

# European Scalable Offshore Renewable Energy Source

(EU-SCORES)

D6.1

'Renewable Correlation of offshore resources.'

December 2022

Delivery Date 29-11-2022

Dissemination Level PU Status Final Version 2.0

Keywords wave energy; wind energy; resource assessment; renewable

energies

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# Document Information

Grant Agreement Number	101036457
Project Acronym	EU SCORES
Work Package	WP6
Related Task(s)	Task 6.1
Deliverable	D6.1
Title	Renewable Correlation of offshore
	resources.
Author(s)	Matias Alday Gonzalez (TUD)
	Harish Baki (TUD)
	Sukanta Basu (TUD)
	George Lavidas (TUD)
File name	D6.1_CrossCorrelation_Final

# Revision History

Revision	Date	Description	Reviewer
1	03-11-2022	Version 1	All partners
2	29-11-2022	Version 2	All partners

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### 1 Executive Summary

This Deliverable, 6.1 Renewable Correlation of offshore resources, aims to investigate the potential for correlation between parameters of different renewable energies.

The analysis is based on a first layer on coarse data, and will allow us to identify which resources have more "connectivity". The resource assessment, even at coarse level, will indicate regions for further high resolution analysis, with better suited wind-wave-solar models. The correlation analysis is expected to showcase the potential of temporal overlaps by the different resources.

The Deliverable examines the overlap of stochastic conditions, the analysis will consider different "time windows" for the base resource, and assess its complementarity with other stochastic renewables. The aim of this deliverable is the estimation of overlap and production of mean maps that indicate to which extend each resource is connected. It is expected that the wind and wave resources will produce higher interest, due to their temporal variability. However, peak solar performance will also be analysed in terms of overlap with wind and/or wave.

#### 2 Climate data

The preliminary wave energy density assessment to estimate the offshore resource availability, was done using the ECMWF ERA5 reanalysis (Hersbach, et al., 2020). The ERA5 dataset was developed using the 4-dimensional (4D) data assimilation method from the Integrated Forecasting System (IFS) Cycle 41r2 and improves upon several previous iterations like the widely used ERA-Interim (Rivas & Stoffelen, 2019). The ERA5 products can be useful for preliminary analysis as they offer good temporal resolution (1 h) of sea state related variables like the significant wave height ( $H_S$ ) and the peak period ( $T_P$ ) or the 10 m surface wind intensities ( $T_P$ ) and directions. However, their spatial resolution and associated shallow water physics (shoaling, refraction, bottom friction) is not suitable to perform power estimates in intermediate to shallow depth areas.

The spatial coverage selected from the dataset includes latitudes  $30^{\circ}$  to  $69.9^{\circ}$  North and longitudes  $-19^{\circ}$  to  $41.9^{\circ}$  East, with a grid resolution (dx and dy) of  $0.3^{\circ}$ . The ERA5 wave product has a time output frequency of 1 hour.

A more in-depth and comprehensive intra-annual, decadal and seasonal analysis of all offshore renewable coarse resources is elaborated upon D6.2 within the EU-SCORES project.

In addition to the wave parameters' statistical characterization, the Pearson correlation index was computed between  $H_{\text{s}}$  and the surface wind intensities ( $U_{10}$ ; also take from the ERA reanalysis):

Equation 1 
$$CC(X,Y) = r_{X,Y} = \frac{\sum_{i=1}^{N} (X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{N} (X_i - \overline{X})^2} \sqrt{\sum_{i=1}^{N} (Y_i - \overline{Y})^2}}$$

Where X and Y are the variables used in the correlation computation, with  $\bar{X}$  and  $\bar{Y}$  the mean values of X and Y respectively.

Correlation Coefficient (CC) measures the degree of correlation between the random variables, determines the direction of this link, and accepts values in [1,1]. Positive values indicate that the two random variables behave similarly; for example, if one random variable is increasing (decreasing), then the other is likewise increasing (decreasing). As the values of CC trend to zero, the link between the random variables weakens, whereas negative values (also known as anti-correlation) suggest the opposite behaviour.

The correlation coefficient (CC) is frequently used to describe how well two renewable energy sources complement one another. In theory, the correlation coefficient (CC) is used to measure the connection between two random variables. The following basic



presumptions guide its implementation: Given that the random variables are normally distributed, there shouldn't be any outliers in the sample, and linearity and homoscedasticity should hold true, among other assumptions. As a result, when there is a nonlinear relationship between the variables, Pearson correlation is not acceptable.

Thus, while evaluating hybrid renewable energy sources, CC values that are negative imply complementarity whereas CC values that are positive show synergy between the sources. Pearson r is the most popular CC type out of all of them.

The aim behind the correlation analysis between wave heights and wind intensities, is to provide a rough idea of how independent the wave resource is from the wind conditions.

#### 2.1 Wave parameters and wind conditions correlation

To provide a general idea of the "level of independence" of the sea state conditions with respect to the local wind, we have computed the mean Pearson correlation (Equation 1) between  $H_{\rm S}$  and  $T_{\rm P}$  with respect to the wind intensity. This mean correlation value is obtained by first computing the Pearson correlation for each year from 1990 to 2020 and then getting the average (Figure 1). Note that this is a crude estimate of the correlation between the sea states and the local wind, and a more detailed relationship could be stablished with the wave age and analyzing wave partitions (e.g.; different swell components and primary wind sea). Nevertheless, the analysis provides enough information on where the local wave power density depends more on the wind conditions.

There are 2 zones that can be easily characterized: Portugal and the North Sea. Off the coast of Portugal is possible so see the low correlation between wind intensity and wave heights ( $\sim 0.45$ ) and basically no correlation between peak periods and the wind intensity. This indicates that the wave field is mostly dominated by swells radiated from far distances and thus, it is expected that the wave resource availability is less affected by local atmospheric conditions. On the other hand the North Sea presents high  $H_S$ -wind intensity (>0.75) and a non-negligible ( $\sim 0.2$ )  $T_P$ -wind intensity correlations which suggests that under low wind conditions it is also expected to have a reduction of the wave power density.

On the contrary wind generated dominant regions such as the Mediterranean and Baltic Seas, pose higher correlation for both wind- $H_S$  and wind- $T_P$ , with both values consistently >0.7.



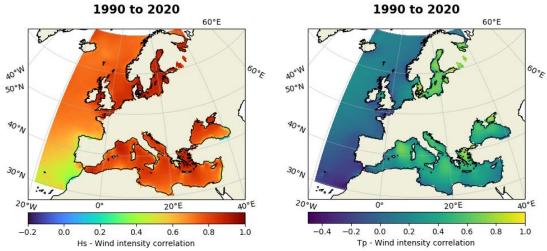


Figure 1.  $H_{\text{S}}$  (left panel) and  $T_{\text{P}}$  (right panel) 30 years mean correlation with wind intensity.

#### 2.2 Wave parameters and solar radiation correlation

Similar to the analysis done in section 2.1, a wave parameter's  $(H_S \text{ and } T_P)$  correlation with the surface solar radiation product from ERA5 was carried out (Figure 2). There is very low to no correlation between solar radiance and local wave conditions, this can be explained with 2 main points.

Firstly, the "day light hours" or "night hours" are not locally related to the wave conditions. In other words, the absence of sun light does not necessarily imply a reduction or increase of the wave heights (or periods) of the sea states. Secondly, it is necessary to consider global mean heat gradients, which are not directly used for solar assessments. Solar radiation plays an evident role in the global heat balance and thus in atmospheric dynamics, but the time scales of atmospheric fronts (or instabilities) development and their evolution depend on complex ocean-atmosphere interactions. These interactions normally take place at time scales much larger than a 24 hours cycle.



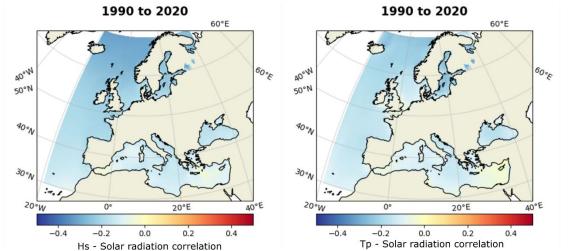


Figure 2.  ${\it H}_{\it S}$  (left panel) and  ${\it T}_{\it P}$  (right panel)30 years mean correlation with surface solar radiation.

Colorbars have been saturated from -0.5 to 0.5 to increase correlation details in figure.

#### 2.3 Wind power density and Solar radiation correlation

The Pearson CC between wind power density and surface solar radiation (SSRD) is calculated using Equation 1 at every hourly interval from 1990 to 2020 and presented in Figure 3. For most regions CC are from -0.3 to 0, indicating the existence of a complementary correlation. However, the CORR values are minimal, implying a weak correlation.

In Portugal and the Iberian Peninsula the CC has the weakest correlation with nearly all of the regions, having a 0 correlation. From France to the North Sea the CC value are -0.2 indicating an inverse low correlation between wind and solar resources. In the Mediterranean most deep water regions show no correlation, while also a weak inverse correlation from -0.4 to -0.2 is present in close coastal areas in Italy, Northern Greece, and Eastern part of Spain and France.



# CORR between wind power density and SSRD during 1990 to 2020

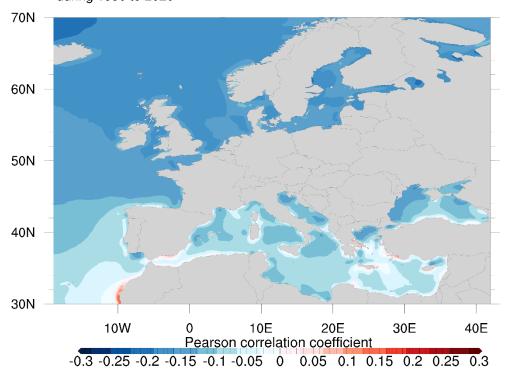


Figure 3: Pearson correlation coefficient between wind power density and surface solar radiation, evaluated at every hour, during 1990 to 2020.

#### 3 Summary

This Deliverable, 6.1 Renewable Correlation of offshore resources, aims to investigate the potential for correlation between parameters of different renewable energies.

- ✓ Cross correlation between wind intensities and waves are higher in North Sea >0.75 of  $H_s$ .
- ✓ Portugal is more swell dominated and hence the correlation is lower >0.4 of  $H_s$ .
- ✓ Cross correlation is higher for  $H_s$  in all instances but lower for  $T_p$  in the same regions >0.3.
- ✓ Mediterranean Sea, Baltic Sea and the Black Sea have high correlation between wind and wave components, consistently > 0.7.
- $\checkmark$  Wave and solar showcase weak inverse correlation, Portugal and the North Sea have approximately 0 and -0.2 respectively.
- ✓ Positive weak correlation between wave and solar can be found in the Mediterranean in Central-South Greece, and Southern Spain with values from 0.1 to 0.2.

Differences between the resources, imply different potential approaches in their combinations. Strong correlations can be beneficial for combined predictability, and hence can be beneficial to reduce variability.

Wind and waves have regions, with strong CC values, and taking into account that waves have less variability in their directional changes and magnitudes, they can offer some level of variability reduction to wind. Wave and solar have low inverse correlation mostly, with some Southern European countries showcasing low positive trends. At a first glance, this can seem as a negative, however, uncorrelated or inverse correlated resources can be beneficial for power production at different temporal scales.



# 4 Bibliography

Hersbach, H. et al., 2020. The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, Volume 146, pp. 1999-2049.

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