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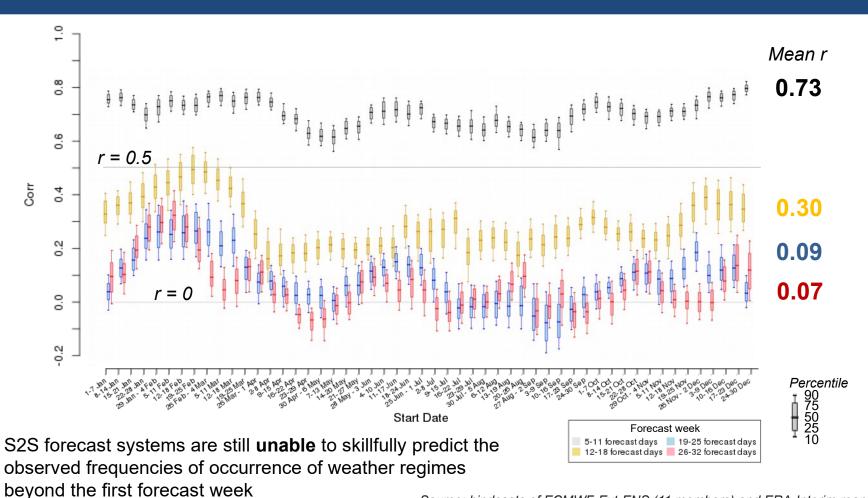


Predictable weather regimes at the S2S time scale

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May 2020

Earth System Services (BSC-ES)

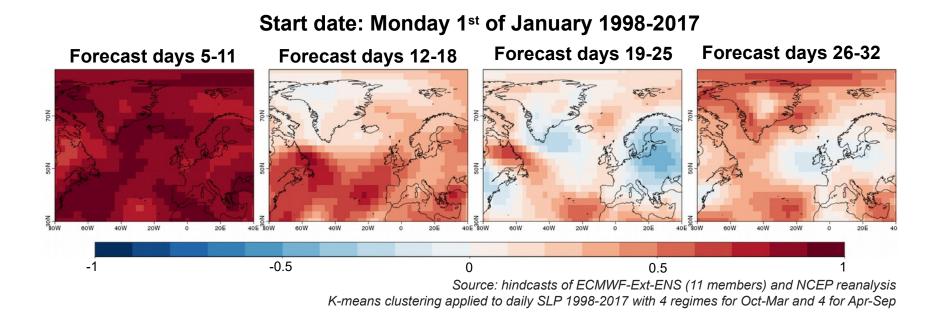


Source: hindcasts of ECMWF-Ext-ENS (11 members) and ERA-Interim reanalysis K-means clustering applied to daily SLP 1998-2017 with 4 regimes for Oct-Mar and 4 for Apr-Sep Correlations in leave-one-out cross-validation and bootstrapped with N=1000





Anomaly Correlation Coefficient (ACC) of sub-seasonal forecasts of SLP

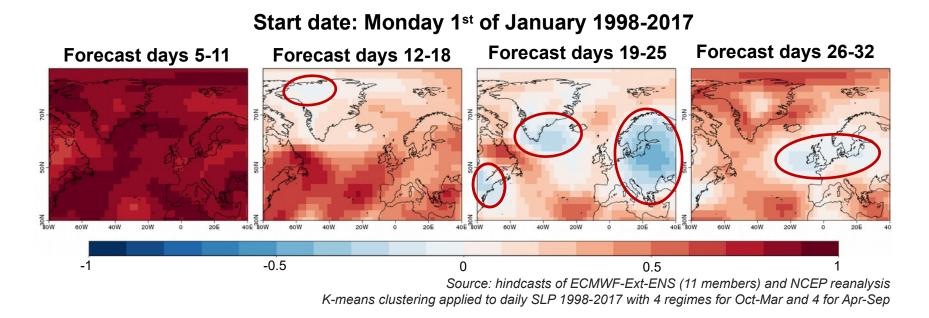


Each S2S forecast system **better simulates certain atmospheric flows** than others. To improve their forecast skill in simulating weather regimes, you can extract the regimes better simulated by the system and employ them for predicting the impact on surface variables. This is the opposite of the common approach of firstly look for the regimes with the highest impact and then measuring their predictability, hoping it is high.





Anomaly Correlation Coefficient (ACC) of sub-seasonal forecasts of SLP

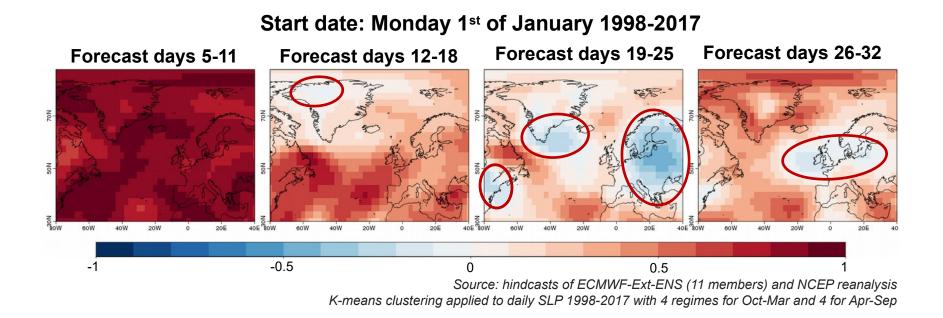


It is possible to **mathematically prove** that to extract the most predictable weather regimes from any forecast system, you just need to weight (multiply) daily circulation anomalies point-by-point by their **Anomaly Correlation Coefficient** (ACC) before classifying the regimes. Also, for the extraction to work, areas with negative ACC values (red circles) have to be **weighted by zero** instead of the ACC. In this way, cluster centroids are moved away from the areas where the forecast systems are bad in simulating atmospheric circulation (SLP in this case).





Anomaly Correlation Coefficient (ACC) of sub-seasonal forecasts of SLP

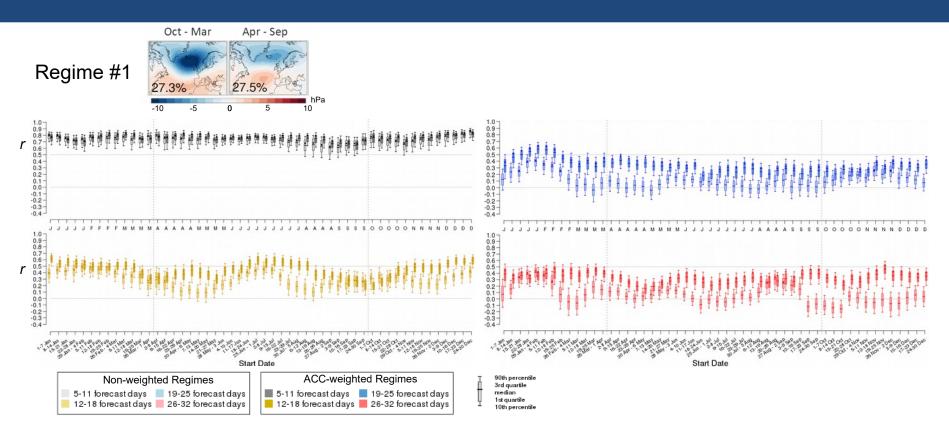


As a consecuence, the difference between the spatial patterns of the observed regimes are the highest possible exactly in the regions where the forecast systems better simulate the observed SLP anomalies. Thus, it is easier for the forecast systems to predict the right regime.







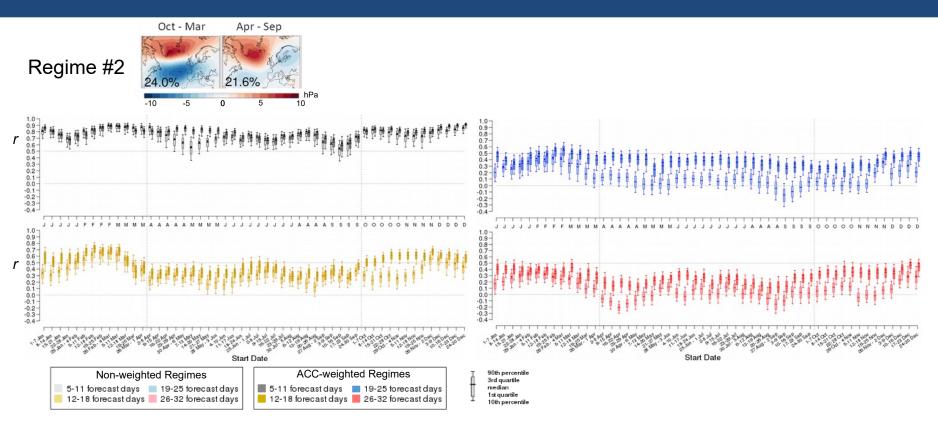


Beyond the first forecast week (5-11 days, gray bars), ACC-weighted regimes have much higher correlations (darker bars) than those of the non-weighted regimes (lighter bars), for the same start date and forecast week.

Source: hindcasts of ECMWF-Ext-ENS (11 members) and ERA-Interim reanalysis K-means clustering applied to daily SLP 1998-2017 with 4 regimes for Oct-Mar and 4 for Apr-Sep Correlations cross-validated and bootstrapped with N=1000







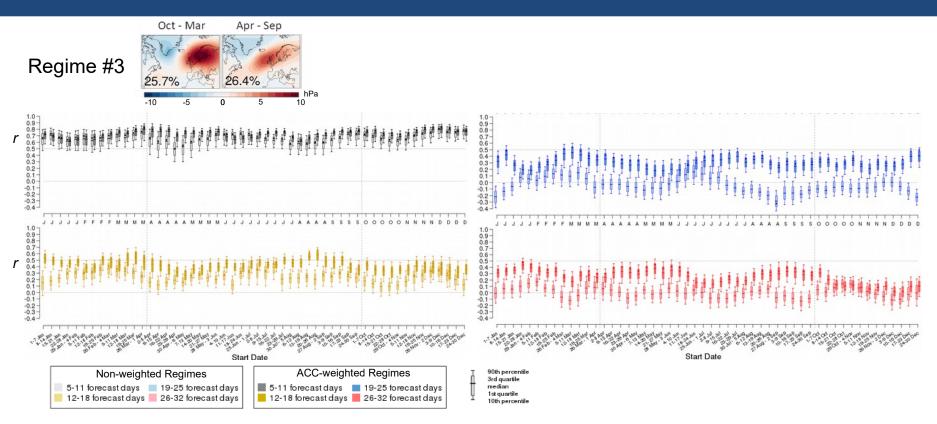
Beyond the first forecast week, forecast skill can still reach values of r = 0.5 or higher, particularly in winter start dates of WR 1 and 2, whose spatial patterns resemble those of NAO+ and NAO- winter (DJF) regimes. ACC-weighted regimes can reach correlations values close to r = 0.5 also in summer start dates.

K-means clustering applied to daily SLP 1998-2017 with 4 regimes for Oct-Mar and 4 for Apr-Sep Correlations cross-validated and bootstrapped with N=1000



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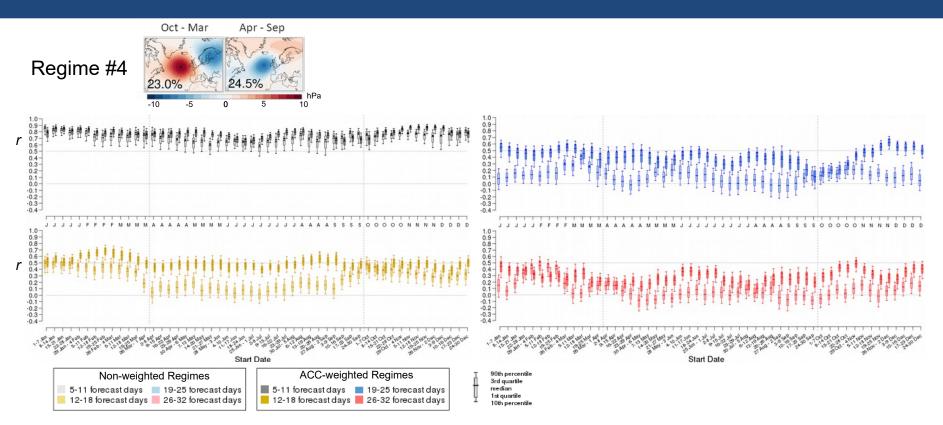
Spatial patterns of WR 3 resemble that of blocking regime in winter. It is the regime with the lowest skill of all, probably because it lacks a strong negative centroid. Beyond the first forecast week (5-11 days), only the ACC-weighted regimes are able to reach r = 0.5.

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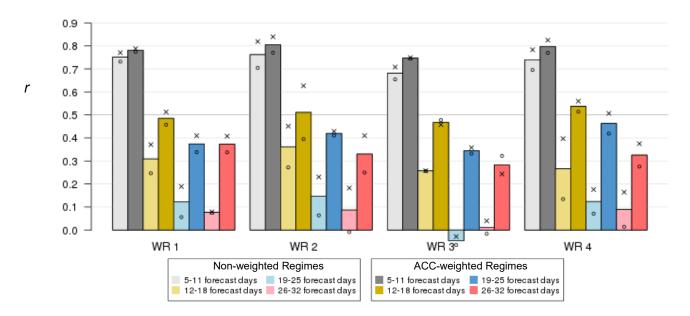


WR 4 resemble in Oct-Mar the Atlantic ridge regime and in Apr-Sep its opposite phase. ACC-weighted regimes largely improve its correlations, especially in summer start dates of the second forecast week (12-18 days, yellow bars), when they can also achieve values above r = 0.5 in case of some February, March and August start weeks.

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Forecast skill was averaged over all 52 start dates and shown in this bar plot, separately for each regime and forecast week (crosses and circles show the average over Oct-Mar and Apr-Sep start dates, respectively). The ACC-weighted regimes have more than three times the average correlation values of the non-weighted regimes, in case of the third and fourth forecast weeks (blue and red bars). Average values of the second forecast week (yellow bars) are also close to r = 0.5 for all regimes.

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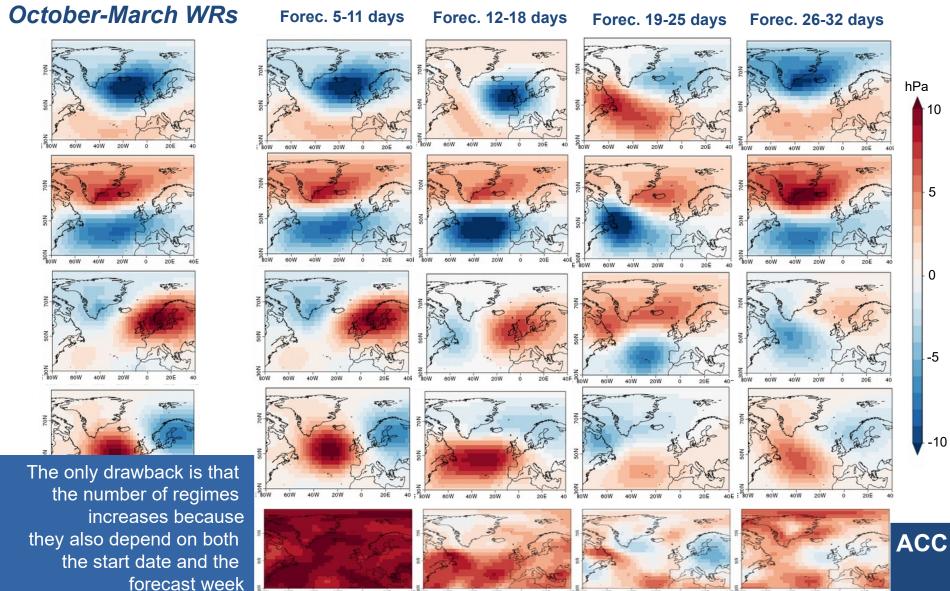


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Example: WR patterns for start date of January the 1st

ACC-weighted regimes October-March



Advantages and caveats of the ACC-weighted regimes

- Iarge skill gain beyond first forecast week (r = +0.3)
 Skill gain is high if ACC shows a large spatial variability inside the study domain
- + can be applied to any WR methodology based on clustering
- + can be transferred to any region where regimes can be defined
- + might improve skill of seasonal forecasts too
- + might improve teleconnection skill too
- ACC-weighted regimes are usually different from traditional ones identified in the literature (NAO+/-, etc). Thus, they also have a different impact on surface variables of users' interest.
- ACC-weighted regimes are much more numerous, as they also depends on the start date and the forecast week



