Integrated approach for the **d**evelopment across **E**urope of user oriented **c**limate **i**ndicators for GFCS high-priority **s**ectors: Agriculture, disaster risk reduction, energy, health, water and tourism

Work Package 6

Deliverable 6.3

Report on the reliability and uncertainties associated with the (hindcast-type) seasonal forecasts of selected sectorial INDECIS indices

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Seasonal predictions of wind-power-derived indices: A case study in the North Sea

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Objective

Seasonal predictions of atmospheric variables start to become available operationally from several sources. However, for sectoral applications forecasts of specific indicators and at the local scale are required. This report aims to study the applicability of the wind-energy indices in INDECIS-ISD for producing seasonal forecasts tailored to the wind energy sector. Anticipating higher- or below-than-normal wind power indices accurately allows quantifying the wind power production over the predicted season. Therefore, wind farm managers can plan their activities accordingly, such as the maintenance activities of the turbines.

To this end, the quality of seasonal forecasts of wind speed, Capacity Factor (CF) and Wind Power Density indices (WPD) at 17 locations in the North Sea region (where high-quality tall tower observations are available from WP2/WP3) have been analysed. This area of Europe is facing a significant increase in the installed wind power capacity.

Methods

Seasonal predictions of wind speed, CF and WPD (see D6.2 for detailed information) from the ECMWF SEAS5 seasonal prediction system have been adjusted to the local scale employing observations from 17 tall towers in the North Sea region (47ºN - 65ºN, 8ºW - 15ºE). The set of 17 tall towers is a subset of locations from the Tall Tower Dataset (Ramon et al., 2020). The area of the case study includes not only the North Sea but also some bordering continental areas such as the British Isles, Benelux, northern Germany, Denmark and southern Scandinavia.

The predictions are presented in the form of probability of occurrence of three tercile categories defined by the 33rd and 66th percentiles of the historical observations. The quality of the predictions is then assessed employing retrospective predictions (the so-called hindcasts). Skill assessment is performed at the 17 tall tower locations, using the nearest 100-metre winds from each tall tower as observational reference. The tall tower wind series were previously reconstructed to cover the 1980-2017 period. For this purpose, a Measure-Correlate-Predict (MCP) approach has been used (Brower et al. 2012, Chapter 12).

Additionally, gridded seasonal predictions have been adjusted with reanalysis-derived observations of 100m winds, CF and WPD. The skill of the gridded seasonal predictions is verified using the ERA5 reanalysis as the observational benchmark. This allows a comparison with the skill obtained at the tall tower locations.

The ECMWF SEAS5 prediction system provides surface wind speed predictions at six-hourly time resolution and 1-degree of spatial resolution. These data starting in 1993 are publicly available for download in the Climate Data Store[1] data portal from the Copernicus Climate Change Service. Seasonal predictions considered here provide information 0, 1, 2 and 3 months in advance of the season of interest. For example, in the case of the seasonal predictions for winter, the zero-lead-month prediction is initialised in December, the one-lead-month prediction is initialised in November, and so on. Forecast data have been interpolated to the 17 tall tower locations with a nearest neighbour interpolation, whereas the ERA5 gridded data are interpolated spatially to a 1-degree grid resolution using a conservative methodology and sub-sampled temporarily to match the 6-hourly resolution of the forecasts.

[1] cds.climate.copernicus.eu

Seasonal prediction systems have systematic biases that need to be corrected before employing the forecasts. That can be done by comparing raw hindcast values to corresponding observations. On the one hand, the local-scale seasonal predictions of surface wind data have been bias-adjusted using the tall tower wind observations. On the other hand, the gridded seasonal predictions have been bias-adjusted using the ERA5 reanalysis data. A simple bias-adjustment approach (Torralba et al., 2017) has been used here. This method adjusts forecasts to have an equivalent standard deviation and mean to that of the reference dataset. The method uses leave-one-out cross-validation so that the prediction to be adjusted and its corresponding observation are excluded from the sample used to estimate the adjustment parameters (see Eqs. 1-4 in Torralba et al., 2017).

After bias adjusting the wind speed values, CFs and WPD have been derived from 6-hourly values employing the methodology presented in D6.2 (in preparation). Then, seasonal averages are prepared and anomalies with respect to the 1993-2016 period are computed. The quality of the probabilistic prediction of terciles is assessed through the Ranked Probability Skill Score (RPSS, Joliffe 2012). The RPSS measures the quality of probabilistic predictions of ordered categorical predictions compared to an easily available benchmark prediction (in this case the climatological prediction, i.e. equal probabilities for the three categories). The Ranked Probability Score (which is the quality metric that RPSS compares) penalises each forecast based on the probabilities associated with each non-observed category and the distance of those categories to the observed category. Positive RPSS values indicate an improvement over the climatology, with a value of 1 indicating a perfect forecast. Negative RPSS values indicate a prediction that is worse than the benchmark.

Results

Results are presented here only for the boreal winter (December-January-February, DJF) since this is the season when the highest winds and variability occur, and so do the CF and WPD. Forecasts of wind speed for two specific locations are presented first, and then a skill assessment for all wind power indices and at all the locations is provided.

Case study 1 - FINO1 lead-0 winter predictions

FINO1 mast monitors the weather conditions at the FINO1 offshore wind farm within the North Sea. The lead-zero seasonal predictions of wind speed for the 1993-2016 period have been explored for this location. Figure 1 presents the 24 seasonal predictions of the three tercile categories (normal, below normal and above normal) and compares them with the observed wind speed seasonal mean value. Overall, there is a good association between the observed wind speed value and the predictions (i.e. when the different members of a forecast show high values the observation is also high and vice-versa). The RPSS obtained for this prediction is 0.23, indicating a 23% of improvement of the SEAS5 predictions with respect to the climatological prediction. In most of the cases the observed category has a good amount of probability in the forecasts. This emphasizes the added value of seasonal predictions with respect to a climatological prediction that would indicate equal probabilities to the three categories.

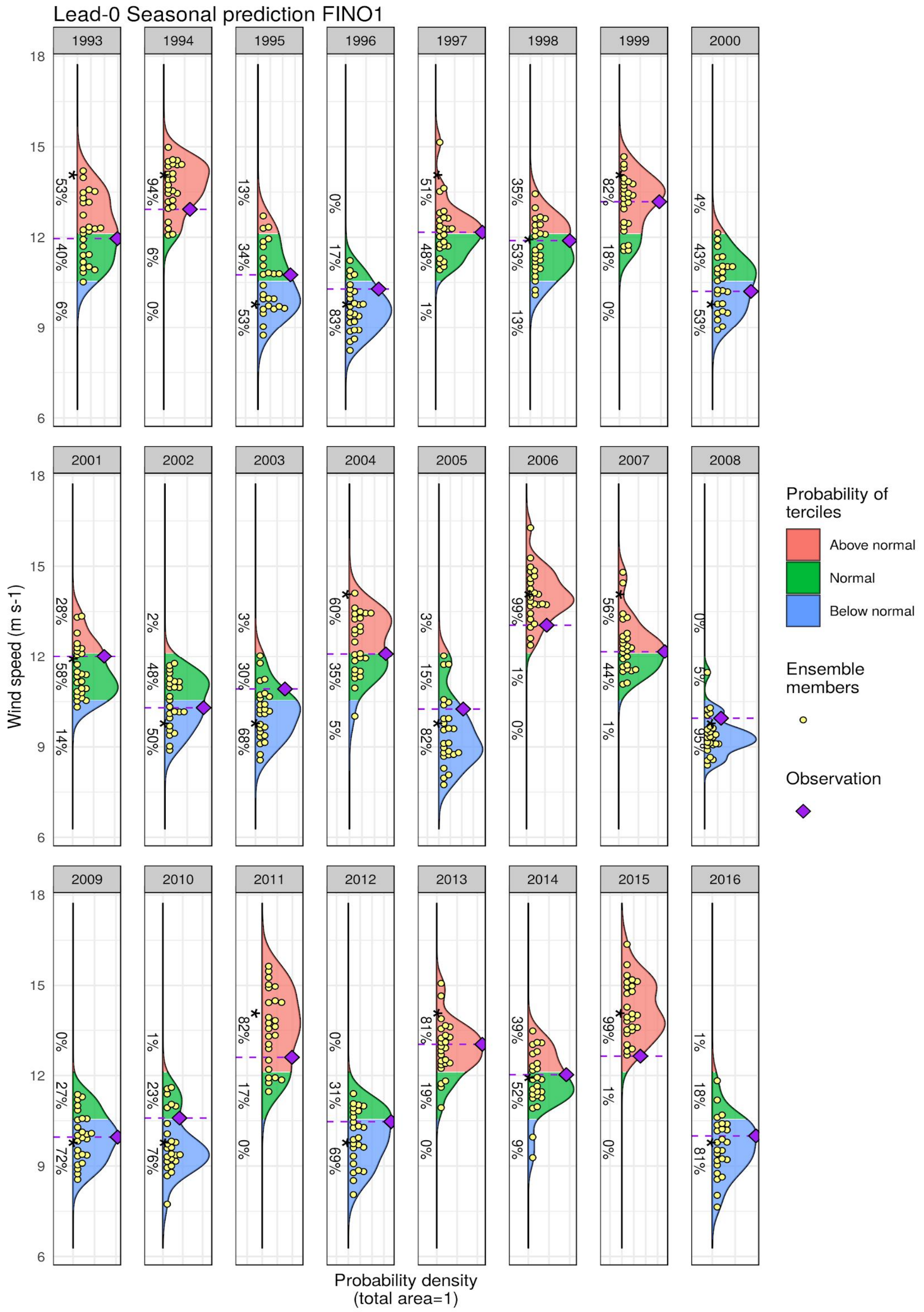

Figure 1.- Lead-zero winter seasonal predictions at FINO1 met mast (54.0ºN, 6.6º E) for the 1993-2016 period.. The yellow dots represent the values for the 25-member ensemble of the ECMWF SEAS5 prediction, whereas the purple square shows the observed seasonal mean wind speed value at FINO1. The Probability Density Functions have been built by dressing the ensemble members with the Kernel Density Estimate method.

Case study 2 - Cabauw 2005/2006

During the 2005-2006 winter, the highest seasonal mean wind speed within the 1993-2016 period was recorded at Cabauw met mast, in the Netherlands. Figure 2 presents the probabilistic seasonal predictions for that specific winter at Cabauw three, two, one and zero months in advance. We note that all of them anticipated a windy winter, displaying most of the members above the P66 of the distribution generated by the seasonal mean wind speeds observed during the 1993-2016 period. Furthermore, in the prediction initialised in December almost all of the members fall within the observed category.

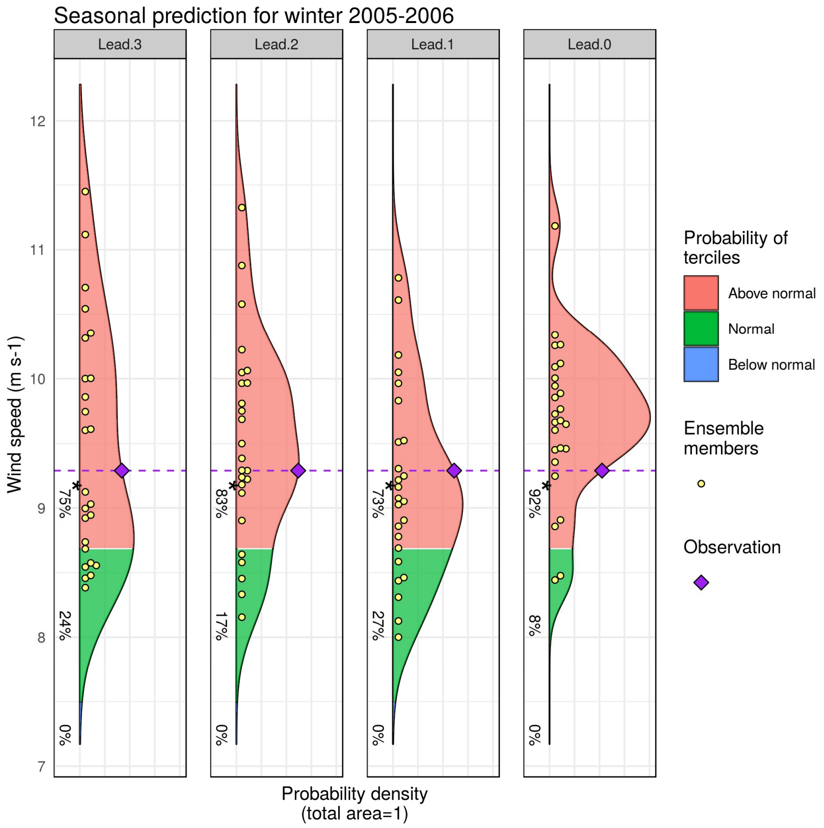

Figure 2.- Probabilistic seasonal predictions for the 2005-2006 winter at Cabauw met mast (52.0ºN, 4.9º W). Different lead times are shown, indicating that the prediction is initialised in September (Lead 3), October (Lead 2), November (Lead 1) and December (Lead 0). The yellow dots represent the values for the 25-member ensemble of the ECMWF SEAS5 prediction, whereas the purple square shows the observed value at Cabauw. The Probability Density Function has been built using a dressing ensemble.

Skill assessment

Figures 3, 4 and 5 show the RPSS of the seasonal predictions of hub-height winds, CF and WPD, respectively. In all cases, the RPSS is maximum for lead time zero, being in some cases above 0.3. Then the skill of the seasonal predictions drops and they barely improve the climatological prediction at longer lead times.

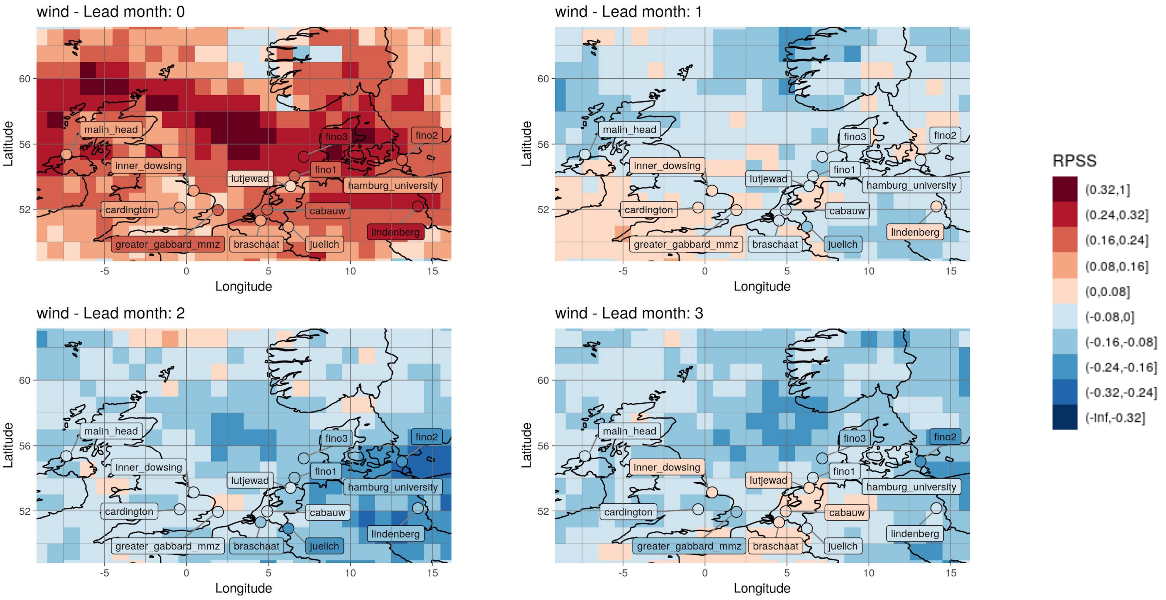

Figure 3.- RPSS of the hub-height wind speed SEAS5 predictions in the North Sea region for DJF. Predictions were initialised in December (lead month 0), November (lead month 1), October (lead month 2) and September (lead month 3). Points indicate the RPSS of the predictions at the 17 tall tower locations.

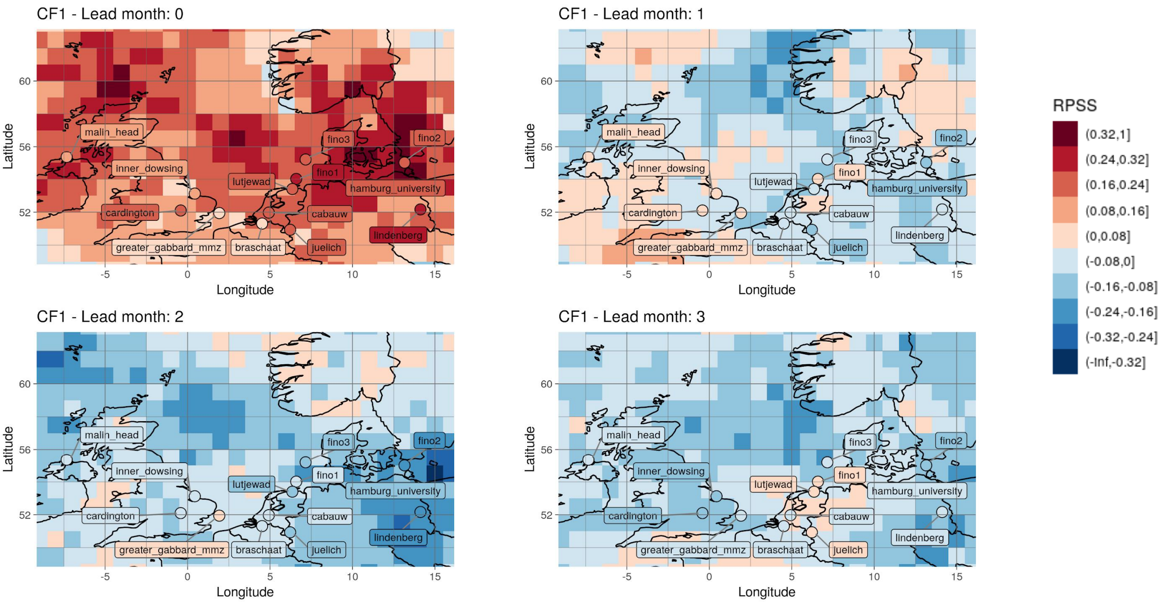

Figure 4.- RPSS of the CF1 SEAS5 predictions in the North Sea region for DJF. Predictions were initialised in December (lead month 0), November (lead month 1), October (lead month 2) and September (lead month 3). Points indicate the RPSS of the predictions at the 17 tall tower locations.

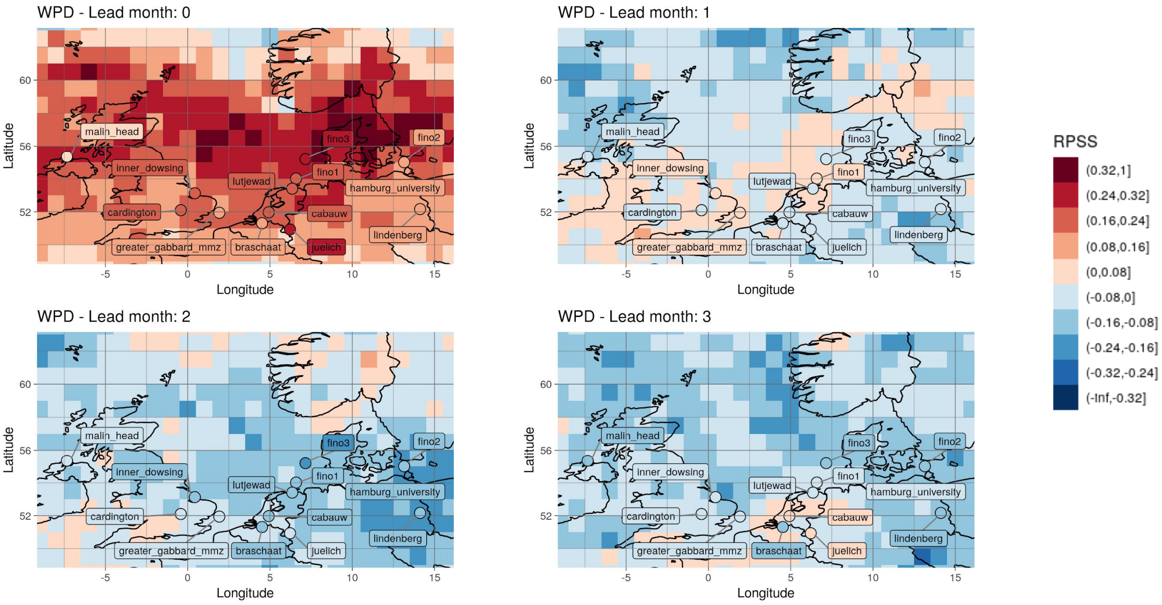

Figure 5.- RPSS of the WPD SEAS5 predictions in the North Sea region for DJF. Predictions were initialised in December (lead month 0), November (lead month 1), October (lead month 2) and September (lead month 3). Points indicate the RPSS of the predictions at the 17 tall tower locations.

At lead 0, seasonal predictions of hub-height winds show skill over almost all the region (Figure 3). The highest values (up to 0.4) are displayed over Denmark, the centre of the North Sea and north of the British isles. The downscaled predictions at the tall tower locations show similar skill. The locations with the highest skill are FINO1 and FINO3, both located offshore over the sea. Predictions initialised in November (lead time 1) show skill in Ireland, England and some parts of France and The Netherlands, and so do the predictions at the tall towers located in these areas. The longest lead times only show skill in some scattered areas inland.

Results for the seasonal predictions of CF (Figure 4) and WPD (Figure 5) are analogous to those described for the hub-height winds. In the case of CF (Figure 4), we only show results for CF1 (turbine class I according to IEC-61400-1 (IEC, 2005)), since results for CF2 and CF3 (turbine classes II and III) are similar to those presented for CF1. CF1 predictions do not show skill for lead times 1, 2 and 3 in the North Sea. However, some spots of skilful areas are seen over the shores, where some wind farms are placed. Similar results are observed for WPD, but in this case, there exists skill in the North Sea not only for lead time 0 but also for lead time 1.

Conclusions

The skill of seasonal predictions of hub-height wind speed, CF and WPD has been assessed for several locations in the North Sea region. Seasonal predictions are obtained from the ECMWF SEAS5 and have been interpolated to 17 locations where tall towers are installed and measure wind speeds at turbine hub heights. To compare with, the skill of the predictions is also computed using the ERA5 reanalysis as observational reference.

Predictions for the three variables show good skill levels for lead time 0. Then, the skill drops rapidly, and only wind speed and WPD show skill for lead time 1. At longer lead times, only a few spots of skilful areas in Belgium and Holland are noticed. The large-scale picture of skill depicted by the gridded ERA5 data shows a good level of agreement with the skill obtained at the set of 17 tall tower locations. Nevertheless, some discrepancies between the grid-scale and local-scale prediction skills are noted, as is the case of Malin Head mast in Ireland (55.3ºN, 7.3ºW) for lead time 0 in the three selected parameters. These sparse differences may respond to the fact that local wind effects, which can explain a considerable percentage of the mean wind, are not taken into account in the gridded ERA5 data. Indeed, the ERA5 reanalysis data represents the average over a grid cell of ~30x30 km^2.

Acknowledgements

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