords: Wave energy resource, wave climate, wave propagation, classification algorithms

1 Introduction

The previous methodology [1] was developed to provide nearshore long-term wave energy resources which are basic for the exploitation of this resource. The proposed methodology included calibration,

classification, propagation processes and statistical models. The steps of that methodology were determined by the use of long-term hindcast databases. These databases are obtained by numerical simulations based on the wave energy equation forced using historical wind fields. Thus, the first step consists of calibrating these numerical time series.

The Self Organizing Maps (SOM) technique was used to classify the calibrated sea states for each reanalysis point in the outer mesh. Although this methodology is effective in terms of producing a representative sample for wave propagation, it takes considerable computer effort. It has been found that the Maximum Dissimilarity algorithm (MaxDiss) [2] produces more appropriate samples than those obtained with the SOM and with much lower computer time.

In [1], the monochromatic wave model OLUCA [3] was used to propagate the representative sample of sea states from the outer mesh points to the coast considering the significant wave height, mean period and mean direction of the sea and swell components provided by the reanalysis database. In this work, the sea states are defined by the compound spectral parameters. Wind data (velocity and direction) has also been incorporated into the propagation model to improve local wave generation. Therefore, a phase-averaged model based on spectral energy balance equation has been used.

The high efficiency of this methodology, in terms of computing time, has allowed propagation of the whole outer database to each point of the wave propagation mesh, using the propagated representative sample and an interpolation procedure. In 2007, a multilinear interpolation procedure was used. In this new approach, the Radial Basic Function Technique has been used because it is more appropriate for multidimensional data (5 dimensions) with non uniform spatial distribution.

The new algorithm implemented in classification step to reduce the number of cases to propagate and the new scheme for interpolation scattered data are described in detail in the following sections.

The entire methodology has been validated comparing the computed mean wave energy flow in the position of Cape Peñas deep water directional wave buoy (water depth 450 m) and in the Gijón directional coastal buoy (water depth 54 m) for the same time window. Results show a very good agreement between measured and computed data.

Using the proposed methodology, any kind of wave statistics can be obtained in any point of the propagation mesh. This methodology has been applied to a 210 Km-wide coastal stretch in the northern coast of Spain (Asturias Region) and some of the results obtained using this methodology are presented.

2 Methodology

In order to estimate wave energy resources, the following phases must be covered (see figure 1). Each of the phases requires the assessment of wave information in deep water, the propagation of the deep water information to the location of interest and the characterization of the wave climate to evaluate the energy resources.

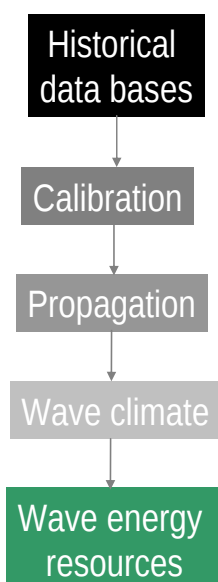


Figure 1. Flow chart of the methodology

a) Calibration

From a quantitative point of view, some differences are found when comparing wave hindcast information (SIMAR-44, Puertos del Estado) with instrumental devices. The limitations in the quantitative validity of these hindcast databases required the development of several algorithms to correct the values of significant wave heights which is one of the key parameters to characterize energy resources. This so-called calibration process is essential, and different approaches may be used depending on the source information, regional characteristics and final goal of the process. In this work, we have applied a directional calibration obtaining very good results (see figure 9 the comparison for the significant wave height between

instrumental data and calibrated reanalysis). The steps of the applied calibration methodology are:

1- The area with similar wave climate to the calibration point is calculated.

2- Instrumental data points (buoys and satellite) that coincide in time with the sea state to be calibrated are selected.

3- The following conversion equation for the zero order moment wave height and the mean period are applied:

$$H_{m0c}(\theta) = a(\theta) \times H_{m0}^{b(\theta)},$$

$$T_{mc}(\theta) = c(\theta) \times T_m^{d(\theta)}$$

Coefficients $[a(\theta), b(\theta)]$ or $[c(\theta), d(\theta)]$ are calculated minimizing the error between the SIMAR-44 and the instrumental zero order moment wave height or mean wave period, respectively. After these directional coefficients were calculated, the conversion equations were applied to all the SIMAR-44 points -.

b) Classification

Hindcast databases including several decades are composed of over 300.000 sea states which require the introduction of techniques which are able to characterize the wave climate and reduce the number of cases to propagate at a specific site.

In the methodology developed in 2007, the Self-Organizing Map (SOM) [4] was used. This non-linear cluster technique calculates a set of prototypes or centroids (with the same dimension as the input vectors), each of them characterizing a group of input data formed by the vectors of a database for which its corresponding prototype is the nearest one. A neighbourhood adaptation mechanism is included in the training algorithm which allows the projection of the topological neighbourhood relations of the high-dimensional data space onto a bidimensional lattice. The clusters projected onto the lattice present spatial organization; similar clusters in the original spaces are located close to each other on the lattice. Thus, an intuitive visualization of the results is provided and the distributions from high-dimensional space are transformed into Probability Density Functions (PDF) on the lattice.

Although this technique is very powerful to characterizing the multi-dimensional wave climate, different selection algorithm has proved to be more efficient in terms of producing a representative sample for wave propagation. A maximum-dissimilarity-based compound selection has been considered. This type of algorithm is commonly used today for the identification of lead molecules in pharmaceutical corporations and has proved to be an effective method to select structurally diverse subsets of chemical databases [5].

The aim of a maximum-dissimilarity algorithm is to select a *Subset* of size m from a database of size N . First, the subset is initialized by choosing one element from the database. The following steps consist of calculating the dissimilarity between each remaining data in database and the elements of the subset and transferring the most dissimilar one to the subset. The

process finishes when the algorithm reaches m iterations. This algorithm was first described by [6] and many variants depending upon the precise implementation are available. In this work, the initial data of the subset is the sea state with the highest significant wave height. The dissimilarity for a wave climate database is defined by euclidean distance for the scalar variables (H_s , T_m) and by distance over a circle for the directional parameters (θ). The most dissimilar data for each iteration has been established as MaxMin.

Considering that n data has already been selected at some stage in the selection process, $N-n$ data is still part of the input database. The dissimilarity between each i data of database and the subset ($d_{i,subset}$) is defined as the minimum distance between the i data and each element of the subset in MaxMin version of this technique. Once the dissimilarity $d_{i,subset}$ for all the remaining $N-n$ data is defined, the chosen data for addition is that with the largest value of $d_{i,subset}$. A slower computation time algorithm for the MaxMin definition of dissimilarity developed by [7] is implemented in this work.

In figure 2, the entire reanalysis database, defined by three parameters $\{H_s, T_m, \theta\}$, is represented as red dots, while the SOM centroids are blue and the subset selected by MaxDiss are green. The MaxDiss algorithm is able to cover all the definition space of input data, even in areas where there is not enough information.

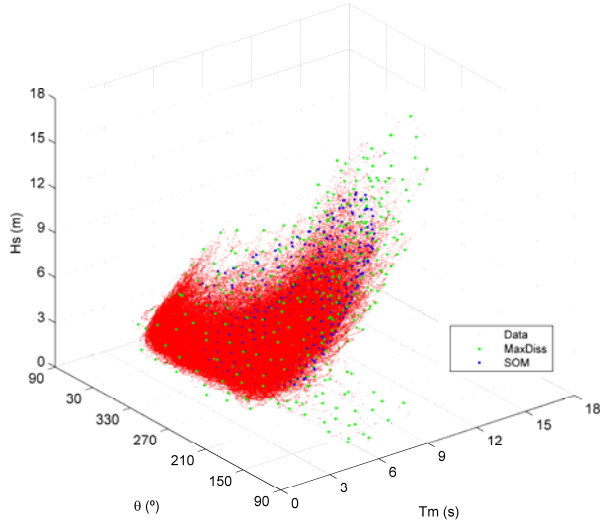


Figure 2. Wave climate, SOM classification and MaxDiss selection

Six different clusters have been selected from the SOM classification and the corresponding ones from the MaxDiss selection to evaluate the capability of these algorithms. Their location in the SOM projection and their definitions in 3D-space and 2D-space are shown in figure 3. The clusters (D and F) represent vector data in the region with more information, and thus they are well defined by both algorithms. Another set of clusters (e.g. A), aims to represent the data with the larger significant wave heights with worse results achieved with the SOM technique. It is clear that the MaxDiss algorithm is able to represent the different

combinations of data while the neighbourhood function implemented in SOM restricts the distribution of the centroids in the input space.

c) Propagation

In [1] the propagation of the SOM centroids was carried out using transfer functions obtained by a monochromatic wave model OLUCA (a mild-slope parabolic model) for a range of frequencies and directions.

In this work, the numerical third-generation coastal wave model SWAN [8], developed at Delft University of Technology [9] was used to propagate the more representative sea states selected by MaxDiss algorithm. The evolution of waves in this model is based on a Eulerian formulation of the spectral discrete wave action balance equation. The generation, propagation and dissipation of waves in small scale with arbitrary wind fields, bathymetry and current fields are all taken into account. The kinematic behaviour of the waves is described with the linear theory for surface gravity waves. The processes of generation, dissipation and non-linear interactions are represented explicitly with state-of-the-art formulations.

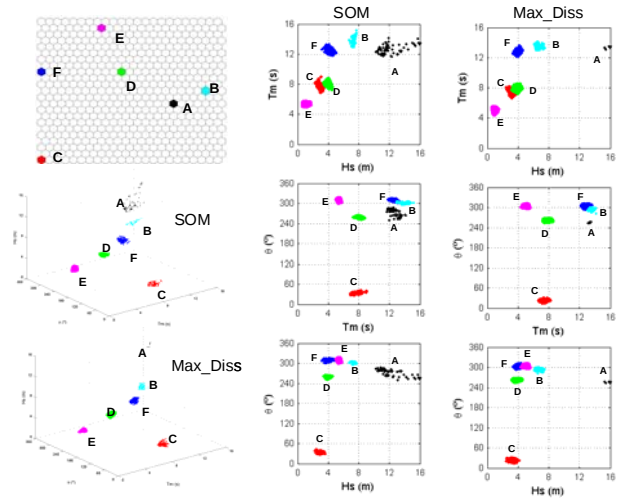


Figure 3. Distribution of the selected clusters

d) Interpolation

In the previous methodology, a linear interpolation procedure was used. Each propagated SOM cluster defined a significant wave height propagation coefficient. The propagation of every sea state of the SIMAR-44 database was carried out by applying the coefficient of each corresponding cluster.

In the present methodology, a method for scattered data interpolation has been considered. The goal of these methods is to find a continuous function calculated from several real function values in scattered data sites that allow the most accurate results to be obtained at a given point of the considered domain. The Radial Basis Function (RBF) approximation has proved

very successful in scattered data interpolation, especially for high dimensional interpolation schemes.

The RBF interpolation considers that the approximation function which we are looking for is formed by a lineal combination of basic symmetric radial functions centred in the points given (see figure 4). We are given scattered points $\{x_1, \dots, x_M\}$ with associated real function values $f(x_i)$, $i=1, \dots, M$. The RBF interpolation assumes that the function we find ($S(x)$) is,

$$S(x) = \sum_{i=1}^M a_i \Phi(\|x - x_i\|), \quad x \in \mathbb{R}^n,$$

and interpolates the given data such that $S(x_i) = f_i$, $i=1, \dots, M$.

Many radial basis functions contain a free shape parameter which plays an important role in the accuracy of the method. In this work, a gaussian function has been used for the interpolation technique and the optimal shape parameter has been obtained by [6] algorithm based on leave-one-out cross validation.

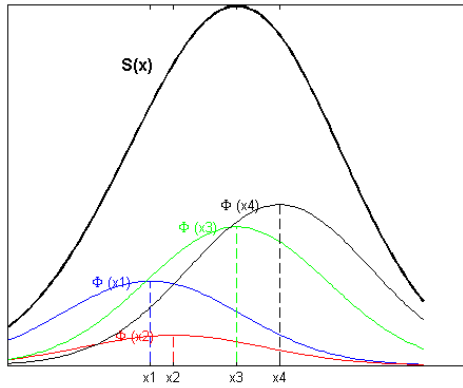


Figure 4. RBF interpolation as a combination of basic radial functions

3 Application to the Asturias coast

3.1. Site location

The Asturias Region is located in the north of Spain, facing the North Atlantic Ocean, see figure 4. The coast's general orientation is east to west, stretching 205 Km from Tina Mayor, in the east (limit with Cantabria Region) and the Ribadeo estuary in the west (limit to Galicia Region). Most of the coast is composed of rocky cliffs with pocket beaches.

3.2. Bathymetry, tides, wind and wave data

Bathymetry data is necessary for wave propagation on the continental shelf. These data have been obtained off the nautical charts from the Spanish Navy Hydrographical Service, see figure 5.

The tidal level can be relevant for wave propagation when waves propagate in shallow waters. As the objective of this work was to map wave energy

resources in waters more than 30 m depth, all wave propagation was carried out using the mean sea level.

Wind and wave data

Wave and wind data have been obtained from the database SIMAR-44. The SIMAR-44 database has 44 years of sea and wind states extending from 1958 to 2001 with a time resolution of 1 hour and a spatial resolution of 1/24 degree. This database was generated using an advanced version of the WAM model with the forcing terms coming from the downscaling of the NCEP (National Center for Environmental Prediction) global atmospheric data which had a spatial resolution of 200 Km. The downscaling was carried out using the REMO (Regional Model) with a final resolution of 0.5°. These forcings were interpolated in the webs used by SIMAR-44 to the final 1/24° resolution.



Figure 5. Location of Asturias in north Spain and bathymetry

Wave data from SIMAR-44 contains 385440 sea states, each one defined by three directional spectra: two swell and one sea. The following sea state parameters have been used in this work:

- Zero order moment wave height, H_{m0} , of the total spectrum.
- Mean period, $T_m = T_{02}$, of the total spectrum.
- Peak period, T_p of the total spectrum.
- Mean direction of propagation, θ_m , of the total spectrum.
- Zero order moment wave height, H_{m0_SEA} , of the SEA spectrum.
- Mean period, T_{m_SEA} , of the SEA spectrum.
- Peak period, T_{p_SEA} , of the SEA spectrum.
- Mean direction of propagation, θ_{m_SEA} , of the SEA spectrum.
- Zero order moment wave height, H_{m0_SWELL} , of the SWELL spectra.
- Mean period, T_{m_SWELL} , of the SWELL spectra.
- Peak period, T_{p_SWELL} , of the SWELL spectra.

- Mean direction of propagation, θ_{m_SWELL} , of the SWELL spectra.
- Mean wind velocity at 10 m above the sea surface, W_{10} .
- Mean wind direction, β_W .

For this work, the SIMAR-44 data has been extracted at 46 points, $1/5^\circ$ apart, of the outer propagation mesh, see blue points in figure 6. Calibration of wave data has been carried out using data from points 9 and 26, the nearest to the deep water wave buoys of Estaca de Bares and Cabo Peñas, respectively (red circle in figure 6). Satellite altimeter wave data has also been used for SIMAR-44 wave data calibration. All simultaneous satellite sea state data located in an area of similar wave climate as the point to be calibrated, has been used for this purpose.

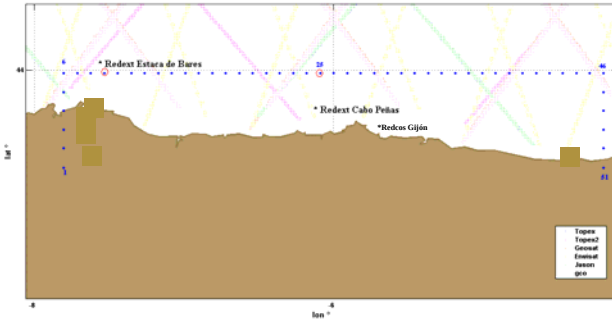


Figure 6. Points of SIMAR-44 used for this analysis. Also satellite data points and the position of directional wave buoys are shown

Wind data from SIMAR-44 database has been extracted in all points inside de propagation mesh, see example in figure 7.

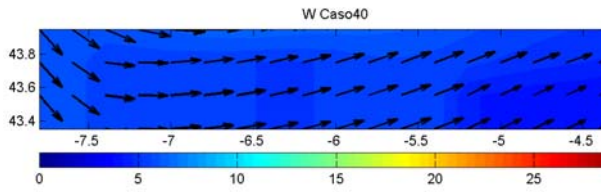


Figure 7. Example of wind field obtained from SIMAR-44 database

3.3. Wave data calibration

The methodology used for SIMAR-44 wave data calibration has been explained in paragraph 2. Using that methodology, SIMAR-44 points 9 and 26, see figure 9, have been calibrated. As an example, figure 8 gives the conversion coefficients for the significant wave height, obtained after calibrating point 26, the one nearest to the directional wave buoy of Cape Peñas. Figure 9 plots, in the vertical axis, the SIMAR-44 calibrated zero order moment wave height, and in the horizontal axis, the instrumental data points used to calibrate point 26. As can be seen in the figure, all points approach the ideal 45° line.

3.4. Wave data classification

To define the wave climate inside the study area, it is necessary to propagate all the SIMAR-44 385440 calibrated sea states from the outer boundary of the area to all the inside points. To make that task computationally affordable, only a representative sample of sea states will be propagated. The methodology used to classify the sea states selected for the propagation sample is the MaxDiss algorithm that has been detailed in paragraph 2. The points selected using this algorithm have an assigned probability.

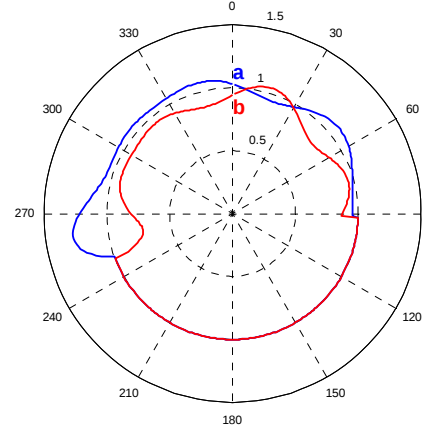


Figure 8. Calibration coefficients $a(\theta)$ and $b(\theta)$ for point 26

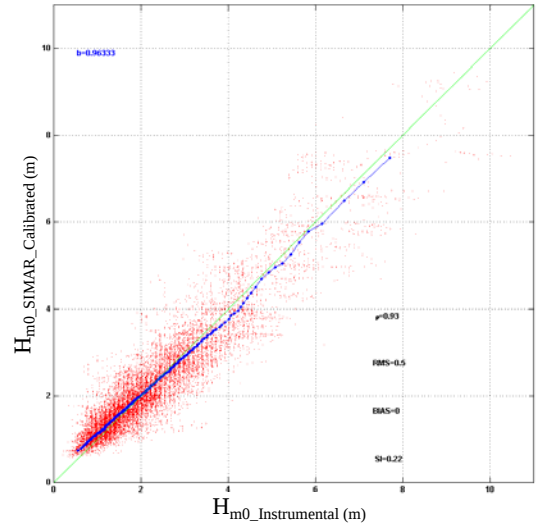


Figure 9. Calibrated SIMAR-44 (vertical axis) versus instrumental (horizontal axis) zero moment wave height. Point 26

The following spectral parameters of the calibrated SIMAR-44 database are used to characterize the sea states:

- Total zero order moment wave height, H_{m0} (m)
- Total mean period, T_m (s)
- Total mean direction of propagation, θ_m ($^\circ$)
- Mean wind velocity at 10 m elevation, W_{10} (m/s)
- Mean wind direction at 10 m elevation, β_W ($^\circ$)

As a result of these selected parameters, each sea state is represented by the 5-dimensional vector

$X_i^* = \{H_{s,i}, T_{m,i}, \theta_{m,i}, W_{10,i}, \beta_{W,i}\}$. The SIMAR-44 point 26 has been used for the classification. Finally, 500 sea states have been selected using the MassDiss classification methodology. Figure 10 shows in red all the SIMAR-44 sea states, and in green the 500 selected sea states for the five variables of the X_i^* vector. As can be seen, in the figure, the MassDiss selected sea states cover all SIMAR-44 data points, producing points also in the outer boundary of the points, a valuable property for the interpolation procedure that will propagate all the database to the inner points of the study area.

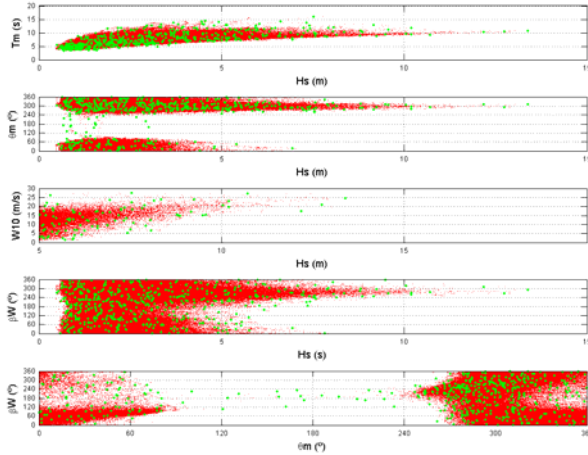


Figure 10. Calibrated SIMAR-44 sea states at point 25 (red points) and selected sea states obtained by the classification methodology MassDiss

3.5. Wave propagation

Wave propagation of the selected sea states has been carried out using the numerical model SWAN, described in paragraph 2. The SWAN model has been run on four different propagation meshes, one outer, 1 Km spatial resolution mesh, A_1 that cover all Asturias coastal waters and three, 200 m spatial resolution meshes: A_2 (Western Asturias) A_3 (Central Asturias) and A_4 (Eastern Asturias), see figure 11.

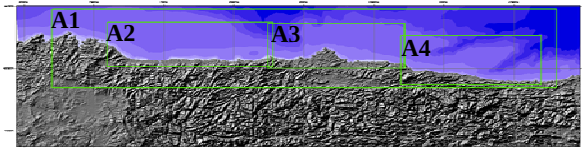


Figure 11. Propagation meshes for the SWAN model

After the propagation of the selected sea states, the following sea state parameters have been stored in each mesh node: H_{m0} , T_m , θ_m , W_{10} , and β_W . Figure 12 shows an example of propagation over mesh A_2 of the selected sea state 141, with the following characteristics at the mesh point 26: $H_{m0} = 7.59$ m, $T_m = 8.65$ s, $\theta_m = 336.20^\circ$, $W_{10} = 19.42$ m/s and $\beta_W = 86.41^\circ$. The upper figure shows the significant wave height ($H_{m0} = H_s$ is assumed) variation inside the mesh and the mean direction of propagation. In the lower figure, the energy flow, in kW/m and the mean propagation

direction of the energy flow are represented. As can be seen in the figure, the wave height on the boundary is variable, responding to the different wave conditions encountered along the W-E boundary of the outer mesh. We can also appreciate how the wave energy coming from the NW is sheltered by the Galician coast and the focusing and spreading of the wave energy near the coast due to the refraction over the variable bathymetry.

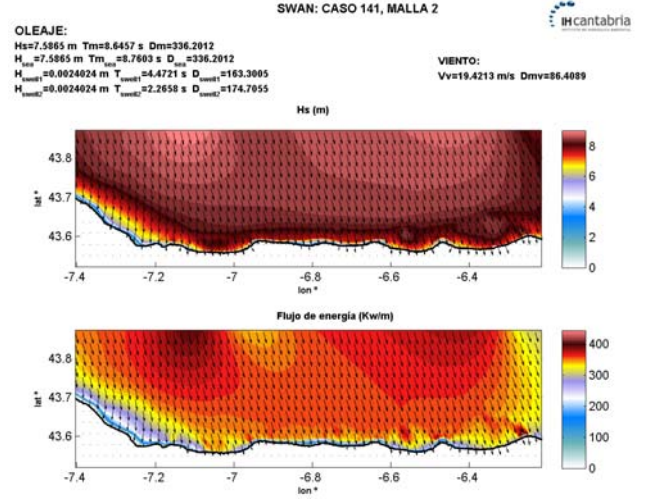


Figure 12. Propagation results of sea state 141 over mesh A_2 . Above, significant wave height; below, energy flow

3.6. Interpolation of sea states

Using the results of the 500 propagated sea states (the 500 sets of 6 sea state parameters H_{m0} , T_m , T_p , θ_m , W_{10} , and β_W stored in each mesh node), the 385440 calibrated SIMAR-44 sea states corresponding to the outer boundary of the A_1 mesh can be propagated to all the mesh points using a multidimensional interpolation technique.

If the 500 calibrated SIMAR-44 deep water sea states selected for propagation are defined by the point 26, 5-dimension vector:

$$D_j^* = \{H_{s,j}^D, T_{m,j}^D, \theta_{m,j}^D, W_{10,j}^D, \beta_{W,j}^D\}; j = 1, \dots, 500$$

and the corresponding vectors with the 500 propagation results in mesh point p are known:

$$D_{p,j}^* = \{H_{sp,j}^D, T_{pp,j}^D, \theta_{mp,j}^D\}; j = 1, \dots, 500$$

the 385440 sea states of the total SIMAR-44 database, represented by the point 26, 5-dimension vector:

$$X_i^* = \{H_{s,i}, T_{m,i}, \theta_{m,i}, W_{10,i}, \beta_{W,i}\}; i = 1, \dots, 385440$$

can be propagated to any point p of the inner meshes using a interpolation technique, obtaining the propagated vector:

$$X_i^* = \{H_{s,i,p}, T_{m,i,p}, \theta_{m,i,p}, W_{10,i,p}, \beta_{W,i,p}\}; i = 1, \dots, 385440$$

The interpolation technique selected in this study has been the Radial Basic Function (RBF) detailed in paragraph 2.

3.7. Validation

With the previous methodology, the calibrated database can be propagated to any point of the inner meshes A2, A3 and A4, with a resolution of 200 x 200 m. That means that the following time series of sea states:

$$\{H_{s,i}, T_{m,i}, \theta_{m,i}, W_{10,i}, \beta_{W,i}\}; i=1, \dots, N=385440$$

can be calculated in any point.

The mean energy flux (MEF) of each sea state can be calculated by integrating the energy fluxes of all the directional wave spectrum components using the expression:

$$P_W = \rho g \int_0^{2\pi} \int_0^\infty C_g(f, h) S(f, \theta) df d\theta$$

where ρ is water density, $S(f, \theta)$ is the directional spectrum and $C_g(f, h)$ is the group celerity of the component with frequency f propagating in a water depth h .

The mean direction of the MEF can be calculated from the directional spectrum using the expression:

$$\theta_p = \arctan \frac{\int_0^{2\pi} \int_0^\infty C_g(f, h) S(f, \theta) \sin(\theta) df d\theta}{\int_0^{2\pi} \int_0^\infty C_g(f, h) S(f, \theta) \cos(\theta) df d\theta}$$

Assuming the scalar power spectrum has an average JONSWAP shape, the previous expressions for the MEF and the mean direction of the MEF can be expressed in terms of the sea state parameters:

$$P_W = 550 H_s^2 T_m (W/m)$$

$$\theta_p = \theta_m$$

Using these expressions, the variable P_W was calculated in all propagation points for the 500 propagation cases. Using the interpolation technique described above, the time series of MEF was calculated:

$$\{P_{W,j}\}; i=1, \dots, N=385440$$

From these time series, any kind of wave power statistics can be calculated.

After the propagation of all the SIMAR-44 data to all nodes of the inner meshes, some tests have been carried out to validate the methodology. Figure 13 shows a time series comparison of H_s measured at the intermediate water (50 m) directional buoy of Gijón and the H_s interpolated from the four nearest A3 mesh points (200 m resolution) of the propagated database. As can be seen in the figure, the propagated database fits very well the measured data, taking into account that this buoy is located under the partial shelter of Cabo Peñas.

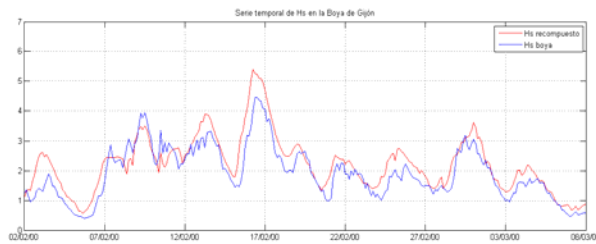


Figure 13. Sample comparison of propagated H_s (red line) versus Gijón wave buoy measured H_s (blue line) time series

Figure 14 shows the H_s scatter diagram of measured versus propagated data points at the Gijón wave buoy position. As can be seen, the slope of the best-fit line is 1.101, the rms error is 0.47 m and the dispersion index is 0.26 cm.

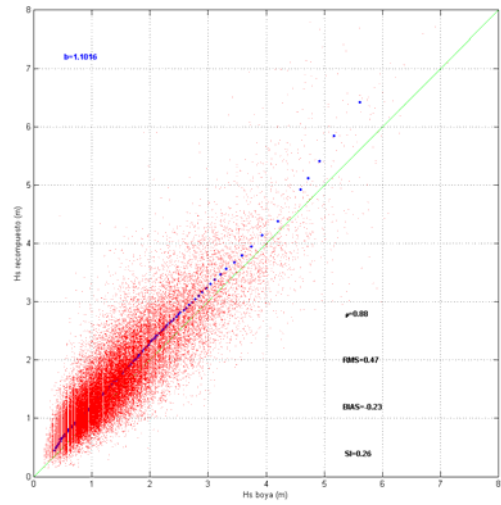


Figure 14. Scatter diagram of propagated H_s data versus data H_s measured by Gijón wave buoy

Figure 15 shows the Annual Average Mean Energy Flux (AAMEF) in mesh A3 and the corresponding values obtained from the directional wave buoys. As can be seen in the figure, the AAMEF measured by the Cabo Peñas deep water wave buoy is 22.80 kW/m, while the corresponding propagated data is 21.95 kW/m (3.7 % error). For the Gijón directional coastal buoy, the measured AAMEF is 12.09 kW/m while the propagated data computes 12.56 kW/m (3.8 % error).

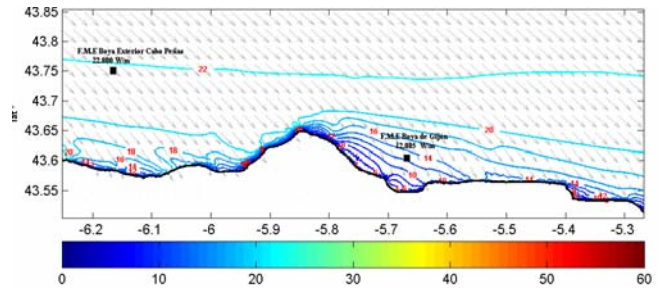


Figure 15. Comparison between the average annual mean energy flux in mesh A3 and the corresponding values obtained by the wave buoys. Arrows show the direction

4. Results

With the methodology described above, the time series

$\{H_{s,i}, T_{m,i}, \theta_{m,i}, P_{W,i}, W_{10,i}, \beta_{W,i}\}; i=1, \dots, N=385440$ can be calculated at any point. With this time series, any kind of wave statistics can be obtained. The mean annual distribution of the MEF is of special importance. For example, figure 16 shows this distribution for a propagation point in 50 m water depth

near Cabo Vidio, where the average annual MEF is 24 kW/m.

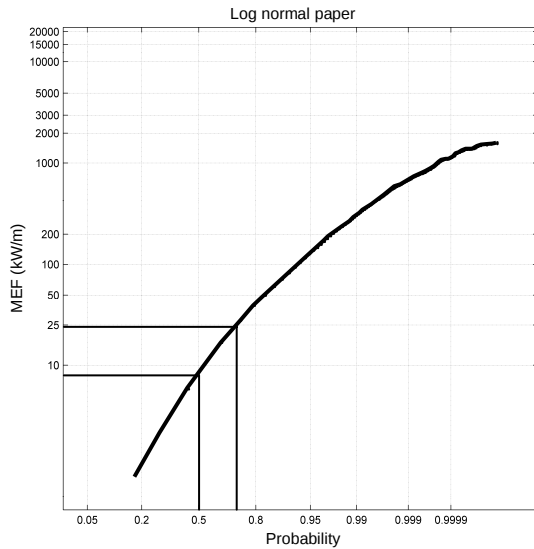


Figure 16. Mean annual distribution of the MEF for a propagation point near Cabo Vidio

As can be seen in figure 16, the mean annual MEF of 24 kW/m is exceeded 30% of the year, while the power that is exceeded half of the year is 9 kW/m. The elevated positive skewness of the distribution is due to the high contribution of storms to the mean annual power. For example, in Cabo Vidio, the incident wave energy is 210240 kWh/m and the sea states whose MEF is exceeded 1% of the time (300 kW/m, 88 hours) contribute with 18.17% (38201 kWh/m) of the total energy of the year. Similarly, the sea states whose MEF is exceeded 5% of the time (120 kWh/m, 438 hours) contributed with 43% of the annual incident energy (90403 kWh/m).

Other examples of statistics that have been obtained are:

- Spatial annual distribution of any percentile of the MEF, figure 17.
- Spatial distribution of the mean annual MEF and mean annual direction of the MEF, figure 15.
- Spatial distribution of the mean seasonal MEF, figure 18.

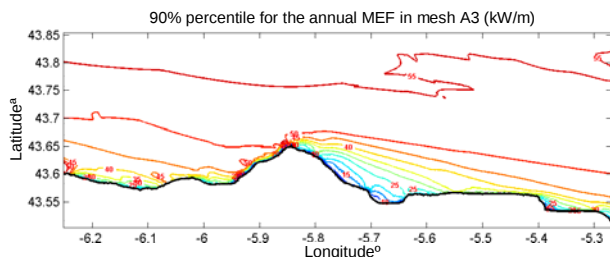


Figure 17. 90% percentile for the annual MEF in mesh A3 (kW/m)

Figure 17 shows that, in deep water, 10% of the year the MEF exceeds 55 kW/m. From percentile figures such as figure 16, the distribution of the annual MEF can be obtained at any point.

As can be seen in figure 18, the winter mean power in deep water exceeds 40 kW/m (in summer is 8 kW/m). In the figure the shelter created to the east of Cabo Peñas can also be seen as well as the focusing and dispersion of wave energy produced by the bathymetry near the coast.

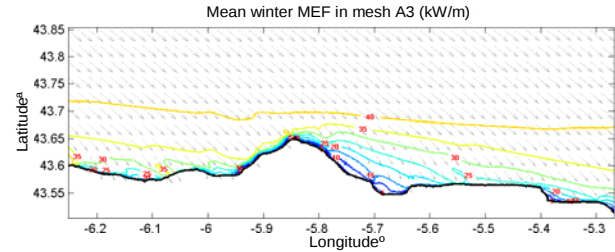


Figure 18. Mean winter MEF in mesh A3 (kW/m)

The seasonality of the energy flux can also be shown in figure 19, which shows the mean monthly MEF for a point in deep water north of Cabo Peñas. 95% and 10% percentiles are shown in the figure.

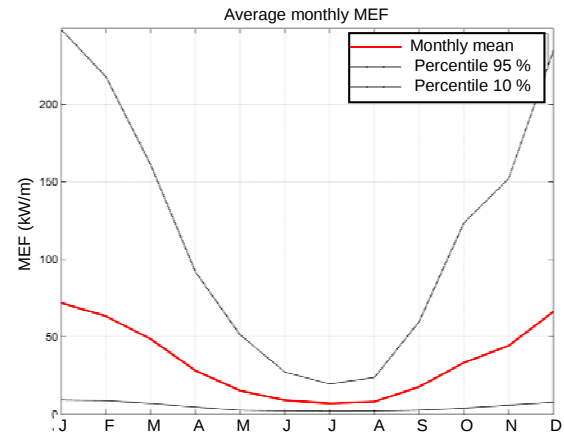


Figure 19. Mean monthly MEF for a point in deep water north of Cabo Peñas

5. Conclusions

In the present paper, the methodology proposed in [1] has been reviewed and some improvements have been introduced.

In the classification process, a maximum-dissimilarity algorithm has been implemented. This technique is capable of extracting the most diverse subset of input data which represents the whole data space, even the outer boundaries. This representation of wave climate in deep water is more convenient for a better propagation of the reanalysis data by an interpolation technique.

The sea states have been defined by five parameters. In more complex wave climates, more parameters (for example SEA and SWELL wave parameters) may be added as the methodology proposed has no limitation in the number of parameters that define the sea states. The wind velocity and wind direction have been included and the wave model SWAN has been used to consider the wind energy generation.

A multidimensional and scattered interpolation technique based on radial basic functions has been applied to transfer reanalysis sea state in deep water to shallow water.

This methodology has been validated using wave buoy data available in Asturias coastal waters. The validation shows very good agreement between the measured and the computed sea state time series of mean energy flow.

After validation, the methodology has been applied to obtain the wave resource statistics of Asturias coastal waters with a 200 m spatial resolution.

The main results are the propagation matrices in all the grid points. With these matrices and the multidimensional interpolation method used, the reproduction of the complete data base and the calculus of any desired statistics in each propagation grid point (200 m resolution) will be straightforward. For example, if the Hs-Tm probability matrices are needed to analyse the production of a specific WEC, they can be obtained for all directions as monthly, seasonally or yearly mean regimes. Also interannual variability can be analysed.

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