Developing Seasonal Wind Energy Forecasts for Germany

Abhinav Tyagi[1,2], Arsalan Muhammad[1], Jan Wandel[3], Clementine Dalelane[3], Alina Happ[1], Andreas Paxian[3], Lukas Pauscher[2,4], Malte Siefert[1]

[1]Fraunhofer IEE, Kassel, Germany; [2]University of Kassel, Department of Sustainable Electrical Energy Systems, Kassel, Germany;
[3]Deutscher Wetterdienst, Offenbach, Germany; [4]Vrije Universiteit Brussel, Acoustics & Vibration Research Group, Elsene, Belgium

- In the past year, wind energy constituted roughly 30% of the total electricity production of Germany, reaching roughly 140 TWh, ahead of all other sources of energy, conventional or renewable[1].
- Seasonal forecasts are dynamic, and their predictability arises due to the boundary conditions derived from slowly changing climate variables like soil moisture, snow cover, sea-ice, and ocean temperatures[2].
- Skillful seasonal energy forecasts enhance short-term forecasts by enabling proactive risk management for traders and grid operators and supporting strategic resource planning.
- Skill for energy forecasts has only been shown for selected regions and/or seasons in literature. This work presents a systematic skill analysis of seasonal wind energy hindcasts for Germany.

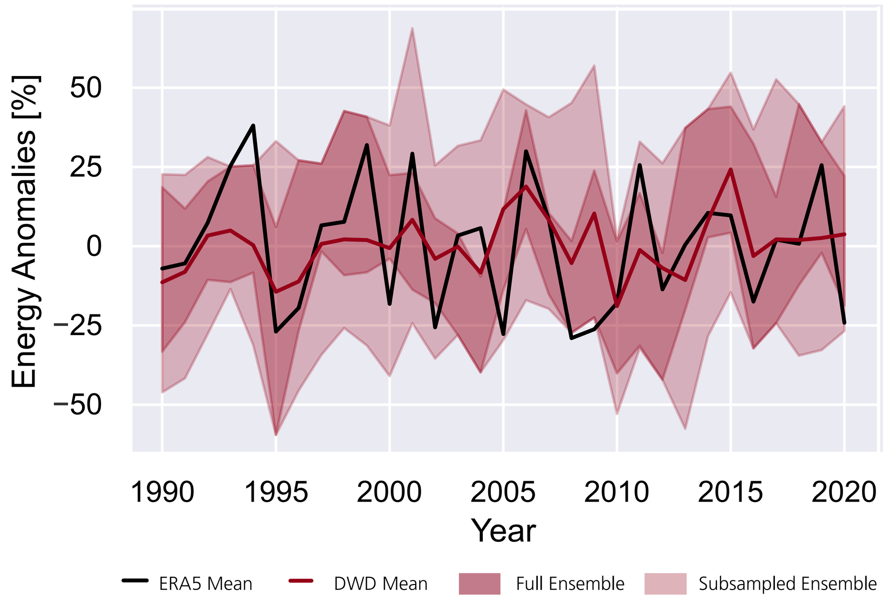

Figure 1
Ensemble hindcasts (DWD subsampled Mean and Ensemble), initialized in December and Reanalysis (ERA5 Mean) plotted as the deviation from climatology in percentage (percentage anomalies) aggregated for season December-February and all of Germany for years 1990-2020. The spread of the subsampled ensemble follows the observations more compactly than the full ensemble. As discussed later, subsampling is more effective in winter than summer, hence the choice of the illustrated time window here.

Preparing the Wind Power Forecasts

Preprocessing the climate forecasts and baseline

- Ensemble Hindcasts (1990-2020) are taken from the German Climate Forecasting System (GCFS) Version 2.1[3] and delivered as an ensemble of 30 members. Forecasts are initialized each month and run six months into the future.
- Reanalysis dataset from ERA5[4] offered as part of the Copernicus Climate Change Service (C3S) is used to validate the seasonal hindcasts.

Converting the wind speeds to power

- 10m wind speeds from hindcasts and reanalysis are converted to power using a power curve (Enercon E-70/2300 obtained from Open Energy Platform Database) that models turbine response to varying wind speeds.

Adjusting the spatial and temporal resolution

- Wind speeds are extrapolated to hub height using a power law and used as inputs for the power curve. The instantaneous powers thus obtained are aggregated over a three month period to give total seasonal energy output at each location.
- Anomalies are calculated individually for hindcasts and reanalysis by subtracting the lead-time dependent (for hindcasts) climatology from the absolute values.

Subsampling

Circulation indices calculated from each ensemble member are compared to those from statistical predictions, and only the members whose indices correspond to the predictions are selected in the subsampling procedure[7] (see Figure 1).

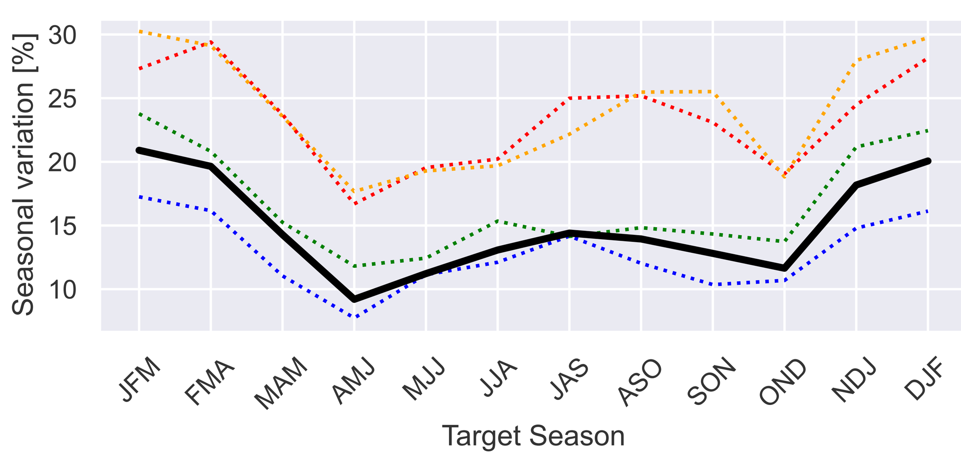

Figure 2
Inter-annual(1990-2020) standard deviation in simulated energy production, plotted as percentage of the mean. Different colors correspond to different regions, as defined in figure 3. South Germany and winter seasons shows a higher variation.

Skill Verification Metrics

- **Anomaly Correlation Coeffecient** (Deterministic metric): Pearson correlation coefficient between the mean forecasted anomalies of the ensemble mean and the reanalysis anomalies
- **Fair Ranked Probability Skill Score** (Probabilistic metric): Ranked Probability Skill Score (RPSS) is the sum of squared differences between the forecasted and reanalysis cumulative probabilities of three events: '**below normal**', '**normal**' and '**above normal**' energy output[3]. Fair RPSS makes the score independent of the ensemble size[5].
- **Mismatch** (Probabilistic metric): Quantifies if the ensemble spread (Standard Deviation) matches the mean displacement of the ensemble mean from the reanalysis (Root Mean Squared Error)[6].

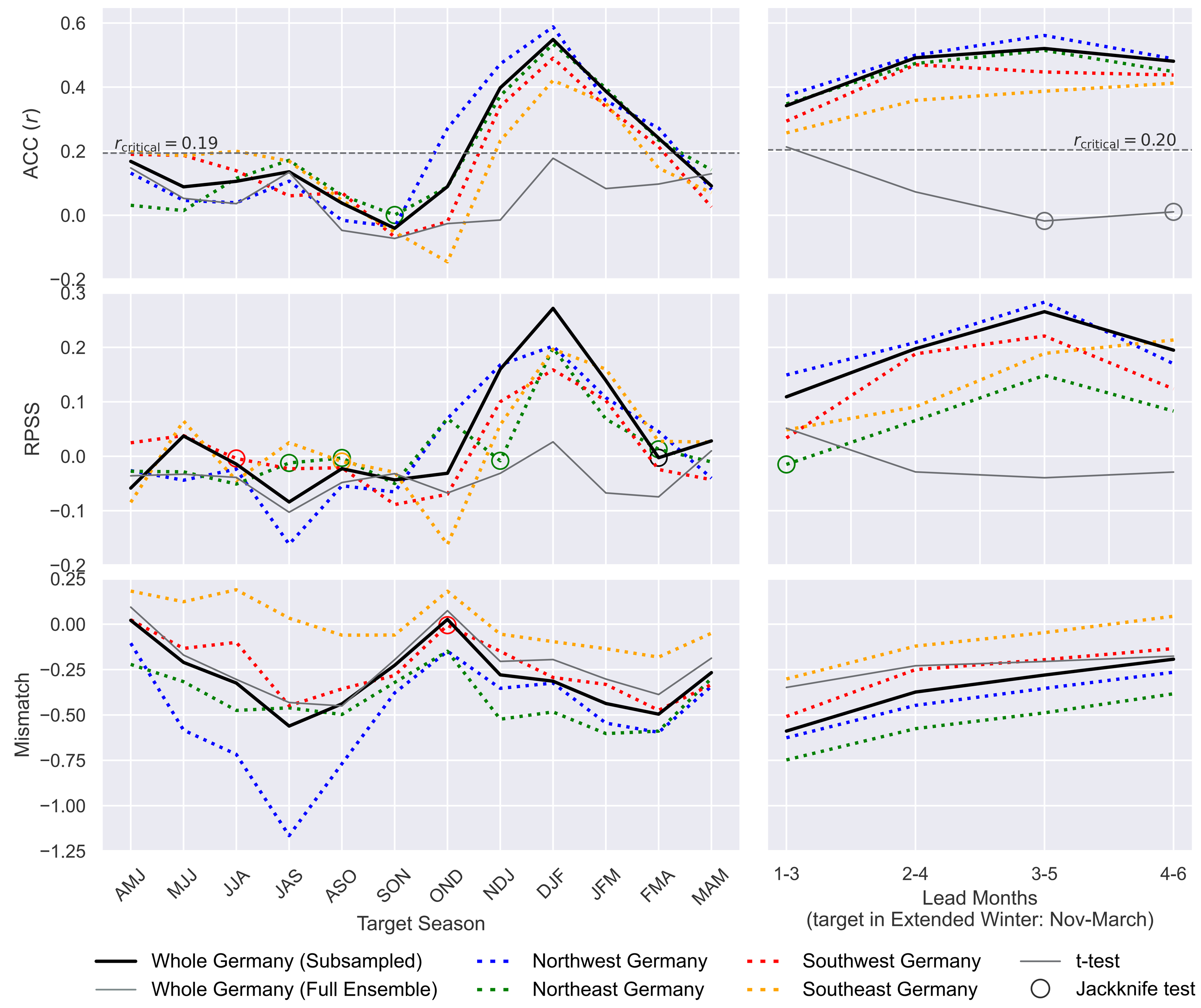

Figure 3
The three metrics are plotted w.r.t target seasons (right) and lead months (left). Only those lead months for which the target season lies in extended winter are shown in the right plot as summer seasons do not show statistically significant skills. All regional curves correspond to subsampled ensemble. The skills calculated using the full ensemble for Germany (grey curve) are typically inferior. The nature of data makes significance estimation difficult as shown by varying results from two tests. Critical threshold ($r_{critical}$) above which correlations are significant was determined using the parametric t-test. Additionally, the statistically insignificant skills with the jackknife test are marked with circles.

Key Takeaways

- Subsampling increases the skill significantly for winter season.
- Winter season also shows the strongest interannual variability (Figure 2)
- Skill gain in winter and north Germany is likely driven by prevailing large scale circulations.
- Dependence of skills on target season is much stronger than that on lead months. Skill increases slightly for lead months 2-5 when compared with the lead months 1-3 and 4-6.
- A robust significance estimation is challenging due to the nature of the data.

Future Developments

- Develop AI models to calibrate forecasts and integrate teleconnections more explicitly (might be challenging due to data requirements).
- Integrate seasonal forecasts into a seamless forecast product (ranging from hours to seasons) at a wind park level.

1 B.W. e.V "Statistics Germany BWE e.V." https://www.wind-energie.de/english/statistics/statistics-germany/.
2 Doblas-Reyes, F.J., et al. "Seasonal climate predictability and forecasting: Status and prospects." WIREs Climate Change, 2013.
3 Paxian, A., et al. "The DWD climate predictions website: Towards a seamless outlook based on subseasonal, seasonal and decadal predictions." Climate Services 30, 2023.
4 Hersbach, H., et al. "The ERA5 global reanalysis." Quarterly journal of the royal meteorological society 146.730, 2020.
5 Ferro, C.A.T., "Fair scores for ensemble forecasts." Q.J.R. Meteorol. Soc., 2014.
6 Tyagi, A., et al. "Evaluating the skill of seasonal forecasts in Germany." Submitted to EEM25 Conference, 2025.
7 Dalelane, C., et al. "Seasonal forecasts of winter temperature improved by higher-order modes of mean sea level pressure variability in the north atlantic sector." Geophysical Research Letters, 2020.

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