Weather regimes as a tool to validate seasonal forecasts

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1. Background and goals

The skill of a forecast system is affected by the atmospheric flows, since some of them are more stable and predictable than others (Ferranti et al., 2015). Detecting which flows are predictable and which are unpredictable allows to increase the forecast skill without having to modify the forecast system itself (Neal et al., 2016).

Here, we aim to verify the skill of the seasonal forecast system of the **ECMWF System-4** (S4) in simulating the observed North Atlantic-European weather regime anomalies and their interannual frequencies and persistencies. SLP data was preferred to geopotential height, even if it is noisier, because it doesn't show any temporal trend (Hafez and Almazroui, 2014).

2. Data and methodology

S4 forecasts of daily mean sea level pressure (SLP) have a spatial resolution of ~80 km and 15 ensemble members during the hindcast period 1981-2015 (Molteni et al., 2011). SLP data was extracted for the North Atlantic-European region (27°N–81°N, 85.5°W–45°E) and daily means were computed as average of 6-hourly data, separately for the **ERA-Interim reanalysis** (Dee et al., 2011) and the hindcasts, referred to the daily climatology filtered by a LOESS polynomial regression to remove the short-term variability (Mahlstein et al. 2015).

To classify the North Atlantic-European regimes, a k-means cluster analysis with N=4 clusters (NAO+, NAO-, blocking and Atlantic ridge) was applied to the data of each month separately.

3.1. Results: spatial correlation

Figure 1 illustrates the simulated and observed **regime anomalies** for the four regimes and for different startdates and lead times for the predicted target month of December. Blocking patterns are the most difficult to reproduce in December, but generally there is a high spatial coherence for all seven previous startdates.

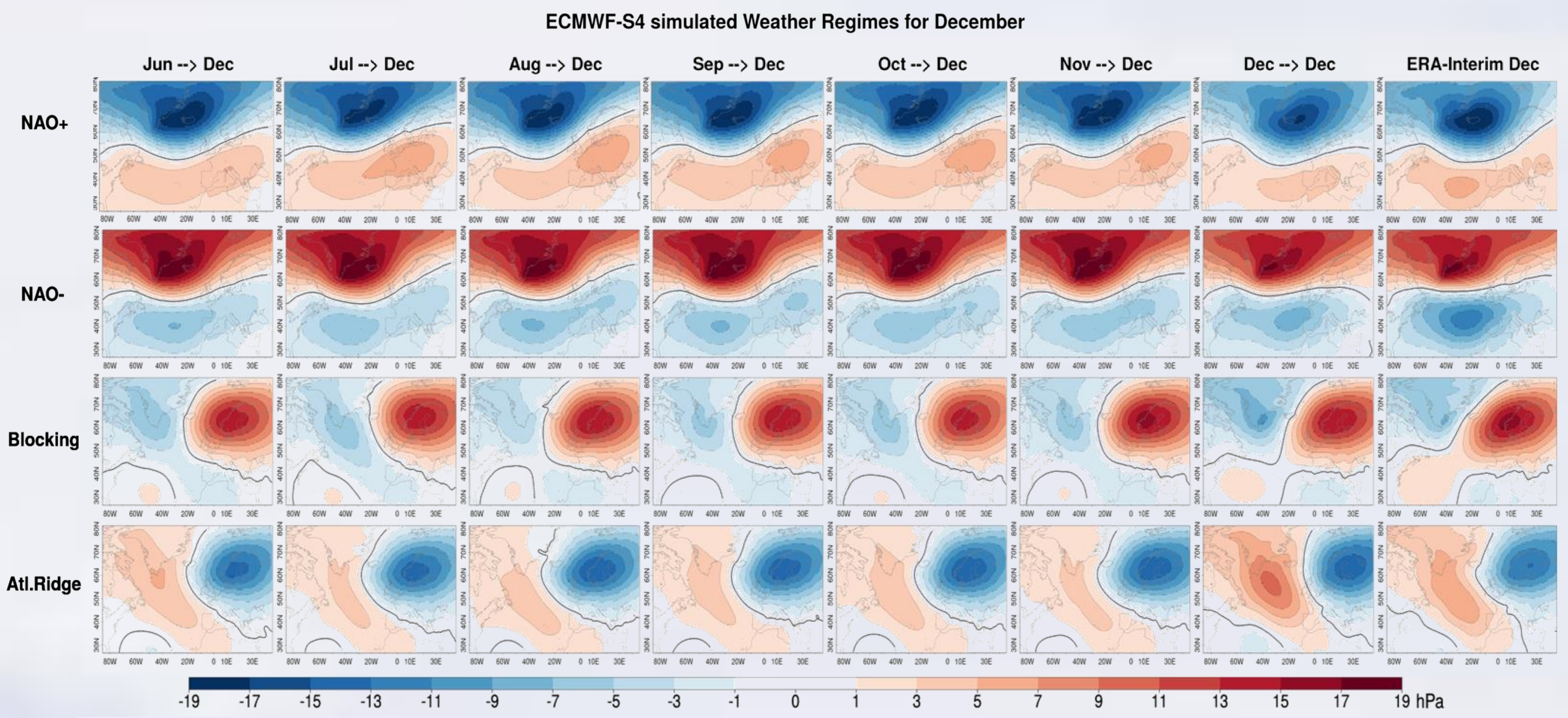

Figure 1. S4 simulated regime anomalies (in hPa) for the target month of December (1981-2015) and different startdates and lead times (from left to right: 6 to 0 months) vs ERA-Interim observed regime anomalies (last column to the right). Black lines show null anomalies.

To summarize all the possible combinations of startdates and lead times (beyond the December example above), Pearson spatial correlations between simulated and observed regime anomalies are presented in Figure 2. Each triangle represents a spatial correlation, depending on its position and orientation (see square in the legend to the right).

The majority of the correlations are above 0.7; lowest values are measured when the predicted target month is September, October or November (diagonal lines with blue triangles in Figure 2); such low correlations are due to ERA-Interim regime anomalies that are unrepresentative of the blocking/Atlantic ridge regimes anomalies (not shown). S4 better reproduces regime anomalies, since it has 15 times the data of ERA-Interim. Hence, sampling daily mean SLP over monthly periods with no reduction of dimensionality (e.g: by a PCA) isn't always sufficient to adequately represent the clustering space.

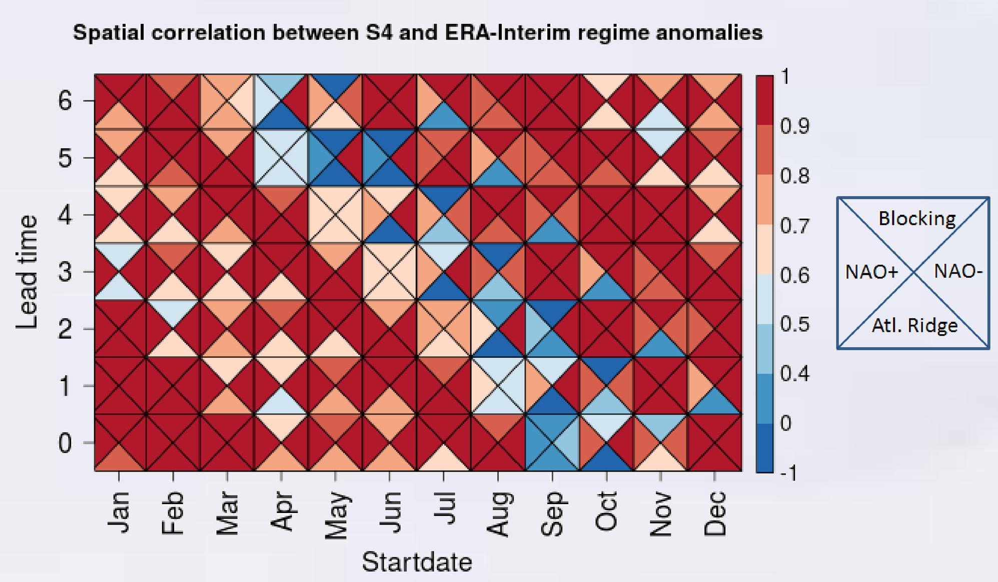

Figure 2. Spatial correlations between simulated and observed regime anomalies.

3.2. Results: temporal correlation

Figure 3 shows the simulated and observed **interannual frequencies of occurrence** of the four regimes for the seven lead times (similarly to Figure 1). Red and blue bars indicate the monthly frequency (in case of S4, of the 15-members ensemble mean) compared to the average monthly frequency for the whole 1981-2015.

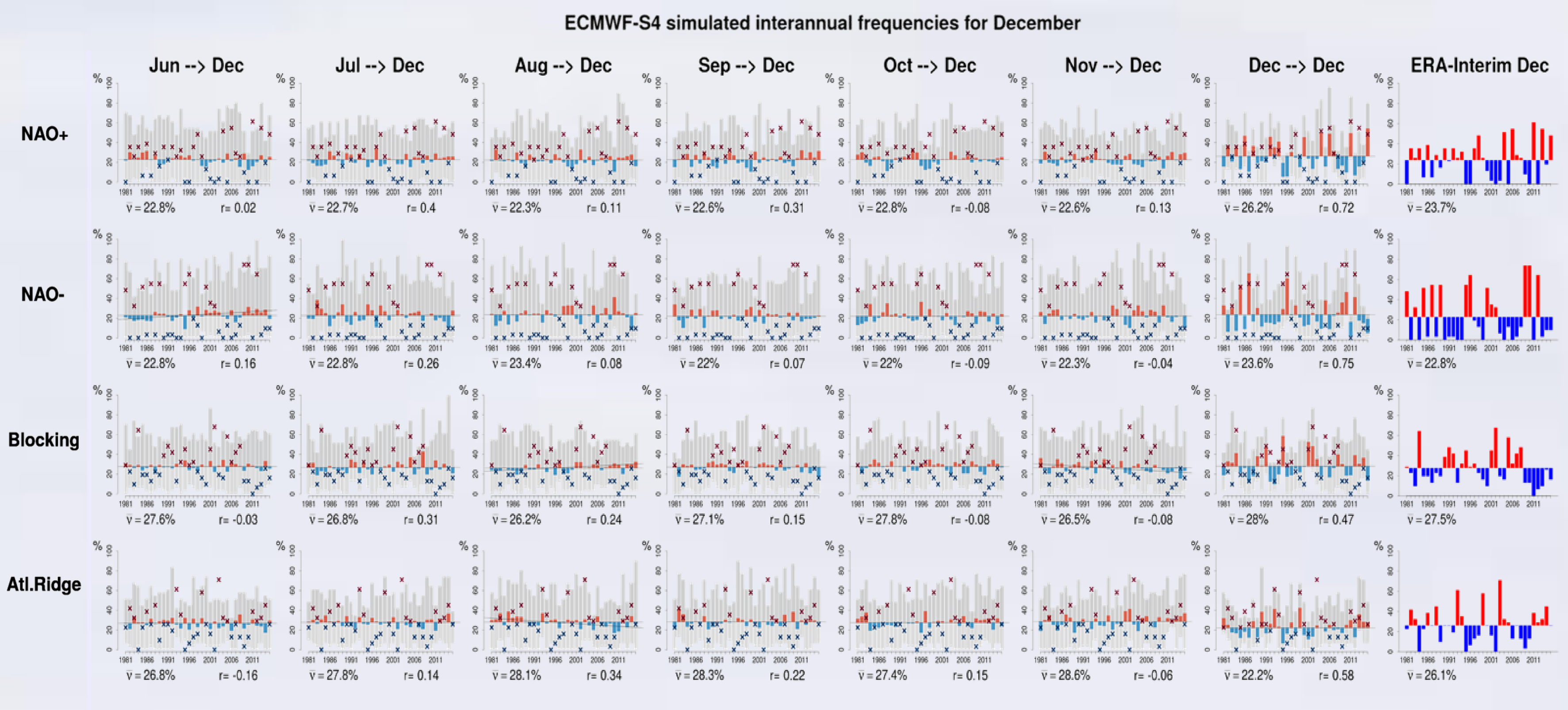

Figure 3. S4 simulated time series (1981-2015) of the interannual regime frequencies (in %) for the target month of December and different lead times (from 6 to 0 months) vs ERA-Interim observed frequency series (last column). Red and blue bars indicate the monthly frequency (in case of S4, of the 15-members ensemble mean) compared to the average frequency 1981-2015. Gray bars show the maximum and minimum monthly frequency of the 15 members, while red and blue crosses show the observed frequency (the same shown by the red/blue bars in the last column). Bottom numbers show the average frequency (in %) and the correlation with the observed one.

The **simulated average monthly frequency is always close to the observed one**; however, the temporal Pearson **correlations between interannual frequencies are above 0.5 only for lead time 0** (second column from right), and quickly drop below 0.5 at higher lead times.

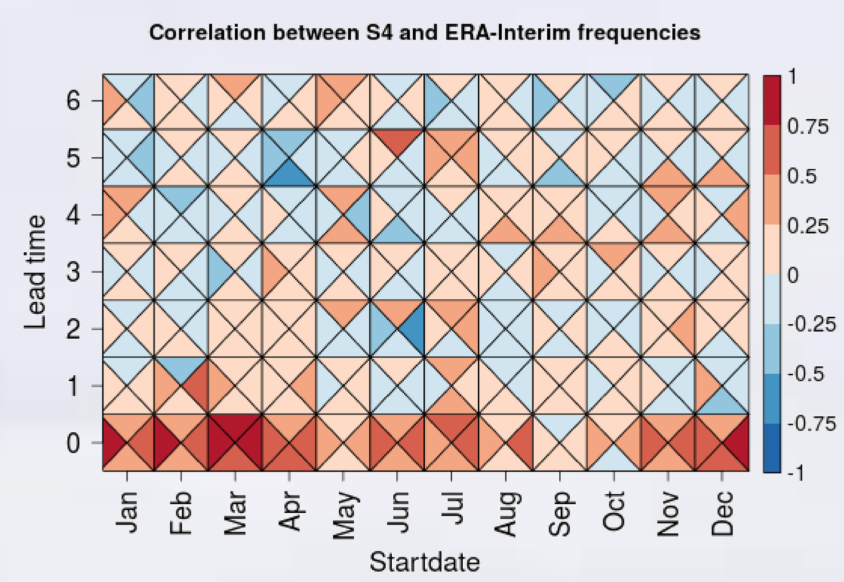

Figure 4. Temporal correlations between simulated and observed interannual frequencies.

The temporal correlation between simulated and observed frequency time series for all regimes, startdates and lead times is visualized in Figure 4.

Results are similar to those for December: even the other startdates show correlations above 0.5 almost exclusively when the lead time is 0, and decrease to zero thereafter, making it impossible to predict the monthly frequency of occurrence of any regime beyond the first month.

3.3. Results: frequency bias

The difference between the simulated and observed average monthly frequency (in %) of each regime is shown in Figure 5.

Forecasts often **overestimate** observations (red triangles) for blocking and Atlantic ridge regimes, and **underestimate** observations (blue triangles) for NAO+ and NAO- regimes. This is consistent with Ferranti et al. (2015), who found a similar behavior for the Medium-range forecast model ENS of the ECMWF.

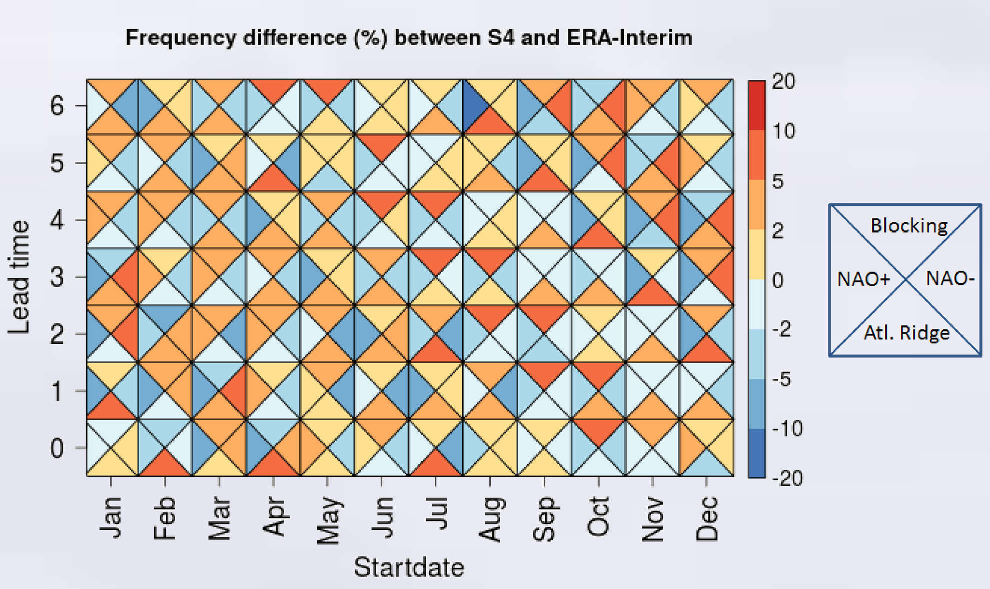

Figure 5. Difference between simulated and observed regime's frequency of occurrence (in %).

3.4. Results: persistence bias

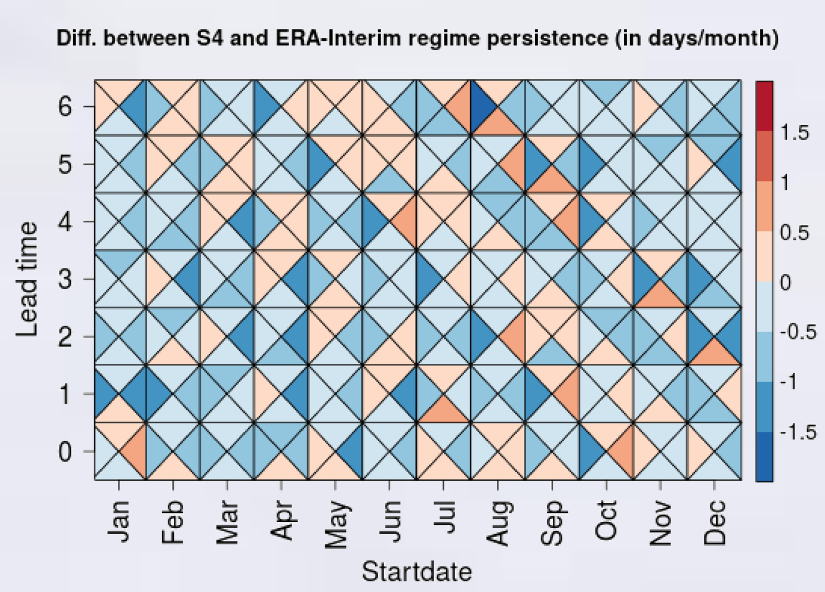

Figure 6. Difference between simulated and observed regime's persistence (in days/month).

Persistence is the measure of the mean number of days before a regime is replaced by a new one; it is typically equal to 3-5 days for North Atlantic-European regimes. The difference between simulated and observed persistence (in days/month) is plotted in Figure 6.

Forecasts tend to **underestimate** persistence (blue triangles) for the two NAO regimes, similarly to the frequency bias (see Figure 5), while blocking and Atlantic ridge regimes don't show any strong bias or any systematic error.

4. Conclusions

- High spatial correlations (>0.7) between simulated and observed regime anomalies are found for almost all startdates, lead times and regimes, indicating that S4 is able to reproduce the observed regime anomalies quite well.
- S4 skillfully reproduces the average interannual frequencies of occurrence of each regime, even for high lead times (six months in advance); however, it doesn't adequately reproduce the interannual frequency correlations at lead times greater than one. Such low skill might be attributed to the intrinsic unpredictability of the regimes, and not to a model fault.
- S4 forecasts tend to underestimate the monthly frequency of occurrence and persistence of the NAO+ and NAO- regimes, and to overestimate the monthly frequency of blocking and Atlantic ridge regimes.

5. References

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SEVENTH FRAMEWORK PROGRAMME

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