Satellite data for high resolution offshore wind resource mapping: A data fusion approach

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Abstract – Wind resource mapping needs accurate high spatial and temporal resolutions wind measurements. Offshore, satellite data are an accurate and economic way to access wind measurements. Previous studies showed the capabilities of some remote sensing instruments to measure the wind. Synthetic aperture radars (SAR) have a high spatial resolution but are associated to a low temporal repetitiveness, preventing resource assessment reliability due to the small number of samples. Scatterometers have a sufficient temporal repetitiveness for assessment reliability but have a low spatial resolution (25 km). In this paper we apply a data fusion method to these different datasets. The fusion of scatterometer and SAR data sets results on a synthetic data set having the high spatial resolution of SAR measurements and the temporal repetitiveness of scatterometer measurements. This synthetic data set, having high spatial resolution, can be used to assess the resource at a high spatial resolution. It meets the requirements of the computation of wind statistics.

Keywords: synthetic aperture radar, scatterometer, data fusion, offshore wind energy resource assessment.

1. INTRODUCTION

Since approximately a decade, spaceborne instruments give information about wind offshore. These instruments have different characteristics. Of interest for wind energy are the radar scatterometers and the synthetic aperture radars. Both of these instruments are active sensors. They emit a microwave signal. This signal interacts with sea surface, specifically, with waves generated instantaneously by wind blowing over the area. An empirical function permits to link the backscattered signal and wind. Scatterometer measurements have a sufficient temporal resolution to establish reliable wind statistics. For example, the satellite QuikScat gives two measurements per day of wind at mid-latitudes. However, these instruments have a spatial resolution that could not permit to achieve a kilometer-scale mapping of wind resource. The spatial resolution of QuikScat is of 25 km. The spatial resolution of wind fields retrieved using synthetic aperture radar images suits the requirements of wind resource mapping offshore (a kilometric spatial resolution) but is associated to a temporal repetitiveness that could not lead to reliable statistics of wind.

In this paper, we apply a data fusion method to benefit from the high spatial resolution of synthetic aperture radar based wind data and from the high temporal resolution of scatterometer data.

2. STUDY AREA

The area of interest is the northern coast of the region of Brittany, France. This region is characterized by one of the most important wind energy resources in France. The dominant winds over this region are westerly winds. In this study, we focus on the area indicated by the red box on Figure 1. We consider the period going from July 1st, 2007 to June 30th, 2008. This one-year-period will permit to avoid seasonal biases.

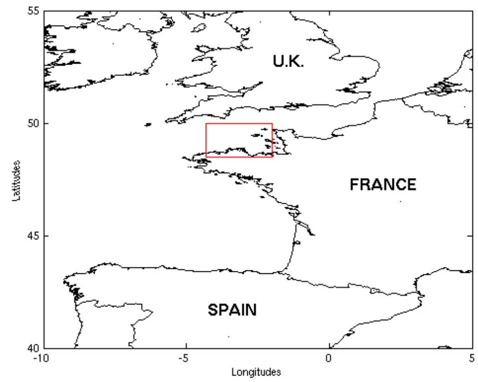

Figure 1. Study area location. Area of interest is indicated by the box.

3. WIND ENERGY RESOURCE MAPPING

Empirical studies have shown that the temporal wind variations over an area can be described, with a sufficient precision, using the two parameter Weibull probability density function (Justus, 1976). This approximation is valid at different spatial scales going from global scale to local scale (Monahan, 2006). It became a standard in wind energy sector thanks to its use in several wind atlases (Petersen, 1981).

The Weibull probability density function is given by the following equation:

$$p(v) = \frac{k}{A}\left(\frac{v}{A}\right)^{k-1} e^{-\left(\frac{v}{A}\right)^{k}} \tag{1}$$

p(v) is the probability of occurrence of wind speed *v* over the area. The parameter A, called scale parameter, is analogous to the mean wind speed and is expressed in (m s^{-1}). The largest is A the highest are the mean wind speed and the wind resource available over the area. The parameter k is analogous to the inverse of the standard deviation. The largest is k the most peaked is the distribution around a given value.

The mean power density of the area can be directly computed using Weibull parameters. It is given by equation (3.2).

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$$E = \frac{1}{2}\rho A^3 \Gamma\left(1+\frac{3}{k}\right) \quad (2)$$

where ρ is air density in kg m^{-3}. The mean power density is expressed in W m^{-2}.

The parameters A and k have to be estimated from a data series of wind measurements collected over the area. In this study, we use the maximum likelihood estimator to compute A and k. It is obvious that the error and the uncertainty on the estimation depend on the number of measurements. In addition, to avoid seasonal biases, at least one year of data have to be considered.

4. WIND DATA SOURCES OFFSHORE

The Wind data sources used on this study are the following.

5.1 IFREMER blended wind fields

At IFREMER a wind field archive, with a global coverage, is available at the following address: http://www.ifremer.fr/cersat/facilities/mwf-blended-nrt/. It is based on several remotely sensed winds (wind speed and direction) derived from the SeaWinds scatterometer on board QuikScat and SSMI radiometers on board DMSP F13, F14, and F15 satellites (Bentamy, 1999). These remotely sensed measurements are blended through an objective analysis (kriging) with ECMWF European Center for Medium Range Weather Forecasting) operational analysis available at synoptic times(0h, 6h, 12h and 18h UTC). The spatial resolution of the IFREMER blended wind fields is of 25 km and the 4 wind fields per day are available (at 0h, 6h, 12h and 18h UTC). It has been shown by (Bentamy, 2006) that Blended wind measurements and *in situ* measurements agree well.

5.2 Synthetic aperture radars

SAR are active microwave radars. They are present in several missions (such as ERS-1, ERS-2, Radarsat, Envisat and TerraSAR-X). The principle of SAR is similar to that of scatterometers. In fact, the signal emitted by SAR interacts with wind generated sea waves. SAR permit to access to high spatial resolution measurements by performing a processing of the phase the backscattered signal. An empirical algorithm is used to retrieve wind speed from SAR images. The typical spatial resolution of SAR images is of a few tens of meters. The wind fields retrieved using these images have, however, a spatial resolution of a few hundreds of meters. Indeed, the measurements taken by SAR have to be averaged over several pixels . This is due to noise (speckle) in SAR images that affects the backscattering coefficient. In order to retrieve wind speeds from SAR images, wind direction is needed as input. SAR wind fields used in this study are obtained from CLS (DAR) at the following address: http://soprano.cls.fr.

5. DATA FUSION METHOD

The fusion method presented in this paper is based on the assumption that, if two wind fields are similar at low spatial resolution, they belong to the same wind situation, also called typical situation.

Based on this assumption, it is only necessary to have one high spatial resolution measurement to infer the high spatial structures (representing local effects and turbulence) of all similar wind fields. The fusion method aims to generating a synthetic data set of wind fields at high spatial resolution and high temporal resolution. Hence, the high spatial structures contained in a SAR wind field are injected on low spatial resolution data belonging to the same typical situation.

The first step of the method is the classification of low spatial resolution wind fields. The classification method is detailed in (Ben Ticha, 2007). The classification results on several classes grouping similar wind fields. Each class represents a typical behavior of wind flow over the studied area. Therefore, under the assumption of the conservation of similarity when the spatial resolution increases, each class could be associated to typical high spatial resolution structures. The classification is followed by the association of a SAR wind field to each typical wind situation. The high spatial resolution (fine scale) structures are, then, extracted from the SAR wind field and injected, using multi-scale analysis, into the wind fields corresponding to the typical wind situation.

The resulting synthetic data have the highest available temporal resolution and the highest available spatial resolution. The data fusion method is detailed in (Ben Ticha, 2007).

6. APPLICATION AND RESULTS

In this study, the inputs of the data fusion method are:

- one year of IFREMER blended wind fields covering the period going from July 1st,2007 to June 30th, 2008.
- 45 SAR based wind fields based on images acquired by the ASAR onboard ENVISAT during the same period. From 3 to 6 images are available per month from October 2007 to June 2008.

The generated data set has the temporal resolution of IFREMER blended wind fields (one wind field each 6 hours) and the spatial resolution of the SAR wind fields (1 km).

Figure 2, 3, and 4 represent the annual mean wind field computed using respectively IFREMER blended wind fields, the 45 SAR wind fields and the data series resulting from the data fusion method. Figures 2 has a spatial resolution of 50 km. Figure 3 has a spatial resolution of 25 km. Figures 4 and 5 have a spatial resolution of 1 km. The mean wind field based on the 45 SAR wind fields (Figure 4) is characterized by an overestimation of the mean wind speed relatively to the other maps. This overestimation is essentially apparent on the northern part of the image. However, a good agreement between the mean wind field spatial patterns based on this short data series (45 SAR wind fields) and the other data series (one year of 6 hourly wind fields) can be seen. This is mainly due to raw data distribution and to the statistical proprieties of the mean as a statistical first moment. As shown theoretically by (Pryor, 2004), the number of samples needed to estimate the mean of data following a Weibull probability density function, with a precision of 10 % at a probability of 90 %, is on the order of 50 measurements. The mean wind fields based on the data generated by the data fusion method (Figure 5) reveals almost the same fine scale structures present in the SAR based mean wind field. However, the wind speeds magnitudes are more in agreement with the IFREMER blended wind fields. The longer data series generated by the data fusion method permits, thus, a better estimation of mean wind speeds.

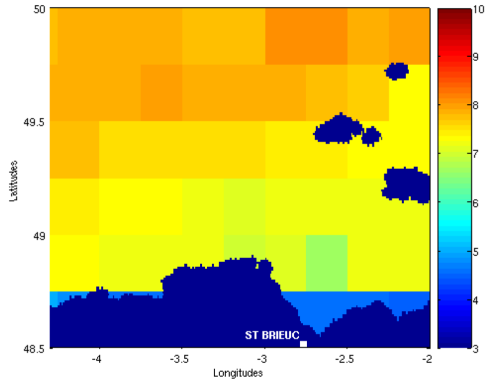

Figure 2. 10-meter height annual mean wind speed computed using IFREMER blended wind fields. Wind speeds are in (m s^{-1}).

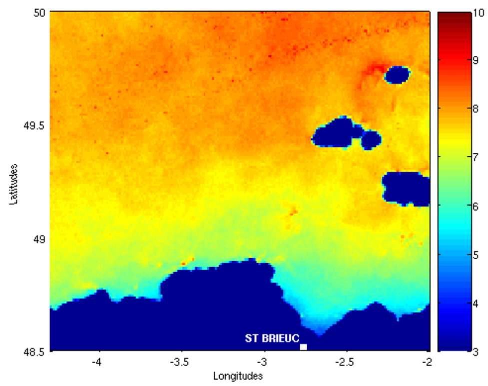

Figure 3. 10-meter height annual mean wind speed computed using SAR wind fields. 45 SAR images are used here. Wind speeds are in (m s^{-1}).

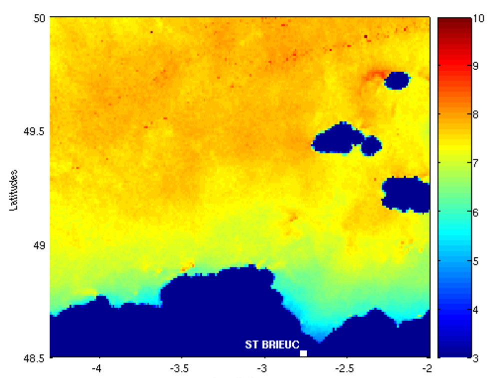

Figure 4. 10-meter height annual mean wind speed computed using the synthetic data series resulting from the data fusion method. Wind speeds are in (m s^{-1}).

To illustrate the effects that are present in the high spatial resolution wind fields generated by the fusion algorithm, we selected the westerly wind situations and computed the mean wind field of these situations. The mean wind field is represented in Figure 5. The mean winds along the transect shown by the black line on Figure 5, are reported in Figure 6 (blue line). This transect crosses Guernsey Island. We can see that a possible shadowing effect after Guernsey, not shown by IFREMER blended data (red line in Figure 6).

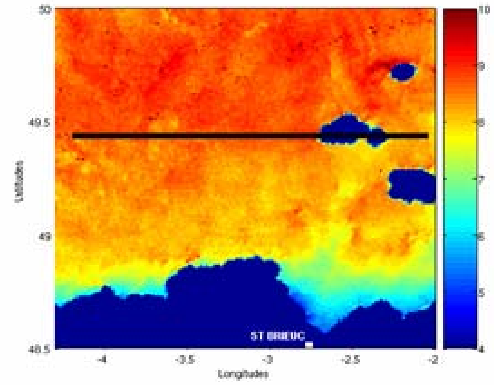

Figure 5. 10-meter height annual mean wind speed computed using the synthetic data series resulting from the data fusion method. Wind speeds are in (m s^{-1}).

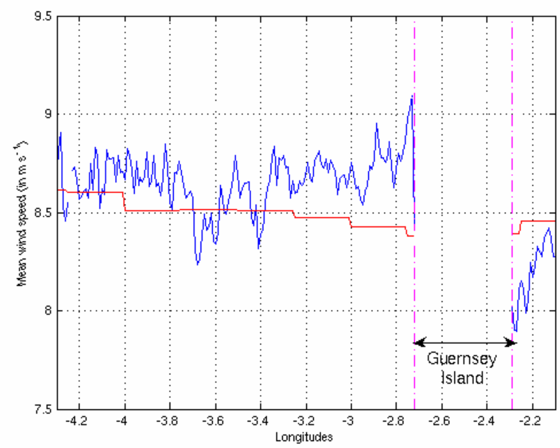

Figure 6. 10-meter height annual mean wind speed computed using the synthetic data series resulting from the data fusion method. Wind speeds are in (m s^{-1}).

As indicated previously, the number of samples needed to accurately estimate a moment of a statistical distribution increases as the order of the statistical moment increases. The estimation of higher moments than the mean (first moment), is greatly improved by the use of the high temporal resolution data set.

Figures 7, 8, and 9 represent the mean power density maps computed from the Weibull parameters estimated respectively from the IFREMER blended wind fields, the 45 SAR wind fields and the synthetic data generated using the data fusion algorithm. We can see that by using only the 45 SAR wind fields (Figure 8) we largely overestimate the mean power density over the area. The mean power density map using the synthetic data (Figure 9) seems more in accordance with the map using ECMWF analysis and blended wind fields. Its 1 km spatial resolution reveals fine scale structures not revealed by the ECMWF analysis and IFREMER blended wind fields. However, we can see some edge effects with an underestimation of mean power density near the northern border of the map.

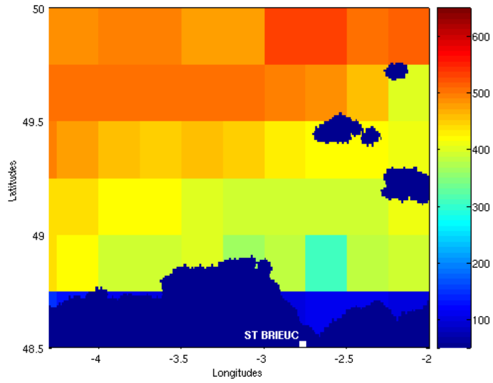

Figure 10. Mean power density (in W m^{-2}) map based on IFREMER blended wind fields.

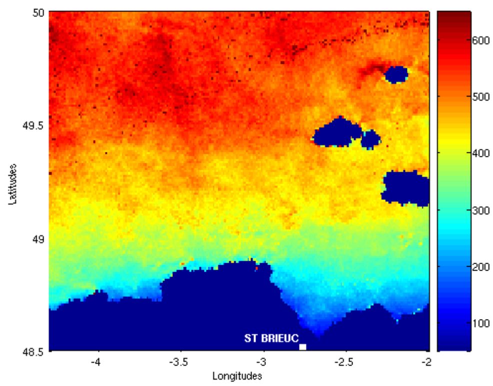

Figure 11. Mean power density (in W m^{-2}) map based on SAR wind fields. 45 images are used here.

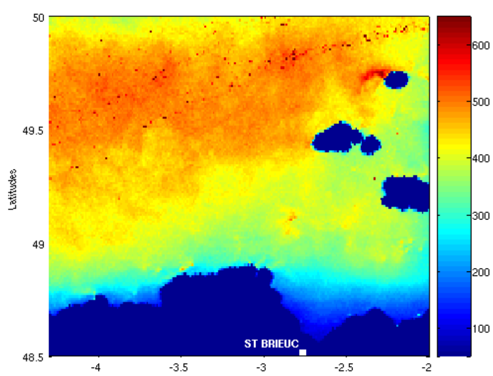

Figure 12. Mean power density (in W m^{-2}) map based on the synthetic data series resulting from the data fusion method.

7. CONCLUSIONS

In this paper, we presented different data sources of wind offshore. A data fusion method, taking benefit of the high spatial resolution of some data sources and of the high temporal resolution of other sources, has been presented. The application of this method to a case study is described. The results show an improvement of data quality. This improvement has been characterized qualitatively. For a quantitative evaluation *in situ* data are needed. The results should be compared to coastal buoy data or offshore masts data. In addition, this study covers a one-year period. A longer, multi-annual data series, have to be considered to make more robust estimation of wind resource. In fact, inter-annual variation of wind mean speed can reach 15%. One advantage of the presented method is that it can be easily extended to several years as multi-annual archives of satellite and analysis data are available. It is important to note that the results showed in this study are indicative, resulting from an undergoing work, and their accuracy should be assessed more in depth before their use in effective wind energy assessment of a site.

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