Supplementary materials: On the use of Weather Regimes to forecast meteorological droughts over Europe

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ABSTRACT

In this supplementary materials, the methodologies employed to attribute the WRs and to assign the predictors are exposed. The different steps involved are illustrated in Fig. 1.

WR classification and attribution

To define the MOAWRs, the first step is WR classification. This step is explained in the main document and the patterns of the geopotential height anomalies for the four seasons are displayed in Fig. 2. The best known WRs occur in winter, namely the NAO- (Fig. 2a), the Blocking (Fig. 2b), the Atlantic Ridge (Fig. 2c) and the NAO+ (Fig. 2d). Once the WR classification done, the closest WR to the daily geopotential of each ENS-member is attributed for both ERAI and ENS (see step 2 in Fig. 1).

Assignation of predictors

The objective of this step is to identify the best SPI-1-predictor within the three or four WRs identified for each season and their 6 to 12 possible combinations (step 3 in Fig. 1). Firstly, this is done by using the MOAWRs provided by ERAI and the SPI-1 based on the observed precipitation (red arrows in Fig. 1). This identification is based on the temporal correlation between the SPI-1 for each grid point and the MOAWRs. Fig. 3 depicts these correlation values for the 16 anomalies of WR (and combination) occurrences provided by ERAI in winter and illustrates the known WR impacts on precipitation. For instance, the positive impact of the occurrence of the Atlantic Ridge (WRc) or NAO+ (WRd) on higher precipitation in the northern part of Europe, or the dry conditions associated with blocking (WRb) in north-eastern Europe (**?**) are clearly visible.

An automatic attribution is then applied based on the maximum of the absolute values of the correlations. The sign of the correlation is recorded to keep track of the type of teleconnection. As an example, Fig. 4 illustrates the strong teleconnection between the occurrence of the best WR predictor and SPI-1 over the Scandinavian Peninsula. It shows the Cumulated Distribution Function (CDF) of dry conditions (i.e. SPI-1$<$-1) and the reverse CDF of wet conditions (i.e. SPI-1$>$1) in relation to the predictors (here, the difference of occurrence between WTb and WTd). While the distribution of the predictor (distribution of WTb-WTd) is close to the normal distribution with the same number of events in both cases, the two CDFs depict a clear difference. More than 90% of dry conditions occur when the predictor is positive (i.e. more WTb than WTd during the 30-day period). The opposite is true for wet conditions. The cross-section of the two CDFs at around 0.1 is also a good indicator for evaluating the ability of the predictor to discriminate between the two conditions (i.e., its resolution, which is good if the intersection occurs close to 0 or 1, null if it is close to 0.5).

When using the ENS forecasts, different methods of predictor assignations have been tested. The first one (called Operational forecast in Fig. 1) is an assignation derived from the ERAI previously described. The best relationship between the observed predictand and predictor is used to define the predictor from the 16 WRs occurrence anomalies and then applied to the forecasts (green arrows in Fig. 1). The advantage of this method is a real assessment of the model ability to forecast both the WRs and the relationship between the SPI and the WRs. As this assignation is fixed, it is also easier to set up operationally and there is no problem when the version of the operational model changes. Indeed, this kind of assignation procedure depends on the reanalysis and the observed precipitation and so it is independent from the model version. The disadvantage is the non-optimization of the forecast, i.e. there is no correction in case of bias in the forecasted WRs.

A second assignation procedure (called Optimized forecast in Fig. 1) is built by applying the same method but using the best relationship between the observed SPI and the WRs occurrence forecasted by the ENS as predictor (instead of those derived from ERAI). Note that in this approach the WR classification is derived from ERAI. This method (blue arrows in Fig. 1) derives the best relationships between WRs forecasted and observed precipitation, and by definition will obtain the best scores even if the WRs are not correctly forecasted. The last predictor assignation (Process; purple arrows in Fig. 1) is built identically to the previous configurations. The only difference is the use of the precipitation forecasted by ENS and so it provides the relationships between the forecasted WRs and precipitation. Therefore, this configuration aims at highlighting the skill of the model in representing observed processes.

A second method for defining the predictors, instead of the best absolute value of correlation, was also tested using the Mixture Discriminant Analysis (MDA, **?**). This method is an extension of the linear discriminant analysis and is a classification procedure based on mixture models. Each class is assumed to be a Gaussian mixture of subclasses. This method is based on a generative model based on the posterior probability of class memberships. By weighting each parameter, each class can then be characterized. Based on the learning period and the derived parameters, the model can then predict a class in the projection period. The model parameters are estimated via an expectation-maximization algorithm. Nevertheless, due to the optimization technique, this second attribution method does not seem to be suitable for predicting extreme events as it tends to overestimate the normal conditions when the distinction is not significant. As a consequence, scores are only visible where the relationships between the WRs and the SPI-1 are the strongest and elsewhere the results remain below the benchmark (not shown). The only benefit of this overestimation of the normal condition is in the strong reduction of the FAR. For these reasons this method is not further explored in this study.

LIST OF FIGURES

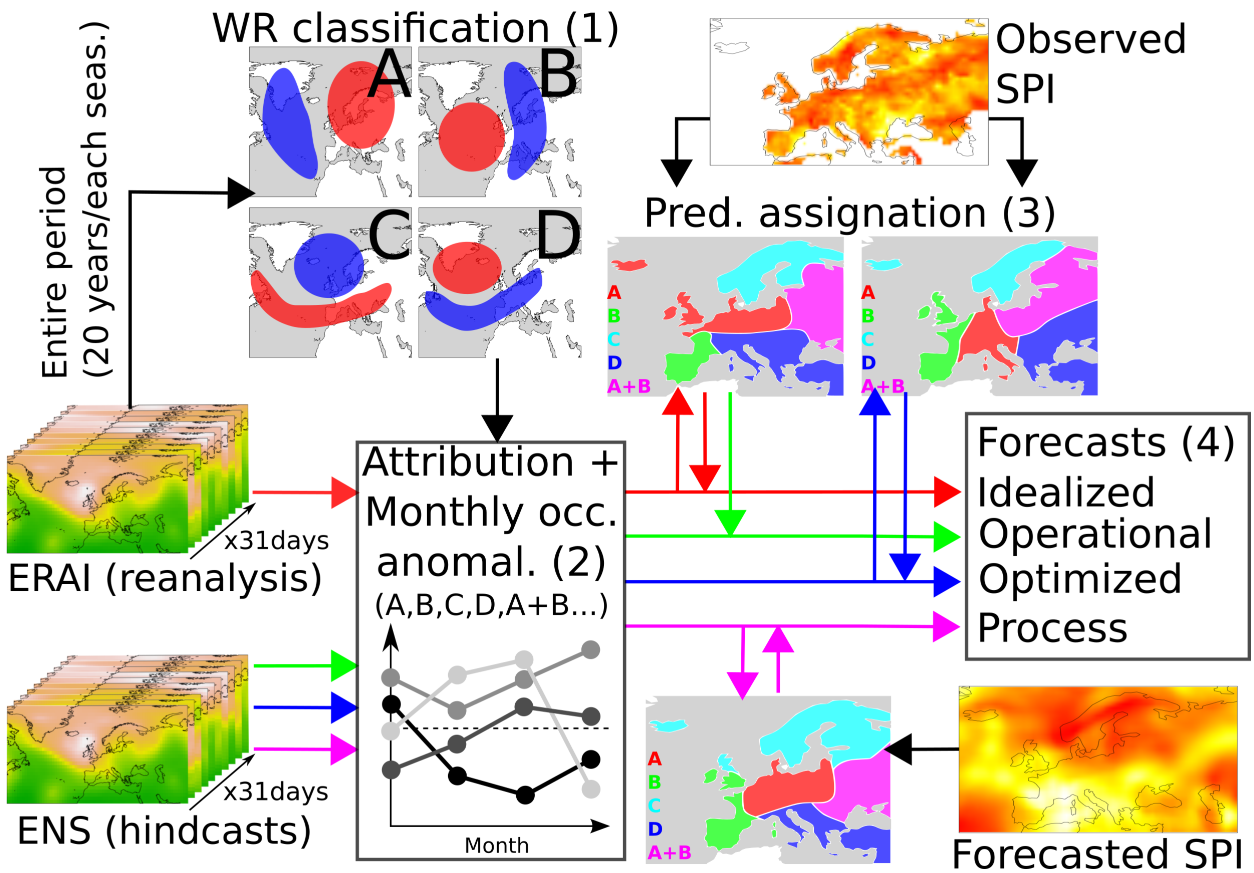

FIG. 1. Schema of the procedures to develop the forecasts by using ERAI and ENS. The process is based on three consecutive steps presented and discussed in the paper. The first one is the WR classification (1), using ERAI. The daily WR attribution (2) and the monthly occurrence anomalies are then calculated using ERAI and ENS. Finally the predictor assignations (3) are realised with 3 different combinations of correlation: i) observed precipitation and MOAWRs, ii) observed precipitation and forecasted MOAWRs, and iii) forecasted precipitation and MOAWRs. The four arrows indicate the four forecasts used in this study.

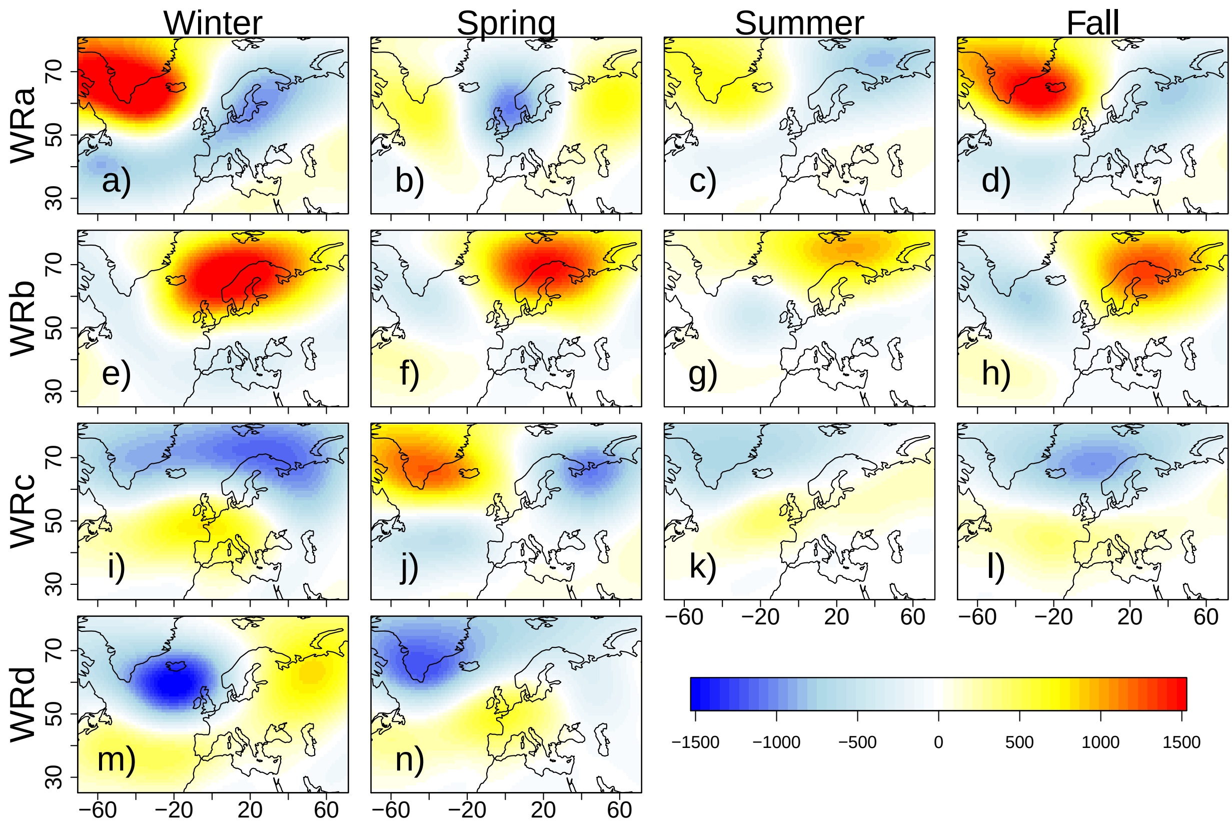

FIG. 2. Geopotential anomalies at 500hPa (in m) for each WR in winter (DJF), spring (MAM), summer (JJA) and autumn (SON). According to the season, 3 or 4 WRs are detected.

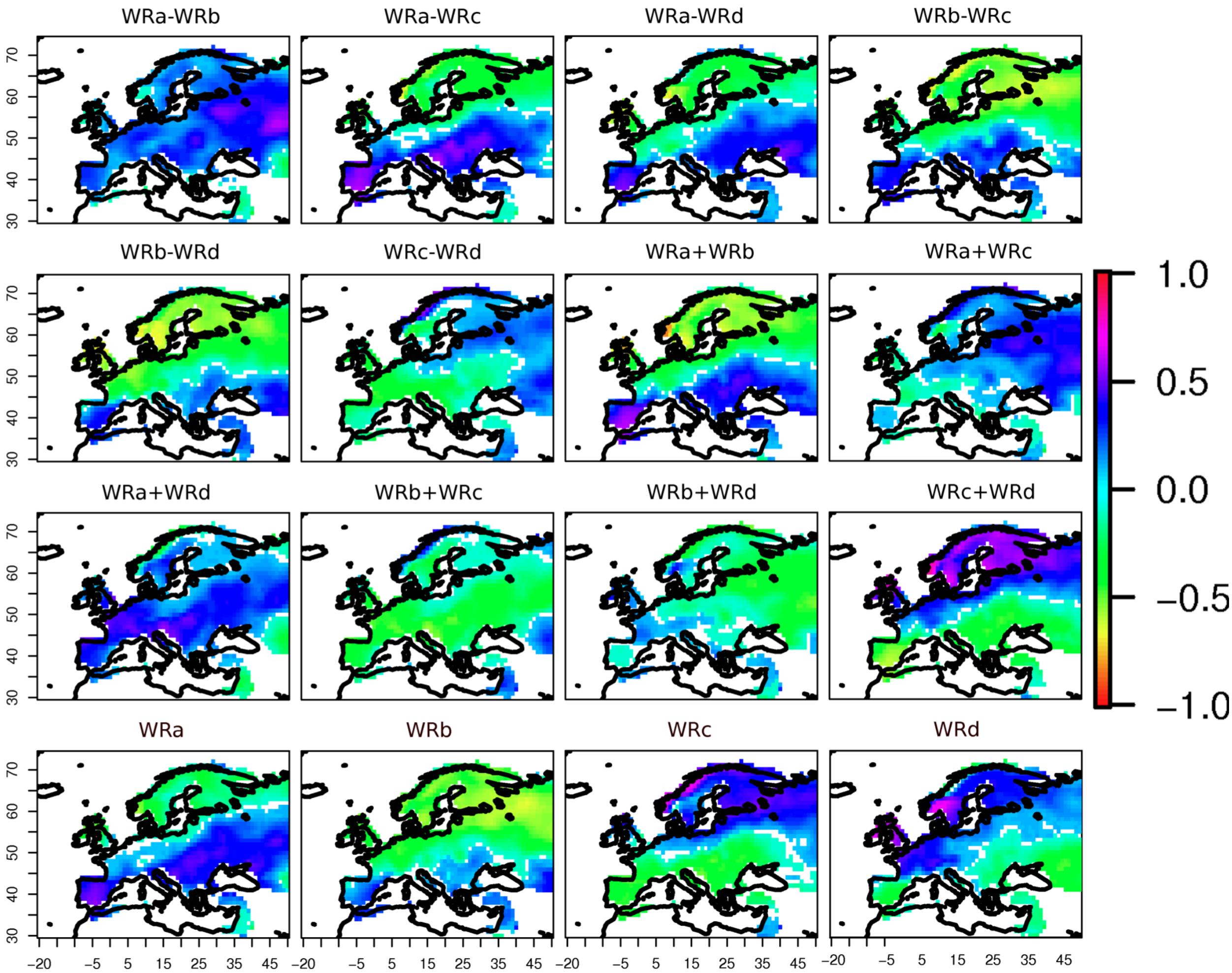

FIG. 3. Temporal correlation between SPI-1 and the 16 WR occurrence anomalies (4 WRs and 12 combinations) in winter throughout the period of hindcast.

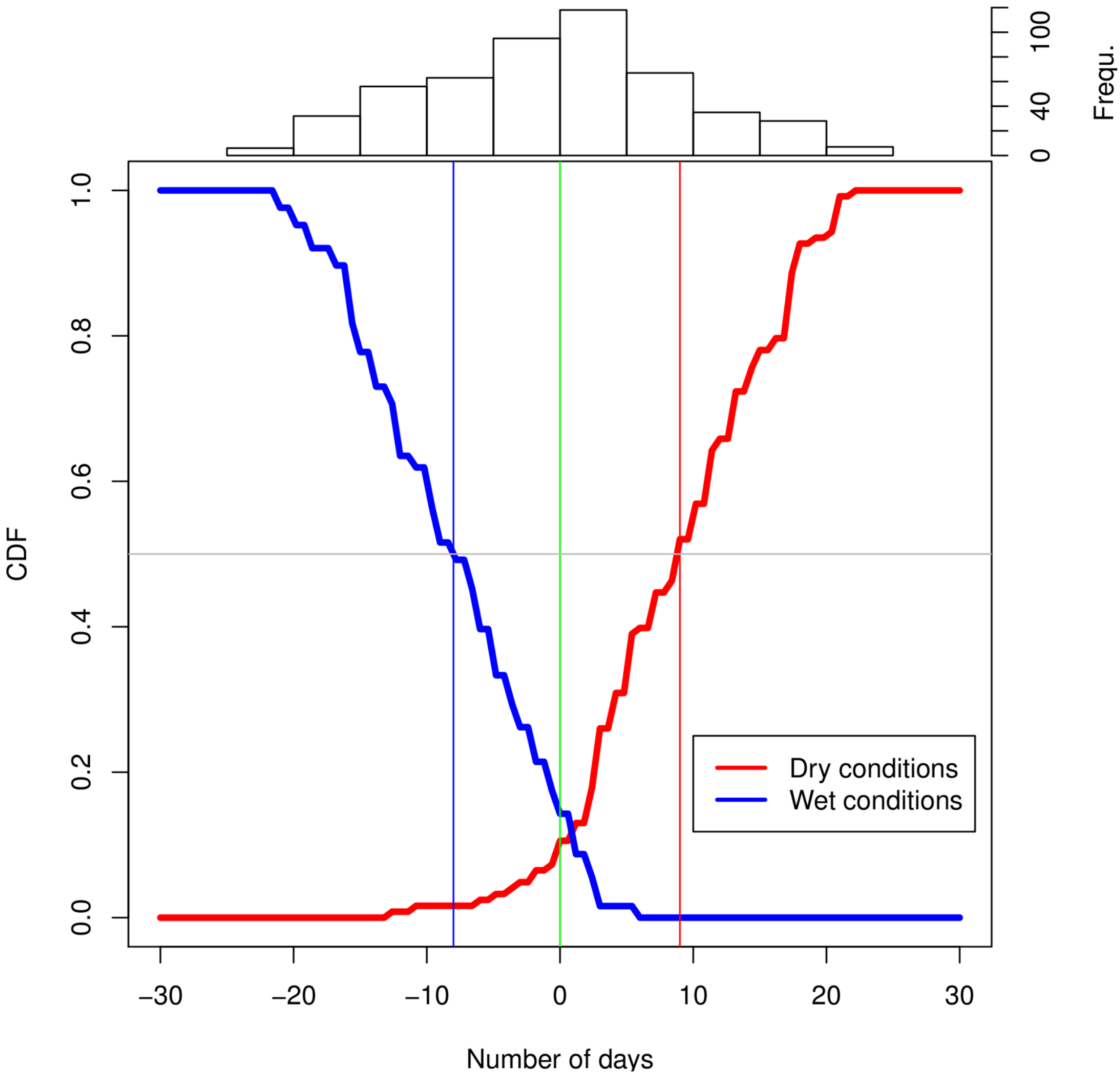

FIG. 4. Climatological distribution of cases of the predictors (here, occurrence of WRb - occurence of WRd) from -30 to 30 days (top panel). CDF of dry conditions (defined as having an SPI-1 lower than -1) following the predictors (red line) over the Scandinavian region. The blue line represents the inverse CDF for wet conditions (SPI-1 larger than 1). Vertical lines indicate the medians of each distribution.