# Wave Energy Flux vectorial prediction at three coastal buoys in Spain

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***Abstract.*** Harvesting energy from the ocean waves involves not only the design of efficient and economically feasible prototypes but also a characterization of the resource from which energy is to be extracted. The first operational wave farms are already putting electricty into our grids but as with other types of renewable energy, the electricity obtained from waves has the problem of intermittency, Having a knowledge of the energy waves will hold a few hours ahead can contribute to a better management of the electricity grid. In this work, three types of statistical models have been used to create up to 24h forecasts of the zonal and meridional components of the wave energy flux levels at three directional buoys located near the coast in the Bay of Biscay. Model's performance has been compared at a 95% confidence level with the most simple prediction (persistence of levels) and also with the forecasts provided by the physics-based WAM model at the nearest gridpoint. The results indicate that for forecasting horizons between 3 and roughly 16 hours ahead, among the statistical models those built on random forests outperform the rest, including WAM and persistence.

***Keywords.*** *Wave Energy Flux, Forecasting, Random forest, Machine learning, Fluid mechanics*

## 1. INTRODUCTION

In the few wave farms that currently are operating, the problem of intermittency in electricity production is an issue of major concern. In this sense, an accurate knowledge of current and forthcoming wave energy levels can contribute to address this problem by developing real-time effective grid management strategies [1].

Wave energy is usually expressed in terms of the Wave Energy Flux (WEF, kW/m) which is a vectorial magnitude so a complete prediction of this variable involves forecasting its zonal (WEFu) and meridional (WEFv) components. This magnitude is not measured directly in buoys but its module is derived by combining the significant wave height (Hws) and the mean wave period (Tz) according to the following equation:

$$WEF=0.49Hws^2Tz \text{ [Kw/m]} \qquad [1]$$

Additionally, the zonal (WEFu) and meridional (WEFv) components can be obtained from the module (WEF, [1]) by projecting it using a third variable measured at directional buoys, the mean wave direction (Mdir).

WEF forecasts a few hours ahead are usually obtained using predictions yielded by physics-based models [2, 3, 4, 5] like for example the WAM, run by the ECMWF. These types of models assimilate observations and then solve the equations involved following the laws of Physics and Fluid Mechanics. Another approach is to learn from the past to forecast the future. Under this approach the problem of forecasting is treated as a "*black box*" in which a statistically-based transfer function is fitted on historical records relating current and future values of WEF at a given location [6,7,8,9]. In this work, we have compared the performance of WAM, persistence and three statistical models in three buoys located in the Bay of Biscay.

## 2. DATA AND METHODS

### 2.1. DATA

The area of study is the Bay of Biscay (Fig. 1). To carry out this study, hourly data from the following three sources corresponding to the 1999-2012 period were used:

1. Data from 3 directional buoys, located near the Spanish coast.The variables used from these three buoys were Hws, Tz and Mdir.. Combining these three variables, local values of WEFu and WEFv were derived
2. Retrospective simulations of the ECMWF atmospheric and wave models as follows:

   2.1 ECMWF (www.ecmwf.int) ERA-Interim

atmospheric reanalysis (Dee et al., 2011) data in analysis mode. The selected variables were mean sea level pressure (MSL), zonal (U10) and meridional (V10) components of the surface wind over the Bay of Biscay [10.125ºW, 43.875ºN, 2.25ºW, 48.375ºN]

2.2 ECMWF WAM model in analysis mode (every 6h)

3. ECMWF WAM wave model (WAM) in forecasting model (hindcasts) at step=12 and step=24h ahead for the same area, variables, period and resolution. As in analysis mode, the original variables (Hws and Tz) were combined using [1] and Mdir to obtain WEFu and WEFv values.

In Fig. 1 it can be seen a map of the area and the location of the gridpoints and buoys.

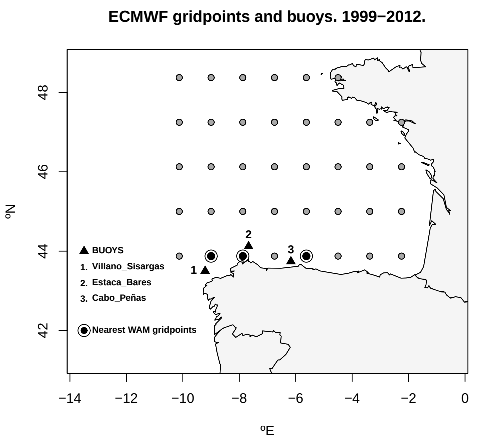


Fig. 1. Location of the buoys used for this study and nearest ECMWF gridpoints

## 2.2. Methodology

### *2.2.1. Extended EOFs*

In this work, extended EOFs have been calculated for the ECMWF atmospheric and oceanic variables corresponding to the Bay of Biscay and with three 6 h steps back in time (18h). These atmospheric and oceanic variables involved were as follows: sea level pressure (MSL), zonal wind speed at 10 m above the sea (U10), meridional wind speed (V10), the module of the flux -derived from [1]- and its zonal and meridional components. The final number of extEOFs retained was 21, and were selected under the condition of retaining at least 90% of the original variance. This allowed a dramatical reduction in the number of variables used while still holding most of the information of the atmosphere-sea state in the Bay of Biscay.

### *2.2.2. Building the models*

With the aim of predicting at time t values of WEFu and WEFv k (k=1,...,24) hours ahead, all the models were fitted according to the general structure of [2] and [3].

$$WEFu\_buoy[t+k]=F_1(extEOF_{1\text{-}21},WEFu\_buoy[t]) \quad [2]$$

$$WEFv\_buoy[t+k]=F_2(extEOF_{1\text{-}21},WEFv\_buoy[t]) \quad [3]$$

To that purpose, three types of statistical models were built to forecast zonal and meridional WEF levels at the three buoys analized: i) analogues, ii) analogues followed by a random forests regression stage and finally, iii) random forests. A more detailed description on the mathematical aspects regarding RF [11, 12] and some examples of its practical applications [13, 14] can be found in the literature. The total amount of models built and tested in this study has been 2366832. All the calculations have been carried out in the frame of R [15,16].

### *2.2.2. Evaluation and intercomparison of models*

The criterion adopted for model intercomparison of WEF forecasts, was the mean absolute error at a 95% confidence level. The models built compared with WAM forecasts and with persistence.

## 3. RESULTS AND DISCUSSION

The main results for both, the zonal and meridional components of the flux can be seen in Fig. 2 and 3. Since the overall behavior is similar at the three buoys, results are given in an aggregated manner.

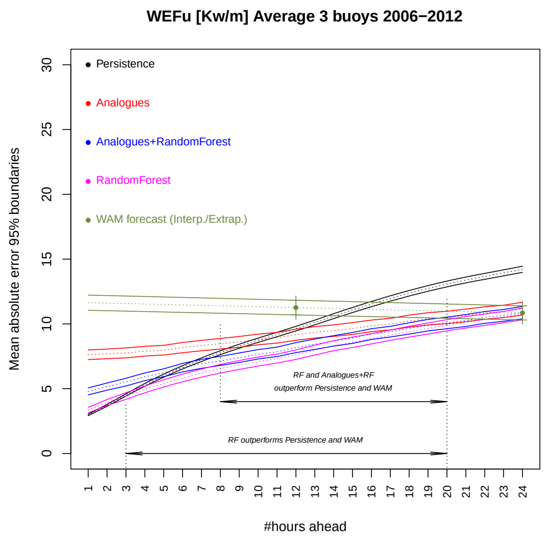


Fig. 2. Mean absolute error for WEFu forecasts.

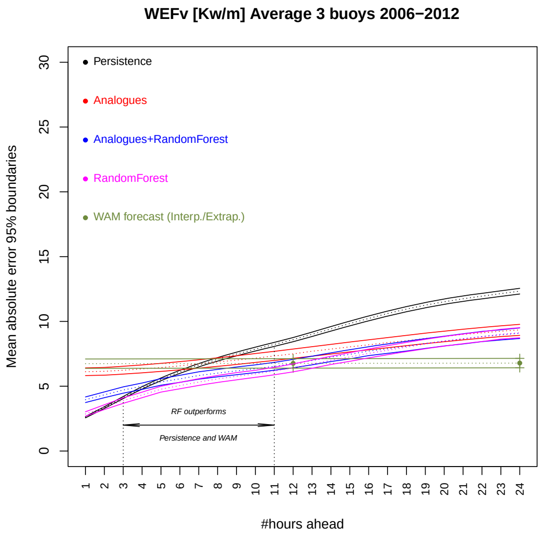


Fig. 3. Mean absolute error for WEFv forecasts.

The results gathered in Fig. 2 and Fig. 3 can be summarized as follows:

1. For WEFu prediction, between 3 and 20h ahead, RF-based models yield the smallest errors outperforming the rest and also WAM and persistence
2. In the case of WEFv the preferential window for RF models ranges between 3 and 11h.
3. These windows represent the forecasting horizons for which RF-based statistical models could be used.

An interesting aspect is that if the error roses are analyzed for the statistical models and for WAM, it can be seen that they have a different structure.

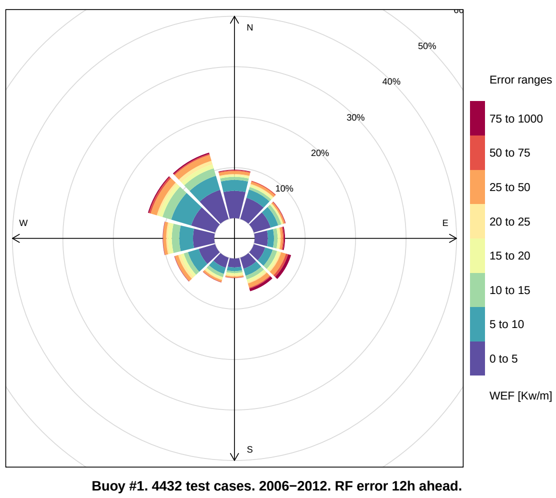


Fig. 4. Error rose for the RF model's 12h forecasts at buoy #1.

In the case of RF model (Fig. 4) errors are equally distributed in all directions and with similar absolute values. However, WAM's error rose (Fig. 5) clearly exhibits a preferential (north) westwards direction. This is the reason why the preferential windows for WEFu and WEFv are different.

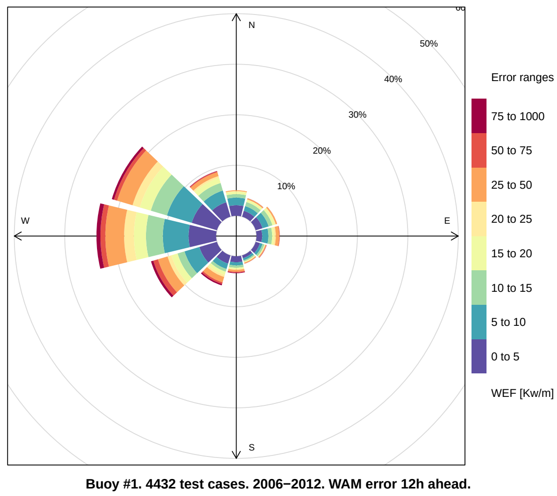


Fig. 5. Error rose for the WAM model's 12h forecasts at buoy #1.

The reasons for this different behavior of WAM in the zonal and meridional directions are not clear, but the bathymetry of the area and the small distance to the coast (Fig. 6) may represent a partial explanation.

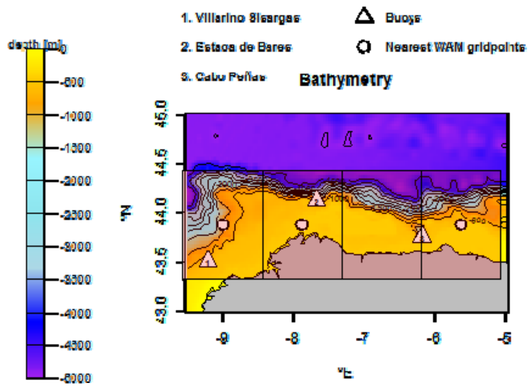


Fig. 6. Bathymetry of the area studied.

Considering the gridsize it uses (overimposed, Fig. 6), WAM model makes the forecasts using the following depths for the [1.125º x 1.125º] cell corresponding to the three nearest gridpoints from the buoys: -990 m (buoy#1), -223 m (buoy#2), -186 m (buoy#3). However, the effective depths at the buoys are as follows: -386 m (buoy#1), -1800 m (buoy#2), -450 m (buoy#3). In Fig. 6 it can be seen that the three buoys are located at places where bathymetry exhibits a strong gradient, while the WAM model considers a flat sea bottom for each pixel of the grid with constant depths as shown above. This means that with the resolution it uses, WAM is probably unable to successfully simulate the effects associated to the complex bathymetry below the buoys. Additionally, coastal effects may not be captured accurately since the area covered by these pixels is not homogeneous and actually includes both, sea and land.

## 4. CONCLUSIONS AND FUTURE OUTLOOK

For the three buoys located in NW Spain, a set of statistical models based on RF outperform other options. RF can capture from a historical database, under a black box approach, the major patterns regarding the evolution of WEF in the timescale of hours. RF also outperforms readily available persistence and WAM models with a combined preferential forecasting horizon for WEF would be between 3 and 16h. The buoys in this study are located near the coast, in the range where future wave farms could be installed. Due to the high number of models tested and cases used in this study, the conclusions can be considered to be solid enough. The overall conclusions obtained for the prediction of the zonal and meridional components of WEF are similar to those obtained for the module alone [17] and highlight the potential of a machine learning technique like random forests may have for short-term forecasting of ocean energy. All this can contribute to address the problem of intermittency and to the development of more efficient grid management strategies.

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