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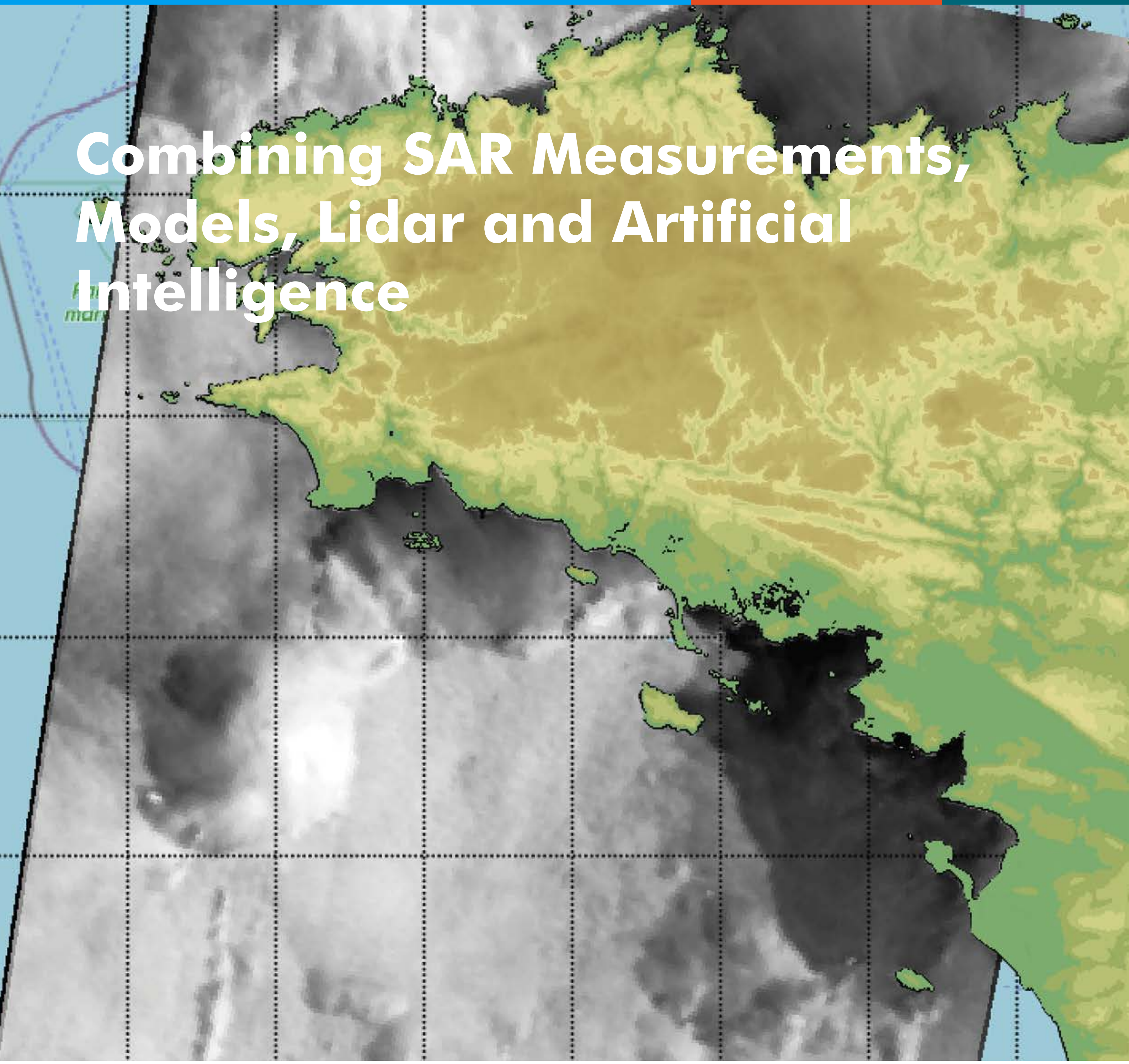
# Combining SAR Measurements, Models, Lidar and Artificial Intelligence



### *Combining SAR Measurements, Models, Lidar and Artificial Intelligence*

# SAR-Derived Kilometric Wind Resource Assessment

*By Mauricio Fragoso, Director, Energies and Infrastructure Monitoring, CLS, France*

Offshore wind resource assessment (WRA) is a challenge due to the scarcity of measurements at hub height. The 18-year database of European synthetic aperture radars (SAR) provides worldwide sea surface wind measurements at 1-kilometre resolution. Through an innovative vertical extrapolation methodology these long-term, wide, high-resolution observations can complement in situ observations and mesoscale modelling for offshore WRA. The methodology is based on four steps: derivation of the 10-minute SAR surface winds from SAR sea surface roughness, a site- and time-independent machine learning algorithm based on a large buoy network to correct SAR surface winds, extrapolation up to 250 metres based on a second machine learning algorithm trained with in situ observations and physical parameters from a high-resolution mesoscale model related to atmospheric stability, and a final post-processing step to correct for low temporal sampling of the SAR database and to retrieve wind statistics.

Recent studies have valued the potential of space-borne sensors for offshore wind resource assessment (WRA) but also for the investigation of the impact of offshore wind farms on atmospheric flow in coastal seas. However, synthetic aperture radar (SAR)-derived wind fields are surface wind fields and it is thus necessary to proceed to a vertical extrapolation within the marine atmospheric boundary layer.

## Surface Wind Speed Retrieval from SAR

Offshore WRA is usually estimated by combining mesoscale modelling and offshore metocean observations. Lidars generally provide short-term precise measurements at a single location, while numerical weather prediction models can provide long time series which, however, tend to smooth extremes and topographic effects. In the end, an important level of uncertainty remains about the actual offshore wind resource, particularly in coastal areas. SAR satellites provide observations of the Earth surface in almost all weather conditions, night and day, regardless of the cloud cover. Over the ocean, they enable visualisation of the fine spatial details of complex atmospheric flows especially in coastal regions.

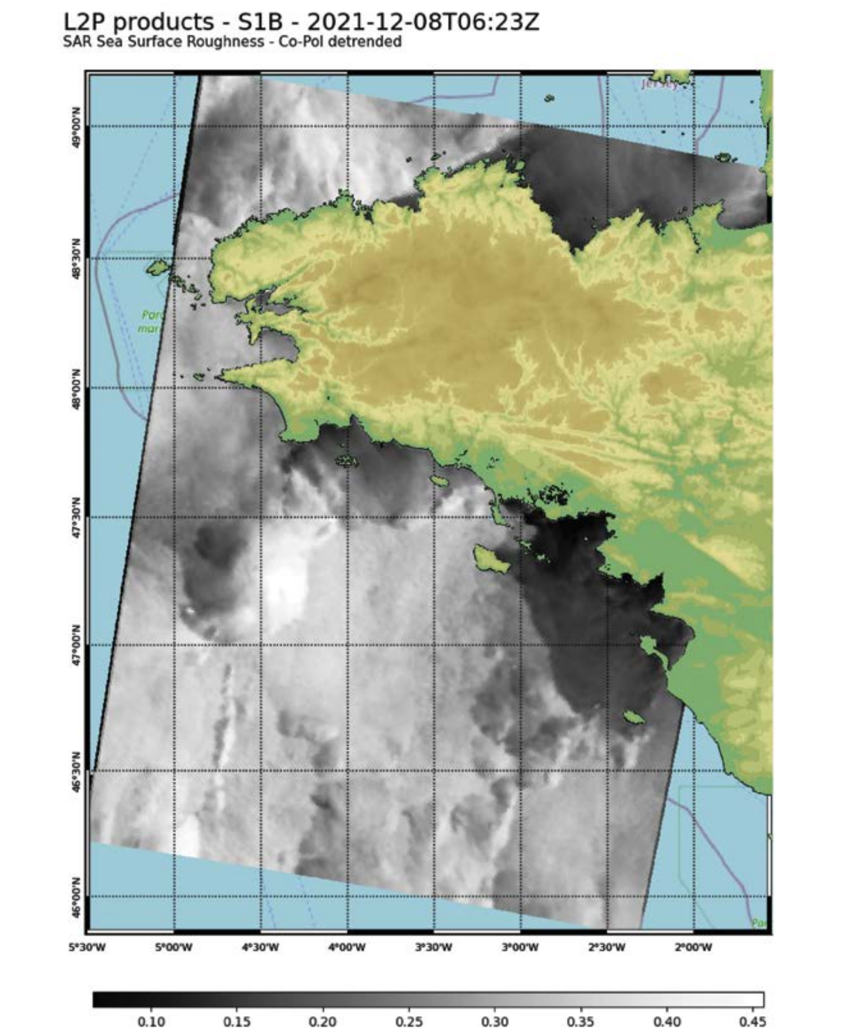



*Figure 1. SAR roughness observation in Brittany (France), 8 December 2021 at 06.23 UTC*

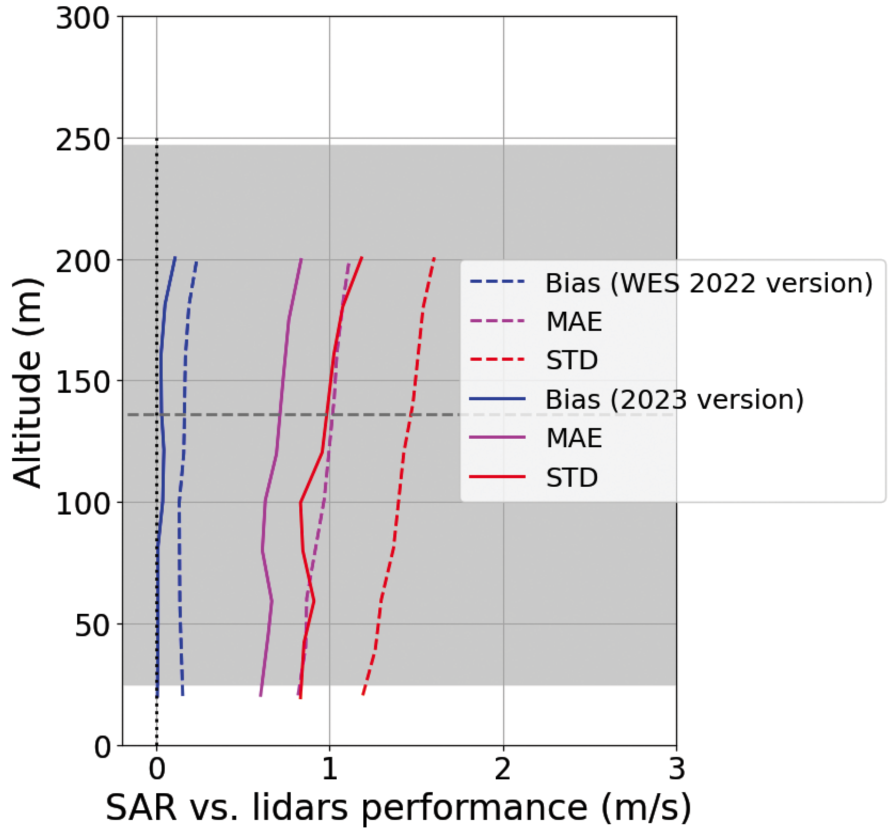



*Figure 2. North Sea extrapolation algorithm performance – comparison with previous extrapolation methodologies*

## SAR Data

SAR data is collected by satellites such as Sentinel-1A and Sentinel-1B (two polar-orbiting satellites equipped with C-band SAR). They are located in the same orbit, 180 degrees apart. The revisit rate in Europe is at best two days (around 06.30 and 18.00 UTC in south Brittany, for example). Sentinel-1A has been operating since mid-2014, while Sentinel-1B operated from mid-2016 to the end of 2021.

SAR Level-1 products measure the sea surface backscatter at 10-metre resolution. Starting from its resolution, the Level-1 image is pre-processed and analysed to detect non-wind-related signal (e.g. intense rain) and filter out bright targets. The image is then downsampled to 1-kilometre pixels before estimating the sea surface wind field. A convective system coming from the Atlantic Ocean together with a downburst and rain cells appearing as white–grey patches can be seen in the southwest part, while an atmospheric front shows a sharp wind discontinuity off the Brittany peninsula.

## Wind Resource Vertical Extrapolation at Hub Height

Surface wind fields are adapted for preliminary screening of large areas, but for WRA application, heights relevant for the offshore wind energy industry are up to 200 to 250 metres, partly or totally covering the marine atmospheric boundary layer. A vertical extrapolation is thus needed. To this end, CLS has developed an extrapolation model based on machine learning. The algorithm has been trained on a large database of lidar measurements in the North Sea corresponding to more than 1,000 colocated data points between the Sentinel-1 SAR and lidars. Input parameters of the extrapolation model are corrected SAR surface wind speeds and meteorological parameters related to atmospheric stability from a high-resolution atmospheric model. The numerical model is the Weather Research and Forecasting (WRF) non-hydrostatic mesoscale model with a resolution of 1 kilometre.

## Generation of a Wind Atlas from SAR Observations

The strong advantage of SAR observations is their long-term database and wide spatial extension. The averaged wind speed is computed over the December 2015 to December 2021 period at 140 metres above sea level (asl) in Figure 3 (right).

This averaged SAR wind speed is corrected for its main drawback, i.e. its low temporal sampling (one passage at the same time every one to two days). This low-sampling correction is estimated from the WRF time series (1-hour sampling) from which the SAR passages have been selected – the resulting mean bias (+0.084m/s average over the total area) is used to correct the averaged SAR wind speed. The averaged SAR wind speed is compared with the corresponding averaged WRF wind speed in Figure 3 (left). As observed in instantaneous wind fields in Figure 3, the averaged SAR wind field shows stronger spatial heterogeneity and a coastal gradient that is limited in the WRF modelling.

## Extractable Wind Power Estimation

SAR data can be used to directly estimate extractable wind power since wind turbines do not usually operate or function on a plateau when very high wind speeds occur. In this study, CLS chose to simulate a typical 10MW turbine operating at 119 metres – the DTU 10MW Reference Wind Turbine V1 (DTU Wind Energy, 2017).

## Incorporating In Situ Data

The extrapolation methodology presented here benefits from knowledge of atmospheric conditions acquired from the use of CLS's lidar

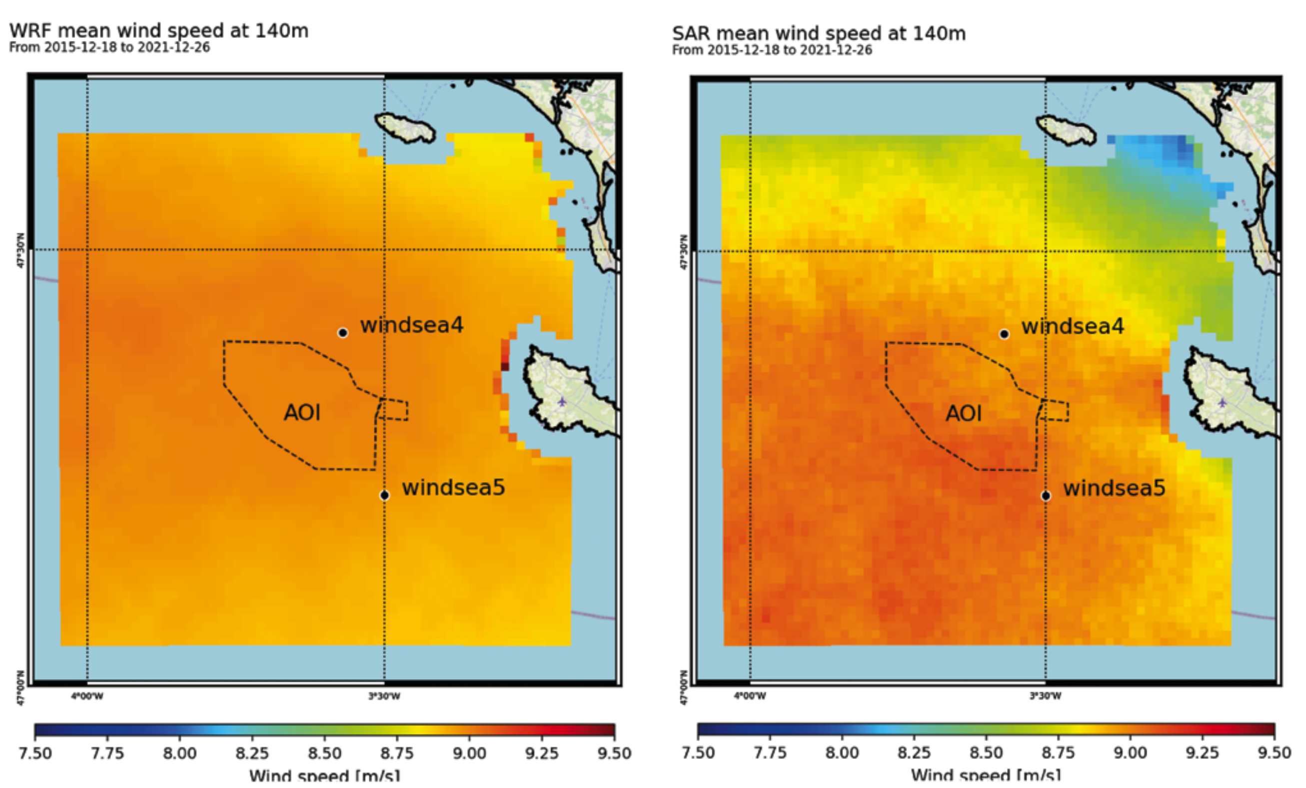



*Figure 3. Averaged wind speeds over the December 2015 to December 2021 period at 140 metres asl from the WRF model (left) and the SAR extrapolation corrected from the low temporal sampling (right)*

database. As atmospheric conditions worldwide may not fully cover this learning database, it is possible to enrich the database in the case of available in situ lidar measurements. The extra information, added to the WRA estimation, will thus benefit from the most precise extrapolation and from the high-resolution and wide coverage that the SAR measurements can provide, thereby avoiding deployment of multiple lidars over a single region of interest.

## Conclusion

SARs provide a long-term database of sea surface roughness high-resolution observations over the globe. Dedicated processing is needed to remove artefacts such as bright targets and to retrieve geophysical quantities such as surface wind speed. A surface correction algorithm has been improved to correct for the bias inherent in the geometry of the SAR sensors – this model is site independent, and its training database was extended to cover a larger range of situations (especially higher surface wind speeds). This improves the performance of the surface correction algorithm which otherwise tends to underestimate high wind speeds.

This new method allows estimation of the offshore wind resource at hub height using SAR and machine learning. CLS concludes that SAR data combined with machine learning can improve the estimation of extractable offshore wind power at hub height, provide useful insights to optimise site and risk management, and reduce the number of lidar deployments necessary to assess the wind resource spatial distribution.


## Acknowledgements

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## Further Reading


DTU Wind Energy. 2017. "HAWC2 Model for the DTU 10-MW Reference Wind Turbine." Roskilde, DK: DTU Wind Energy. https://www.hawc2.dk/Download/HAWC2-Model/DTU-10-MW-Reference-Wind-Turbine. Accessed January 23, 2021.


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