Seasonal forecasts for the wind power industry within the CLIM4ENERGY project

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1. Introduction

Seasonal forecasts of wind speed and power generation can be of great help for the management of wind farms (Fig 1).

Interested stakeholders:

1) owners and shareholders
2) operation and maintenance teams
3) grid operators
4) energy traders

Fig 1. Wind turbines near Barcelona.

CLIM4ENERGY is an on-going Copernicus Climate Change Service project. It aims to produce tailored forecasts for the energy sector. BSC is leading work package 1, that focuses on wind power generation applications.

Predictability of seasonal mean wind speed can be achieved using ensemble simulations of coupled ocean-atmosphere modelling systems that include in their formulation ocean temperature, snow cover, soil moisture, ice extent and other slow-evolution and high-inertia variables that have a significant impact on weather conditions in the next season[1].

2. Previous expertise

As part of the EUPORIAS project, BSC has published a demonstrative website to visualize seasonal wind forecasts (Fig 2). CLIM4ENERGY goes one step further and derives power generation anomalies. Within RESILIENCE project the impact of ENSO and NAO on wind anomalies across the globe has been assessed (Fig 3).

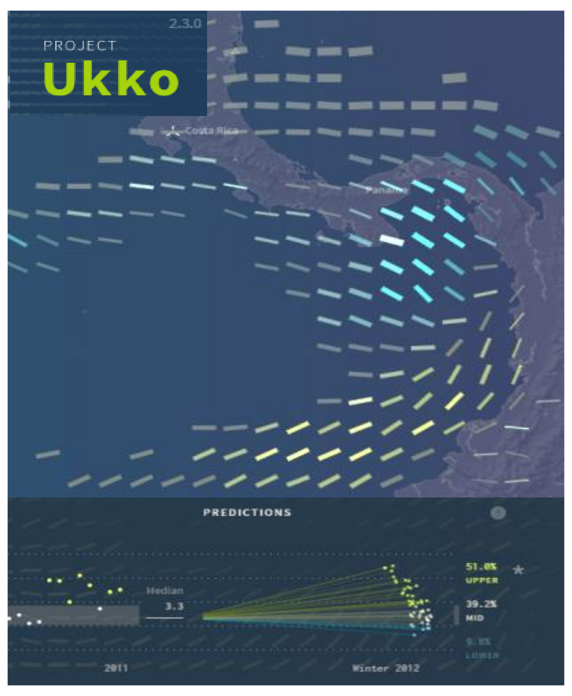

Fig 2. The Project-Ukko prototype displaying seasonal forecasts of wind speed (project-ukko.net).

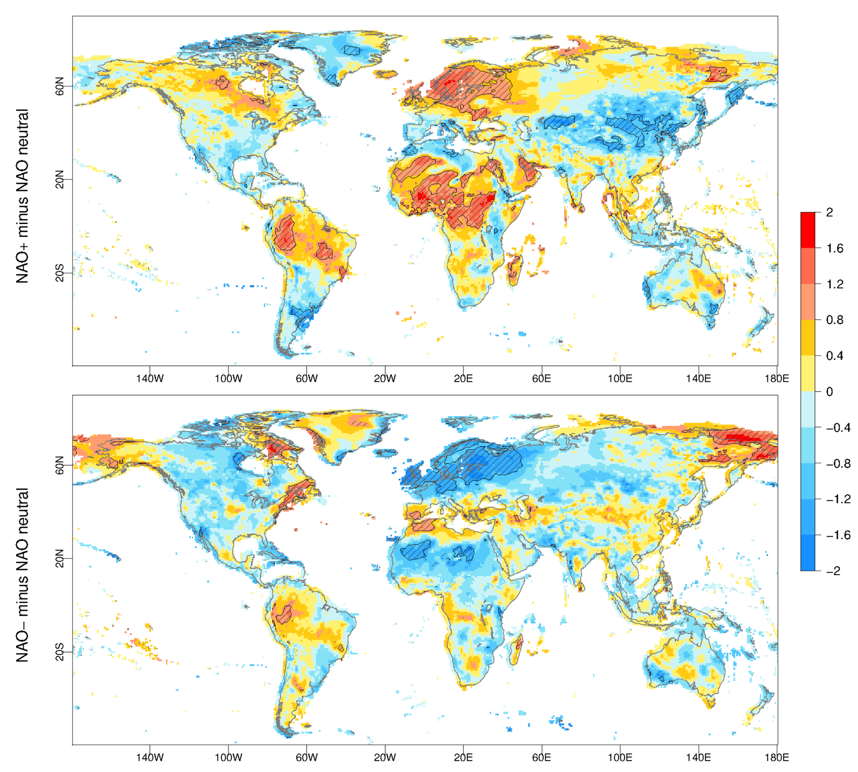

Fig 3. Stratification of ERA-Interim wind speed for boreal winter (DJF) in 1981-2015 period, according to NAO index (PC-based). Differences have been normalized with the standard deviation of the climatology. Dashed areas show a confidence level of 95%.

3. Post-processing model output

We use 51 ensemble members of ECMWF System4 seasonal forecasts of 6-hourly near-surface wind speed to feed an impact model that derives power generation for the next winter season (1 month ahead). But some model post-processing is needed before using it.

Winds at hub height are higher than near the surface. We use a power law with a shearing exponent of 1/7 and a hub height of 100m to **extrapolate** them:

$$\mathrm{WSPD100} = \mathrm{WSPD10}\left(\frac{100}{10}\right)^{0.143}$$

Dynamical models of the atmosphere and ocean system exhibit biases. We correct them with an **Empirical Quantile Mapping** (EQM) technique[2].

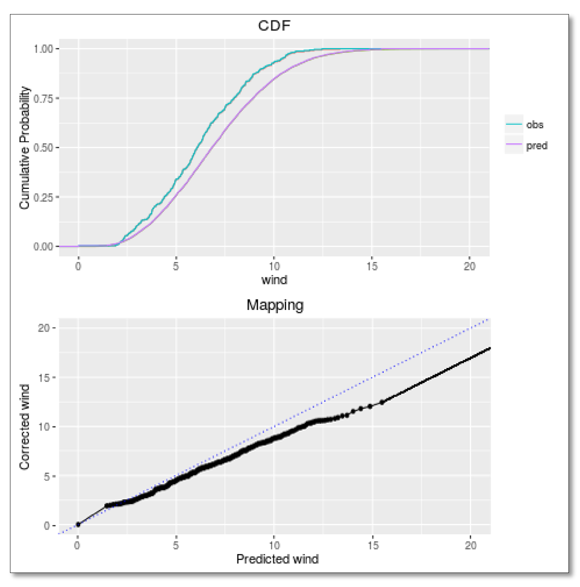

Fig 4. An EQM correction example. On top the two CDFs. Below the transfer function. In this case System4 produces higher winds than ERA-Interim.

For each grid point we compare the cumulative distribution function (CDF) of System4 hindcasts with ERA–Interim reanalysis. Then we create a transfer function that relates each quantile of the model distribution to the observed quantile with the same cumulated probability (Fig 4).

4. Computing capacity factor

Capacity Factor (CF) of an installed wind farm measures how good have been the meteorological conditions for producing energy during a specific period:

$$CF = \frac{Actual\ generation}{Maximum\ theoretically\ possible\ generation}$$

Actual generation can be estimated using wind speed and a power curve (Fig 5). The result is very sensitive to the selected power curve. But computing terciles of above normal/normal/below normal conditions contributes to reducing the sensitivity. Terciles are also a good way to summarize information from the ensemble members and convey the information to a more user-friendly format for decision making processes.

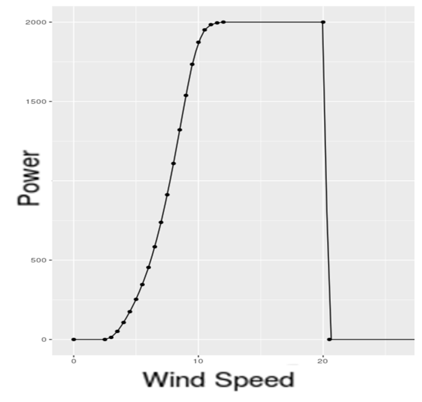

Fig 5. A Vestas V100-2MW power curve, relating 10-minutal wind speed at hub height to power output.

5. Evaluation

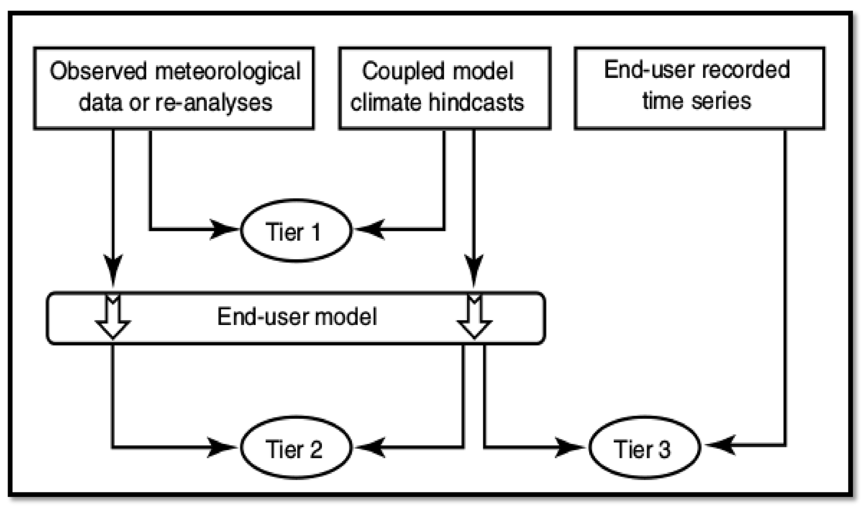

Fig 6. A 3-tier validation approach for validating an impact model (from Morse et al. 2005).

We propose a **3-tier validation** (Fig 6) as in Morse et al. (2005)[3].

Tier-1: validate System4 wind speed predictions that are used as input to our impact model (Fig 7). Using ERA-Interim reanalysis allows to have results for the whole model grid.

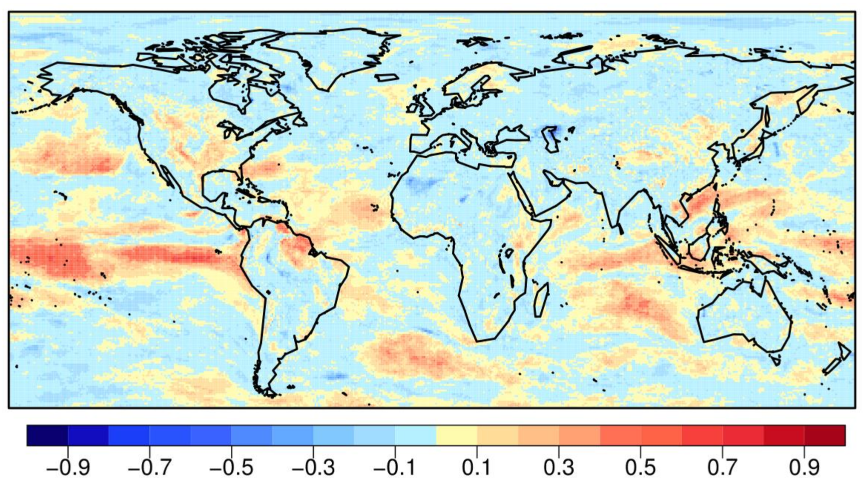

Fig 7. Fair Ranked Probability Skill Score for tercile events of bias corrected ECMWF System4 forecasts of wind speed, initialized the first of November. The map corresponds to boreal winter (DJF) in 1981-2013.

Tier-3: evaluate the final impact model forecasts with end-user observations at specific locations. We will employ generation and tall tower winds at several sites (Fig 8).

Tier-2: the difficulties of having a significant number of validation sites encourages an intermediate evaluation of the capacity factor for the whole model grid. We estimate observed capacity factor feeding the impact model with reanalysis data (ERA-Interim). System4 and ERA-Interim have similar resolutions: this produces the benefit of isolating unrepresented local phenomena from the validation.

Fig 8. Instrumented tall tower near Boulder, Colorado.

6. Conclusions

- The wind power industry can largely benefit from seasonal forecasts and recent model improvements.
- To generate confidence and foster widespread use of seasonal forecasts it is key to produce tailored products. Also it is important to highlight strengths and limitations through validation and skill assessments
- Within CLIM4ENERGY, BSC will produce a proof-of-concept seasonal forecast of power generation for the winter season using an impact model fed by ECMWF System4 wind speed predictions.
- A validation with on-site observations is very sensitive to local behavior of selected locations, penalizing those that experience local effects not resolved by coarse models. Using reanalysis data (of similar resolution) to feed the impact model helps to validate the impact model itself and sets aside the effects of not resolving small scales.

7. References

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- *3. Morse, A. et al. (2005). A forecast quality assessment of an end-to-end probabilistic multi-model seasonal forecast system using a malaria model. Tellus, 57A, 464-475.*

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