Indecis

Sectorial Climate Services

Integrated approach for the **d**evelopment across **E**urope of user oriented **c**limate **i**ndicators for GFCS high-priority **s**ectors: Agriculture, disaster risk reduction, energy, health, water and tourism

Work Package 6

Deliverable 6.3

Report on the reliability and uncertainties associated with the (hindcast-type) seasonal forecasts of selected sectorial INDECIS indices

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Seasonal predictability of Fire Weather Index (INDECIS-ISD 128) components over Europe

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UC/IHC

Summary

Wildfires constitute a major natural hazard in many areas of the world. In this study, we analyze whether dangerous episodes can be predicted months in advance using the seasonal predictions of coupled ocean-atmosphere models, focusing the analysis in the EuroMediterranean (EUMED) region, where the serious wildfires of the last years are of serious concern. We built upon previous studies showing the adequacy of the Fire Weather Index System (FWI, INDECIS-ISD 128) in order to characterize actual fire danger conditions and the potential seasonal predictability of FWI in certain areas of EUMED, further advancing this knowledge by analyzing the differing seasonal predictability of the various intermediate FWI components. To this aim, we consider two different forecasting systems of sufficient hindcast length and input variable availability (NCEP-CFSv2 and ECMWF-System4) and bias-corrected predictions of the different FWI components, in order to account for the systematic model biases present.

When considering the whole European domain, the seasonal forecast skill for the different FWI System components is similar to that of FWI. However, the results show that some of these components may improve fire danger predictability for particular regions, even at lead times of 2 months, and even 3 months for some particular regions/forecasting systems. Due to the differing forecasting system performance across regions/components, our results suggest that multimodel ensembles of FWI component predictions may improve the seasonal predictability of fire danger over significant areas of Europe.

Introduction

The use of coupled ocean-atmosphere prediction systems to inform decision-makers is currently receiving great interest from different sectors of economic and societal relevance such as land management, agriculture, hydrology and energy among others (see e.g.: Falloon et al. 2018, De Felice *et al.* 2015, Hamlet *et al.* 2002), due to their potential to assist decision-making through the provision of actionable, sector-relevant climate information a few months in advance (Kumar 2010). In the framework of wildfire prevention, seasonal predictions have a great potential to aid decision-making (see e.g. Bedia et al. 2018, Turco et al. 2018), helping fire agencies to improve the efficiency of wildfire suppression efforts during severe fire seasons and optimize the available economic, technical and human resources through the provision of actionable information. Even marginal improvements in suppression efficiency have the potential to prevent significant damages and economic costs derived from wildfires (Preysler and Westerling 2007); in this sense, the prediction of dangerous fire seasons a few weeks to months in advance may help to more efficiently reallocate resources to fire prevention and suppression in a given period/region.

Fire danger can be defined as the chance of a fire to start and its potential spread, intensity and difficulty of suppression, given the current meteorological conditions. Specific indices are routinely used by fire agencies across the world based on fire weather variables, providing a synthetic measure of fire danger based on the meteorological conditions. As a result, fire danger indices act as meters (see, e.g. Fugioka *et al.,* 2009) that provide a quantitative measurement by which to compare fire seasons and to contrast fire problems among different regions. One of the most widely used indices internationally is the Canadian Fire Weather Index System (FWI, van Wagner 1987). The ability of FWI to adequately characterize actual atmospheric dangerous conditions, as reflected by the interannual correspondence between FWI and burned area has also been shown both in the EUMED region (Viegas *et al.* 1999; Bedia *et al.* 2014). It is currently the fire danger system adopted by the EFFIS (European Forest Fire Information System) to provide harmonized operational fire danger forecasts throughout Europe (San-Miguel-Ayanz 2013). In the context of the INDECIS Project, FWI is the index 128 of the INDECIS-ISD list (INDECIS Deliverable 4.2).

In the framework of short-term weather forecasting, Di-Giuseppe *et al.* (2016) found that three different fire indices, including FWI, were good predictors of dangerous conditions, skillfully detecting large fires on a global scale, highlighting the potential of fire danger modelling to predict dangerous episodes over large land areas of the globe a few days in advance. In the context of seasonal prediction previous studies have shown that coarse-scale seasonal predictions of FWI are skilful in areas of USA (e.g. Roads *et al.* 2005,2010) and the Euro-Mediterranean regions (Bedia *et al.* 2018), highlighting their potential usefulness in operational fire danger seasonal prediction. However, the multi-variable nature of the FWI System and the different intermediate components involved in its calculation calls for a more detailed analysis of the contribution of the different components to the overall skill, which remain largely unknown, thus allowing for a more precise analysis of the seasonal FWI predictability and permitting the identification of those components more skillfully predicted. In fact, each component of the FWI system can be regarded as a fire danger index in itself revealing particular aspects of fire danger (see e.g. Wotton 2009) that can have their own relevance in fire danger modelling and prediction (see e.g.: Amatulli *et al.* 2013, Bedia *et al.* 2014a).

The aim of this deliverable is contributing to our knowledge on the predictability FWI on seasonal time scales in Europe, by analysing the predictability of the different FWI system components, helping to improve the fire protection in the Euro-Mediterranean region. The potential improvement of seasonal FWI predictions is investigated through the skill assessment in the prediction of other components of the FWI system tracking changes in fuel moisture, and therefore more directly dependent on humidity (e.g. drought, duff moisture and/or fine fuel moisture codes): Drought Code (DC), Duff Moisture Code (DMC), Fine Fuel Moisture Code (FFMC), Built-up Index (BUI) and Initial Spread Index (ISI).

Data and Methods

The Canadian Forest Fire Weather Index (FWI) System

The FWI system (van Wagner 1987, Stocks *et al.* 1989) is a daily weather-based system calculated upon local noon standard time records of observed temperature and relative humidity (measured at 1.4 m above the ground in a radiation shielded screen), 10-m open wind speed, and 24-h accumulated precipitation. The FWI System consists of six components rating the effects of fuel moisture content and wind on a daily basis, based on various factors related to potential fire behaviour (Fig. 1). The first three components, Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC) and Drought Code (DC), rate the average moisture content of fine surface litter, decomposing litter, and organic layers respectively, and are based on an exponential model of moisture exchange. The DC is a simple moisture ŏbookkeepingò system that uses an estimate of a dayôs potential evapotranspiration and daily rainfall to track increases in wetness of the layer (Girardin and Wotton 2009). Wind effects are then added to FFMC to form the Initial Spread Index (ISI), used as an indicator of fire spread. Furthermore, DC and DMC are combined to produce the Build Up Index (BUI), rating the total amount of fuel available for combustion. BUI is then combined with ISI to produce the Fire Weather Index (FWI), a dimensionless index rating the potential fire line intensity given the meteorological conditions in a reference fuel type (mature pine stands) and level terrain. FWI can be later converted to the Daily Severity Rate (DSR) through a power function before averaging over weekly to seasonal time frames (van Wagner 1970), responding to the principle that higher fire danger should receive greater weight than lower fire danger when averaging over longer time periods or larger areas.

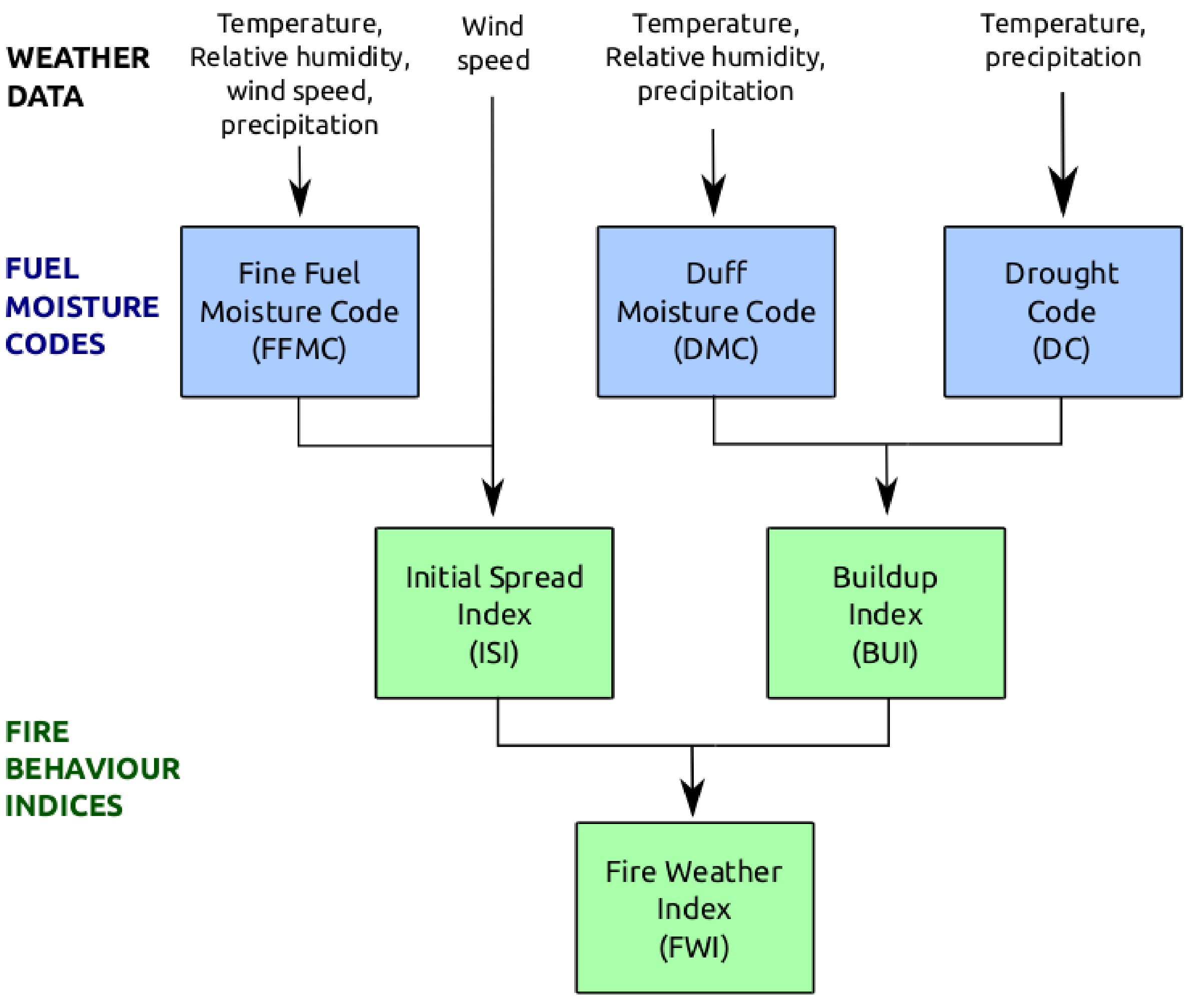

Figure 1. Schematic representation of the Canadian FWI system (adapted from Van Wagner 1987).

Obtaining representative noon local standard time records from model outputs is not always possible due to the relatively coarse temporal resolution of model data (6-hourly in this study), a problem that is particularly relevant in the case of areas with a relatively large longitudinal extent encompassing different time zones (e.g.: the EUMED region). These problems are further commented and exemplified in Bedia *et al.* (2018, see also supplementary material). In this study, and in order to obtain directly comparable predictions for the whole European domain analysed, we have used the appropriate input proxies of daily resolution, following previous work by Bedia *et al.* 2014. In particular, we calculated FWI using mean daily temperature and wind speed (instead of the corresponding instantaneous noon values) together with 24-accumulated precipitation and daily minimum relative humidity. This combination of proxy inputs has been shown to yield the most similar results when using model data (Bedia *et al.* 2014). The methodology for FWI system calculation from seasonal forecast datasets is further detailed in Bedia *et al.* (2018, see also additional details provided in the supplementary information of the aforementioned study).

Seasonal prediction model data

Data requirements

The datasets used in this deliverable have been carefully chosen in order to fulfill some basic requirements. First, a proper assessment of the quality of a forecasting system requires a long enough hindcast period available to provide robust validation statistics. However, at the moment of preparing this deliverable, the hindcast period of the state-of-the-art seasonal prediction systems shipped by the Copernicus service encompasses the common period ~1993-2016 (with the following exceptions: for forecasts issued up to October 2018 it is 1993-2015 for ECMWF and Met Office and 1993-2014 for Météo-France; for all NCEP forecasts it is 1999-2016; see e.g. https://climate.copernicus.eu/charts/c3s_seasonal/c3s_seasonal_plume_mm).

On the other hand, relative humidity is an important fire-weather variable, and it is an input for the calculation of the Canadian Fire Weather Index. Unfortunately, neither relative humidity, nor surface specific humidity (from which the latter can be accurately derived) are currently available from the C3S multimodel through the Climate Data Store (https://cds.climate.copernicus.eu/cdsapp#!/dataset/seasonal-original-single-levels?tab=overview). In its place, derivation of relative humidity would be possible from surface dew-point temperature (currently available), but our preliminary tests have demonstrated that this approximation is far from reliable for low humidity values, as highlighted by the authors of the formula (Lawrence 2005), proposed for the estimation of relative humidity of moist air only (>50% humidity).

For these reasons, the results presented in this Deliverable correspond to the European Centre for Medium Weather Forecasting (ECMWF) seasonal forecasting system 4 (Sys4, Molteni *et al.* 2011) and the National Center for Environmental Prediction (NCEP) coupled forecast system v2 (CFSv2, Saha *et al.* 2013). We use their common 27-year period 1983-2010. Here we assess the skill of retrospective forecasts (or re-forecasts) of the FWI system components considering lead-times of 1, 2 and 3 months with regard to a predefined fire season, established from June to September (JJAS). Here, the *lead time* refers to the period of time between the issue time of the forecast and the beginning of the forecast validity period, as defined by the Standardised Verification System for Long Range Forecasts of the World Meteorological Organisation (WMO, 2000). Thus, a seasonal forecast issued one month before the beginning of the validity period is said to be of *one month lead time*.

In addition, the model predictions of the previous month (May) were also used to calculate the FWI component series, in order to have a spin-up period for the stabilization of the different FWI System components, and then removed for the analysis. Further details regarding the target season rationale and the methodology for FWY System calculation are provided in Bedia *et al.* 2018.

Reference observations

The WFDEI dataset (Weedon *et al.* 2011; 2014) consists of eight meteorological variables at 3-hourly time steps and as daily averages, for the global land surface at 0.5º resolution for the period 1979-2012. The information provided by the WFDEI dataset is essentially that of ERA-Interim, but providing an already available spatial resolution better suited for regional studies. Unlike other reference observational datasets considered in INDECIS (e.g. E-OBS), we have chosen WFDEI due to the availability of all the variables required for FWI calculation.

Data calibration

The systematic errors of current general circulation models (GCMs) used for seasonal forecasting and their relatively coarse spatial resolution, prevent the direct application of their outputs in most vulnerability and impact assessment studies, thus requiring some form of processing prior to their use (see, e.g., Doblas-Reyes *et al.* 2013, Manzanas *et al.* 2017). There is a wide range of statistical techniques currently available aimed at reducing the model biases, that can be roughly classified into two main families, namely bias adjustment (BA) and ensemble recalibration (RC) methods (see Manzanas *et al.* 2019 for a discussion on this aspect).

Acting directly on the variable of interest, these techniques are aimed at adjusting the model outputs towards the corresponding observed reference to make them statistically compatible

with the local climatology, typically by mapping the predicted distribution onto the corresponding observed one based on a representative historical period. Adjustments can be done to the mean and/or variance or higher order moments or even the entire distribution (e.g., quantile-mapping). In this work, we use the Mean and Variance Adjustment (MVA) method (Leung *et al.* 1999). The ensemble mean and variance are adjusted towards
the corresponding observed ones in the following form:

$$y'_{m,t} = (y_{m,t} - \hat{y})\frac{\sigma_o}{\sigma_f} + \hat{o}$$

Where ym,t and yôm,t denote the original and calibrated values for the ensemble member m at time t, yis the average of the ensemble mean on all times t, ois the average of the observations on all times t, fis the standard deviation of the complete ensemble (pooling all member interannual time-series) and ois the standard deviation of the observed interannual time-series.

Even though MVA is a relatively simple approach, it has been recently shown that it provides an overall good performance when compared against more demanding approaches (such as ensemble recalibration techniques, which rely on the underlying correlation between the ensemble mean and the corresponding observations), with a low computational demand (Manzanas *et al.* 2019).

Data sources and analysis tools

All seasonal forecast and observational data have been obtained from the Santander Meteorology Group User Data Gateway, formed upon different open-source software components publicly available: The UNIDATA THREDDS data server, the THREDDS Access Portal implementing fine-grained user management and authorization, and the climate4R R-based framework providing data access and postprocessing tools (including bias adjustment, downscaling and visualization) based on the R language and computing environment. Further details on the seasonal forecast database availability and configuration, including worked examples and reproducible code are available in Cofiño *et al.* 2018 (see also Frías *et al.* 2018 for an overview of seasonal forecast verification tools).

In order to undertake the different tasks dealing with seasonal forecast data in the framework of INDECIS, we have used the Santander Meteorology Group User Data Gateway (UDG) as the main entry point providing harmonized data access to state-of-the-art seasonal forecast datasets. A description of the UDG infrastructure, focused in the retrieval and analysis of seasonal forecast data for impact studies is provided in Cofiño *et al.* 2018. Furthermore, data post-processing and analysis, including downscaling/bias correction and visualization (Frías *et al.* 2018) will be done using the climate4R suite of tools (Iturbide *et al.* 2018), seamlessly integrated with the UDG infrastructure. The ensemble forecast data calibration has been undertaken with the *climate4R* package *downscaleR* (Bedia *et al.* 2019). This provides a comprehensive framework for end-to-end applications of seasonal predictions in the context of impact studies, including those involving sector-specific indices like fire danger (see Bedia *et al.* 2018).

All the skill maps presented are computed at the 0.5 degree resolution of the WFDEI dataset, inherited in the process of MVA correction.

Results

For brevity, in the following panels the results for just 4 of the 7 components of the Fire Weather Index System will be displayed, namely the drought code (DC), the duff moisture code (DMC), the fine fuel moisture code (FFMC) and the fire weather index (FWI). As a reference, in Fig. 2 the observed climatologies of the 4 components are displayed. Overall, the spatial pattern indicates the higher values over the southern part of Europe, as expected.

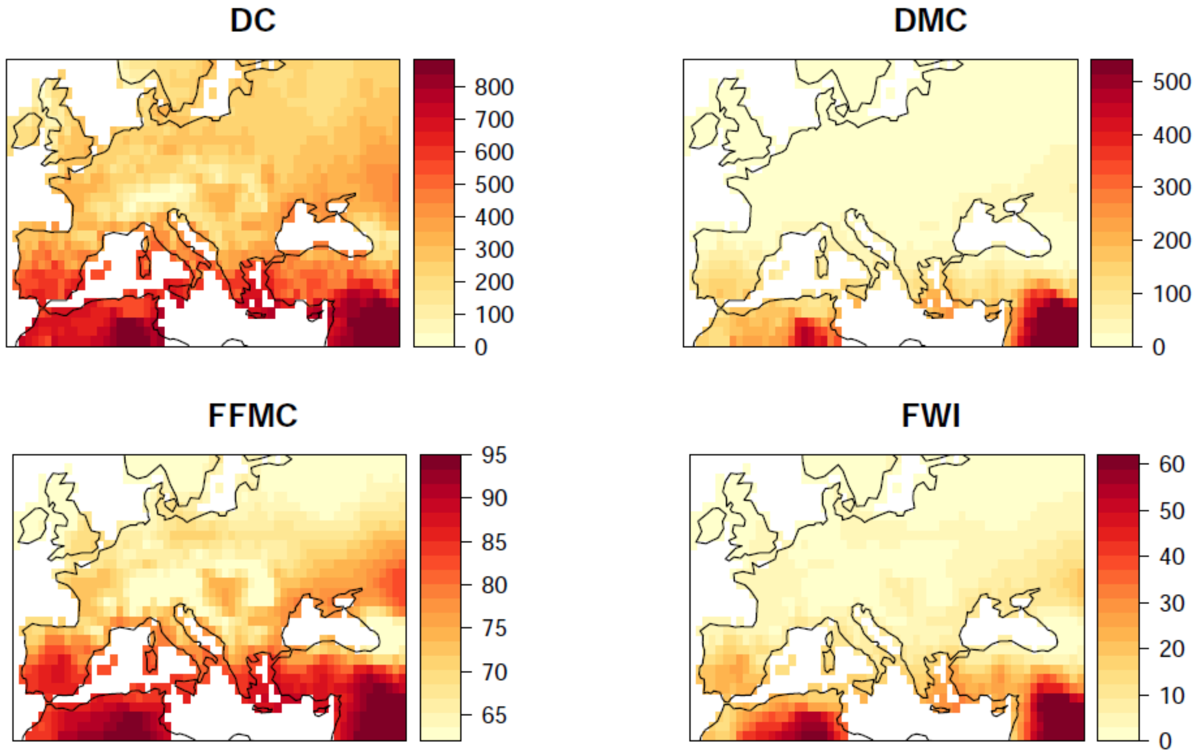

Figure 2. Climatological maps of the DC, DMC, FFMC and FWI components of the Fire Weather Index System, according to the WFDEI observational gridded observations. The period represented is JJAS 1983-2010.

Model Biases

In general, the CFSv2 forecasting system exhibits much higher bias magnitude than Sys4 for most of the study area, although the spatial pattern of errors is heterogeneous across the study area (Fig. 3). For some indices, such as DC in southern Europe or FFMC in Atlantic Europe, the bias is even of the opposite sign depending on the forecasting system. In any case, the large errors found warn about the need for correction prior to their application in an operational context, or in order to establish a comparison between both systems on common grounds. For brevity, relative biases have been omitted here, but are presented in the Appendix (Fig. A2).
After the application of the MVA calibration, all biases were eliminated (see Fig. A3 in the appendix). Furthermore, the biases from the remaining FWI components not shown here are depicted in Fig. A2.

Therefore, all the validation results presented in the following sections correspond to MVA-corrected predictions (i.e., after bias adjustment).

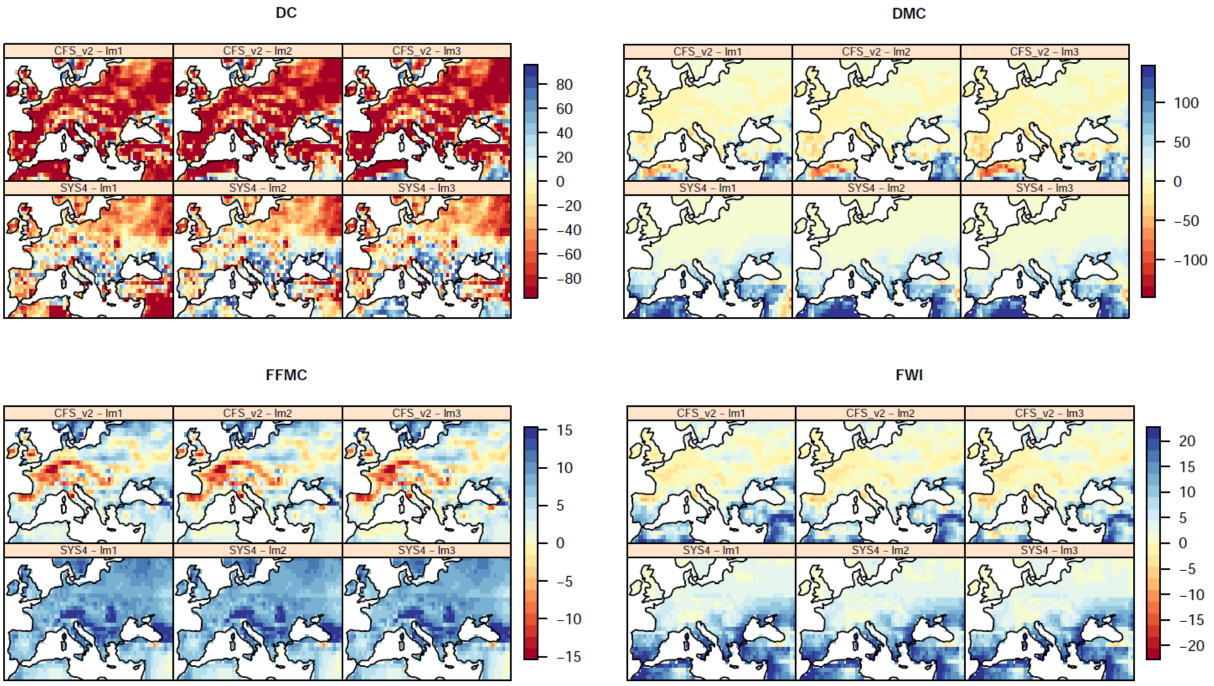

Figure 3. Bias of the selected components of the Fire Weather Index system (arithmetic difference between the observed and ensemble mean climatologies).

Ensemble correlation

The overall agreement between predictions and observations largely varies across regions, forecasting systems and FWI components, although overall the larger positive correlations are found in southern Europe and the Middle East portion within the study area. Both Sys4 and CFSv2 yield high correlations (above 0.5 and up to 0.85 at some locations) for DC and DMC in the middle east. More interestingly, a high correlation is also found in the southern Iberian Peninsula for Drought Code for lead months 1 and, to a lesser extent, lead month 2. In this particular subregion, CFSv2 outperforms Sys4 in the prediction of DMC and FFMC for lead month 1 predictions.

When looking at ensemble correlation, there is not a clear added value in the use of the different FWI components that FWI itself. Notably, CFSv2 yields slightly higher correlations in the Iberian

Peninsula for FFMC and FWI, although this holds true only for lead month 1 predictions. DC predictions attain very high correlation values in the SE corner of the analysis domain, and also improves the results of the FWI predictions in the Iberian Peninsula. In the particular case of Sys4, the predictions of DC have also high correlations in areas of central and East Europe (lead times 1 and 2 months). There are also large areas of central and northern Europe where strong negative correlations are found. In this case, although the negative correlations can be interpreted as potentially useful for seasonal prediction, must be taken with caution owing to the implicit low quality of the models in these areas.

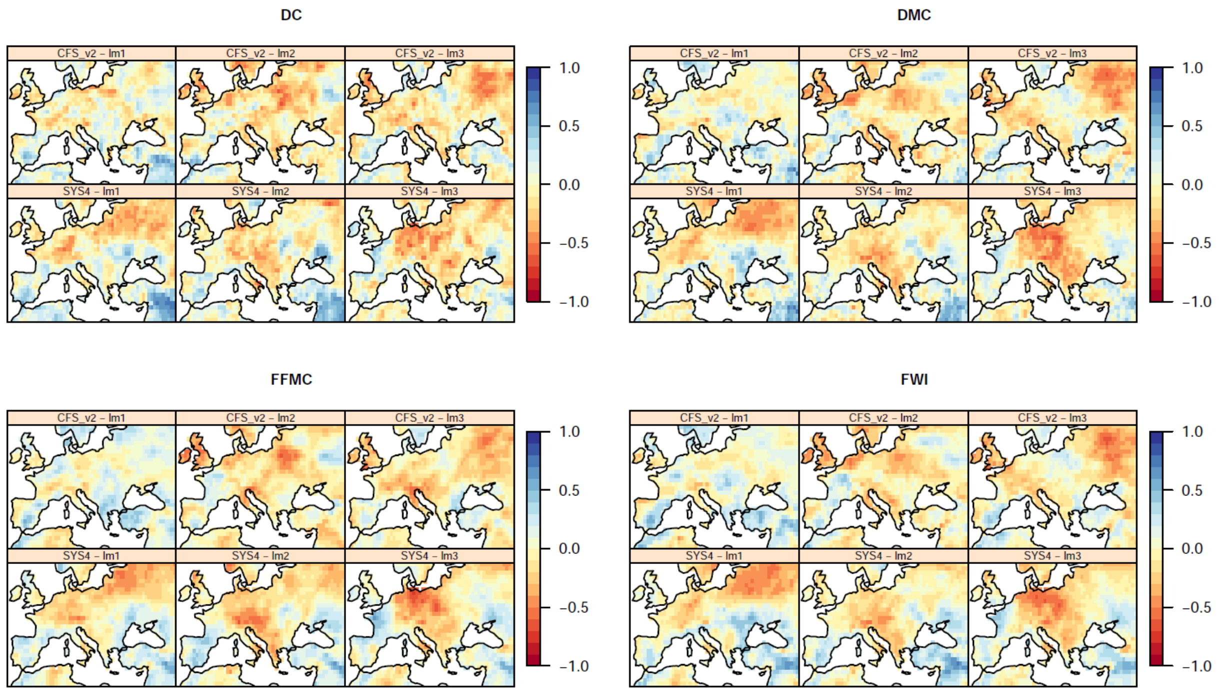

Figure 4. Ensemble correlation (Pearson's correlation coefficient) between the inter-annual predicted and observed fire danger predictions.

ROC Skill Score

Discrimination measures the ability of the forecasts to distinguish between an event and the corresponding non-event. Here, discrimination is quantified through the ROC Skill Score (ROCSS), that is directly derived from the area under the ROC (Receiver Operating Characteristic) curve, and it is an indicator of the quality of a forecast by describing the system's ability to discriminate correctly between the binary variable occurrence/non-occurrence of a certain event (Jolliffe and Stephenson, 2003).

As a result of using ROC Skill Score (instead of the direct Area Under the Curve -AUC-), values above (below) 0 indicate that the particular calibration method improves (degrades) the raw model prediction. Moreover, ROC is used here for tercile-based probabilistic predictions. Thus, terciles are independently computed for the observations and the predictions, which implicitly introduces a bias adjustment in the forecasts. Thus ROCSS is bias-insensitive, hence allowing to analyze the difference performance of CFSv2 and Sys4 beyond the expected (by construction) model bias reduction.

For brevity, here we show the results obtained for the upper tertile predictions (i.e., those events predicted as "higher than usual"), associated with particularly dangerous years. Lower tertile predictions are indicated in Fig. A3 in the Appendix. The skilful areas in regard with discrimination are indicated in the figures by the bluish colors (Fig. 5). The overall spatial pattern exhibited by ROCSS is more heterogeneous than for correlation, although again, the highest skill areas are located in the southernmost regions of the study area and the Middle East.

In the case of the DC, high discrimination values are found in the central and southern Iberian Peninsula and the Middle East for 1-month lead time predictions in both CFSv2 and Sys4 forecasting systems, while for lead month 2 the skill is preserved by Sys4, but no longer for CFSv2 predictions, whose skill decays sharply in this case. Sys4 also shows high skill in certain areas of Eastern Europe (North of the Black Sea) up to lead month 2, not shown by the CFSv2 predictions. A similar pattern is shown by the DMC, with an overall lower skill values than DC. In regard with the FFMC, CFSv2 has high skill in Southern Iberian Peninsula, Greece, Eastern Europe and Turkey for lead month 1 predictions, overall exhibiting a better performance than Sys4. However, the skill is reduced for larger prediction horizons.

Overall, 3-month ahead predictions attain low skill in all zones, with the remarkable exception of mean FWI over the Mediterranean Iberian Peninsula (CFSv2) and DMC, FFMC and FWI in the Atlantic area of France, and FWI in Turkey.

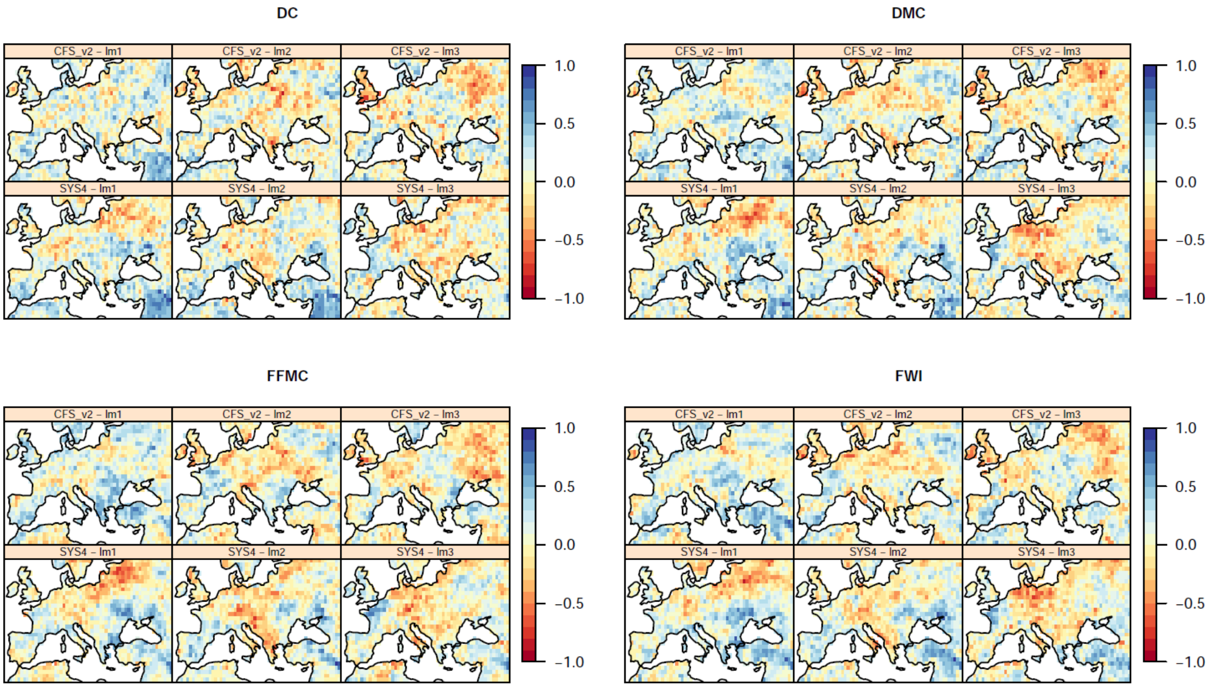

Figure 5. ROC Skill Score of the upper tertile predictions of DC, DMC, FFMC and FWI.

Discussion and Conclusions

The results highlight on the one side, the large biases of both forecasting systems, and on the other hand that these biases largely differ depending on the model and region considered. Therefore, calibration is a necessary step prior to the usage of seasonal FWI component predictions, due to the large errors present. As it has been shown, the MVA approach for bias adjustment provides an effective, yet relatively simple approach to this aim. Furthermore, the bias correction reinforces the signal over areas with predictability, introducing an additional advantage from an operational standpoint.

Several FWI components can improve FWI in terms of predictability (e.g. FFMC, DC, DMC), although this is found only locally and for certain subcomponents. Similarly, forecast skill doesn't degrade drastically for increased lead times of 2 months in many areas for some FWI components (i.e. DC in Southern Iberian Peninsula), suggesting potential for the application of FWI component forecasting at time horizons larger than 1 month in some occasions.

The simulations of current GCMs seem to adequately represent the soil-moisture-heat wave (see e.g. Hirschi *et al.*, 2011). Given the memory associated with soil moisture storage, this is an important factor that could explain the predictability of above-normal DC seasons in large areas of the mediterranean and the Middle East (ROCSS > 0.6, Fig. 4). Previous studies show the relatively good skill attained by the seasonal predictions of near-surface relative humidity and surface air temperature (Bedia *et al.* 2018). With this study, we show that the prediction of other components of the FWI system, and in particular those tracking changes in fuel moisture, and therefore more directly dependent on humidity and precipitation (DC, DMC and FFMC) can outperform the predictability of FWI itself, helping to locally improve the skill of seasonal fire danger predictions. Furthermore, these components of the FWI system have been shown to be closely related to monthly burned areas in different countries of the the EU-Med region (Amatulli et al., 2013), being therefore closely related to actual wildfire occurrence, thus helping to anticipate potentially dangerous fire years.

Therefore, the varying skill of different components over different areas and forecasting systems suggests the potential improvement of the fire danger predictions through the construction of multimodel ensembles of the different FWI components.

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Appendix

Model biases

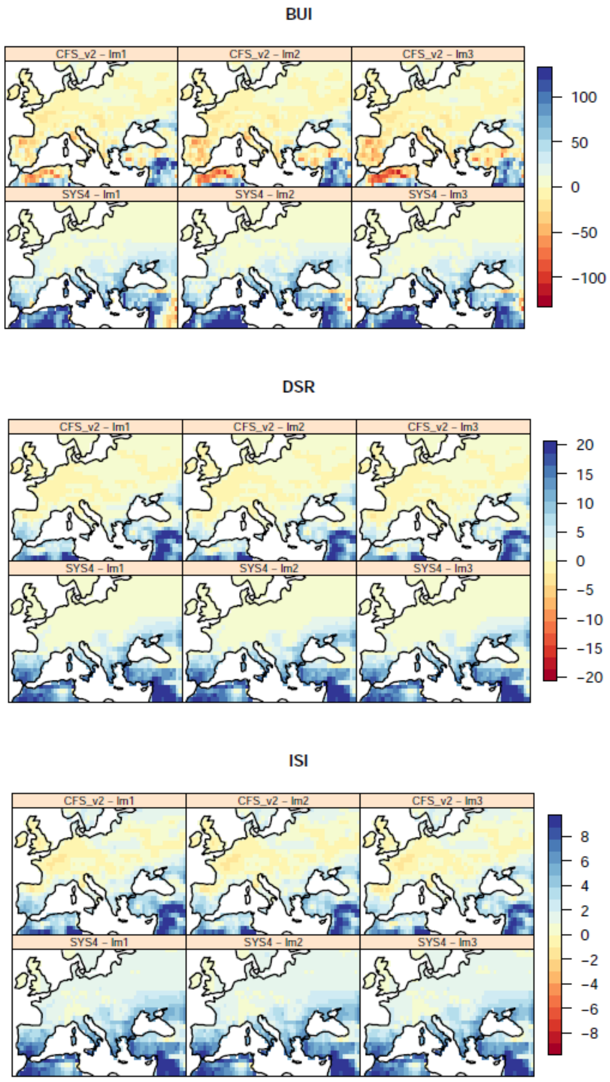

Figure A1. Same as Fig. 1 (mean bias) but for the remaining FWI system components (BUI, DSR and ISI).

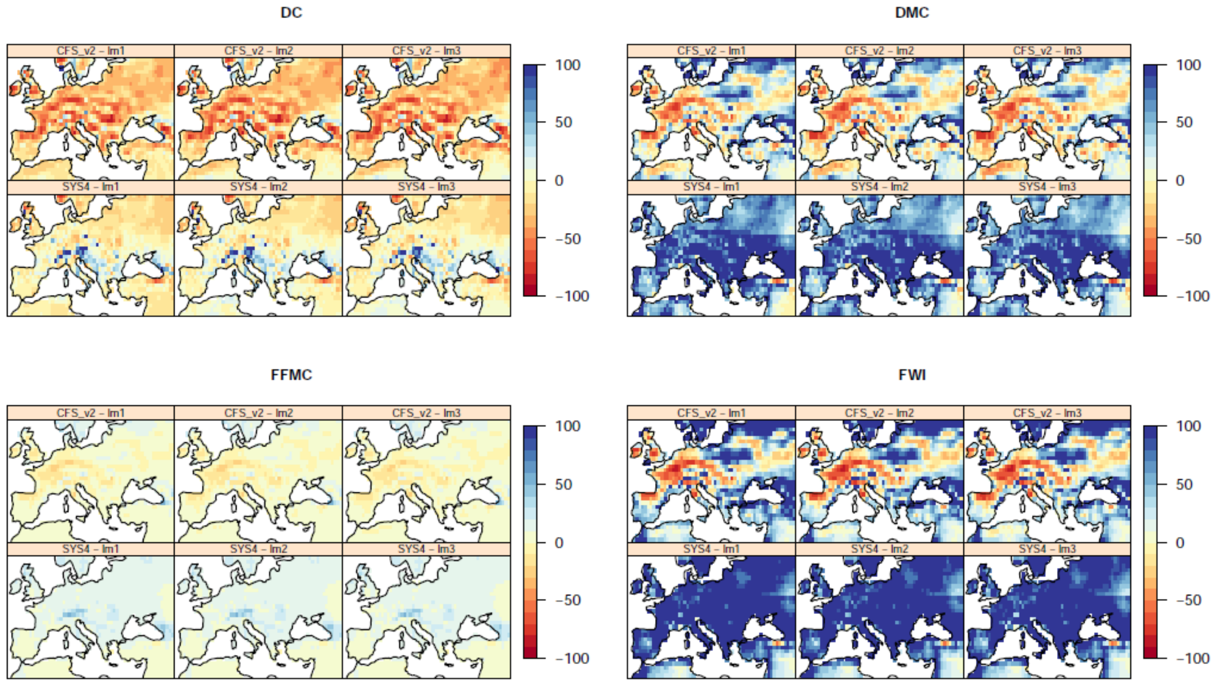

Figure A2. Same as Fig. 1 in the main body of the document, but considering the relative biases instead of the absolute ones. In this case, relative bias is computed as the difference between predictions and observations, divided by the observed mean.

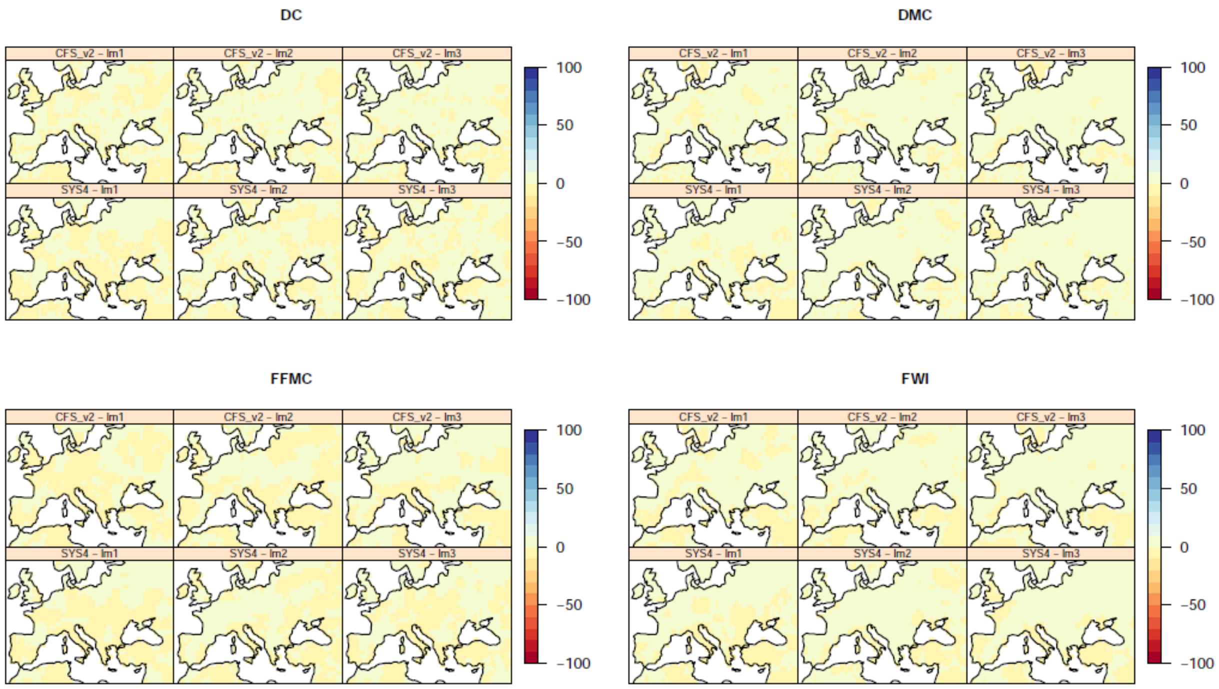

Figure A3. Same as Fig. 1 after the application of the Mean-Variance Adjustment. The relative biases displayed in Fig A2 are removed after the bias adjustment.

Ensemble correlation

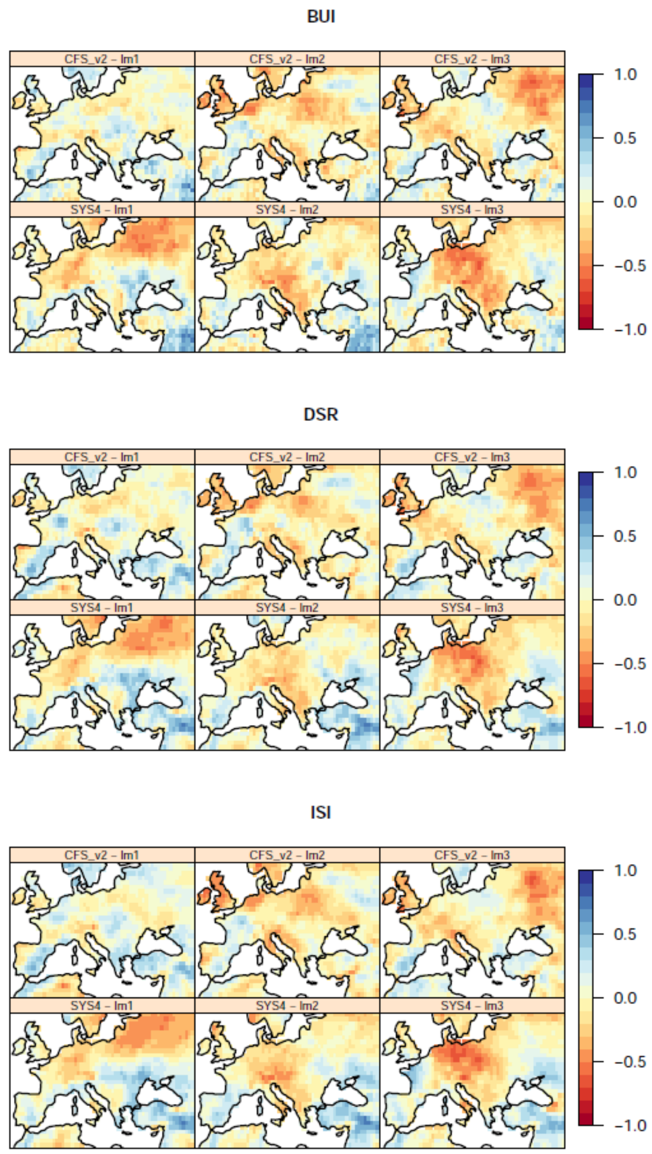

Figure A4. Same as Fig. 3 (Ensemble correlation of bias-corrected predictions), for the remaining FWI components (BUI, ISI and DSR).

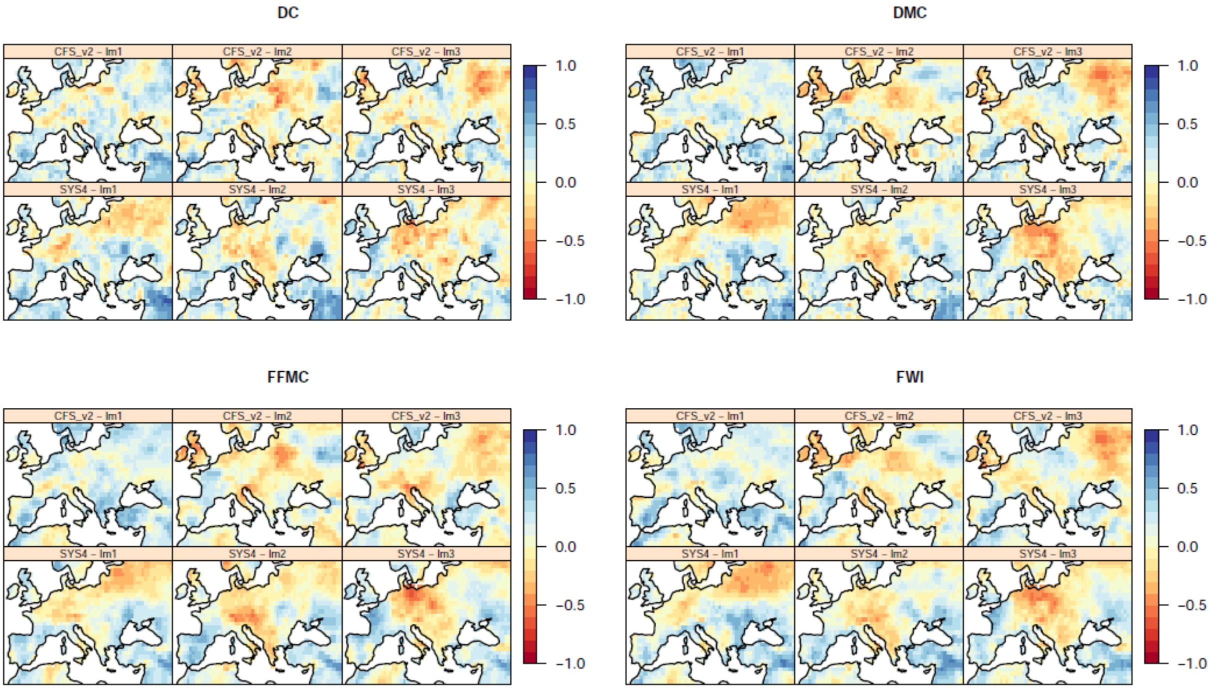

Figure A5. Same as Fig. 3 (ensemble correlation), but considering the uncorrected predictions. The spatial pattern is very similar to the corrected predictions, but the correlation values are slightly better in some areas after the correction.

Summary by countries

In this section a summary by countries of the ensemble correlation is presented at a country level (NUTS1, Fig. A4). It must be noted that the spatial pattern of forecast skill is finer than country-level in many countries (i.e., a more regional analysis is required for a better analysis). However, these panels have been prepared in order to gain a quick overview of overall skill across countries and its evolution through lead times from 1 to three months.

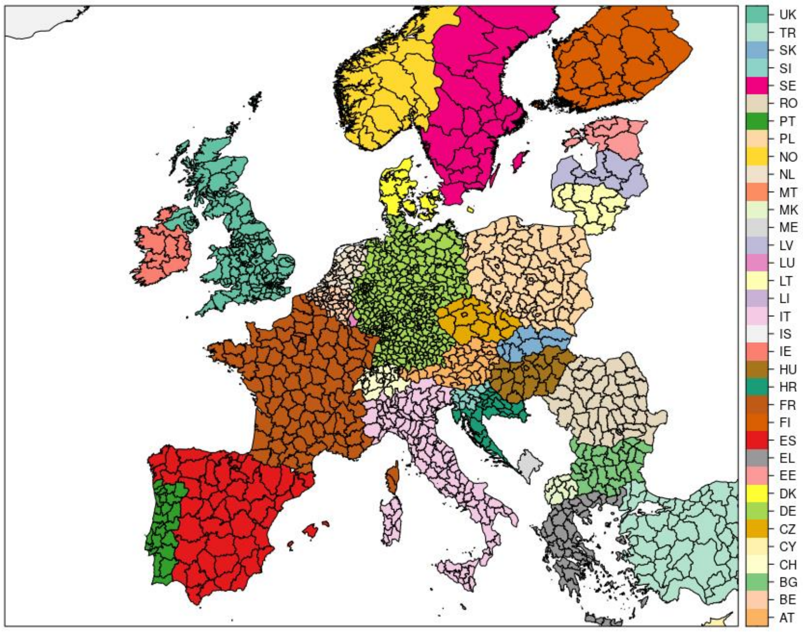

Figure A6. NUTS1 level aggregation of European regions. Countries are indicated by colors, as used for the summary correlation results displayed in Figs. A7-A9.

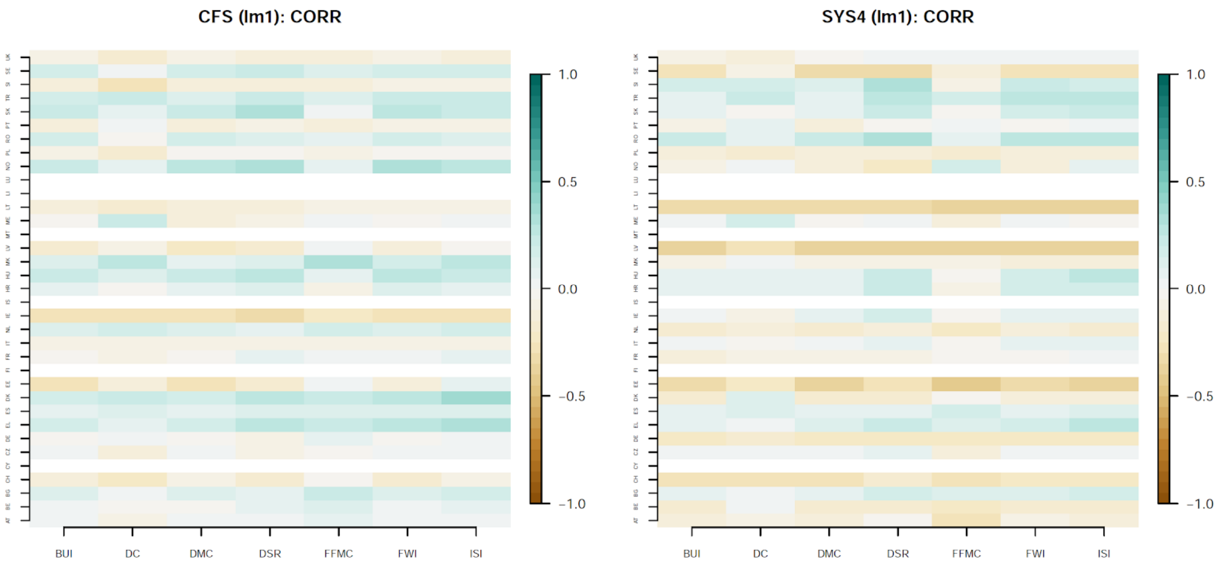

Figure A7. Aggregated results of the different FWI components ensemble correlation considering NUTS-0 aggregation (country level, see Fig. A6 above), for the 1 month lead time predictions of CFSv2 (left) and System4 (right).

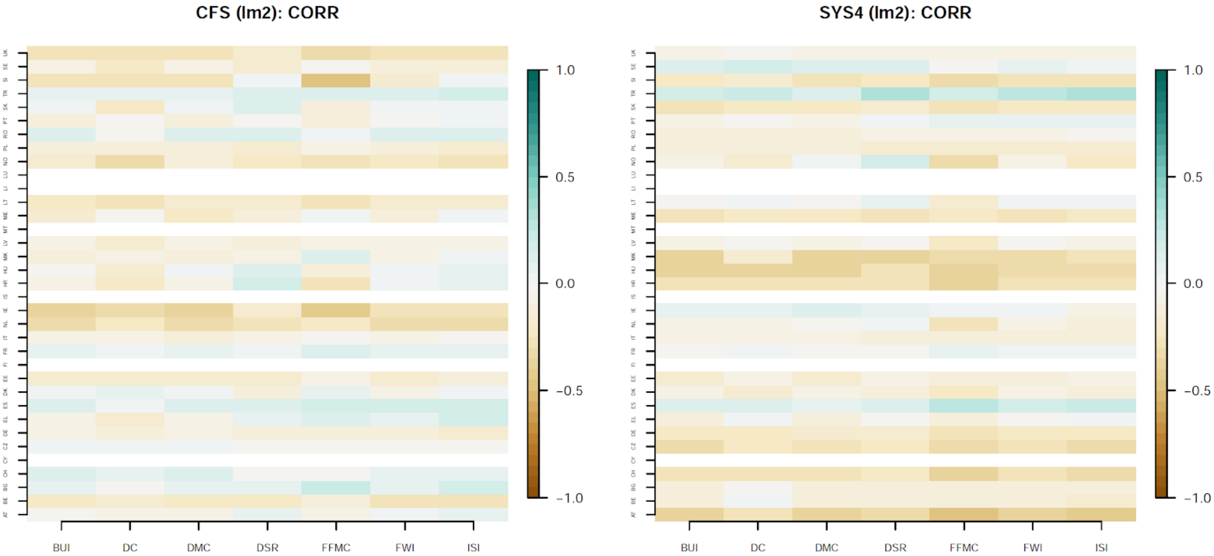

Figure A8. Same as Fig. A7, but for the 2 month lead time predictions.

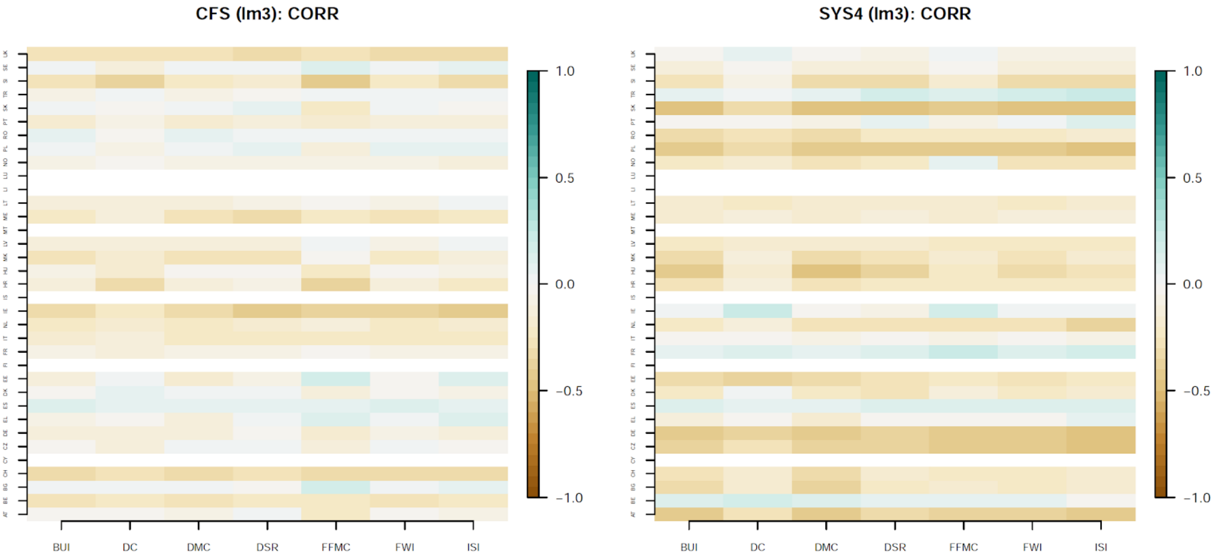

Figure A9. Same as Fig. A8, but for the 3 month lead time predictions.

ROC Skill Score

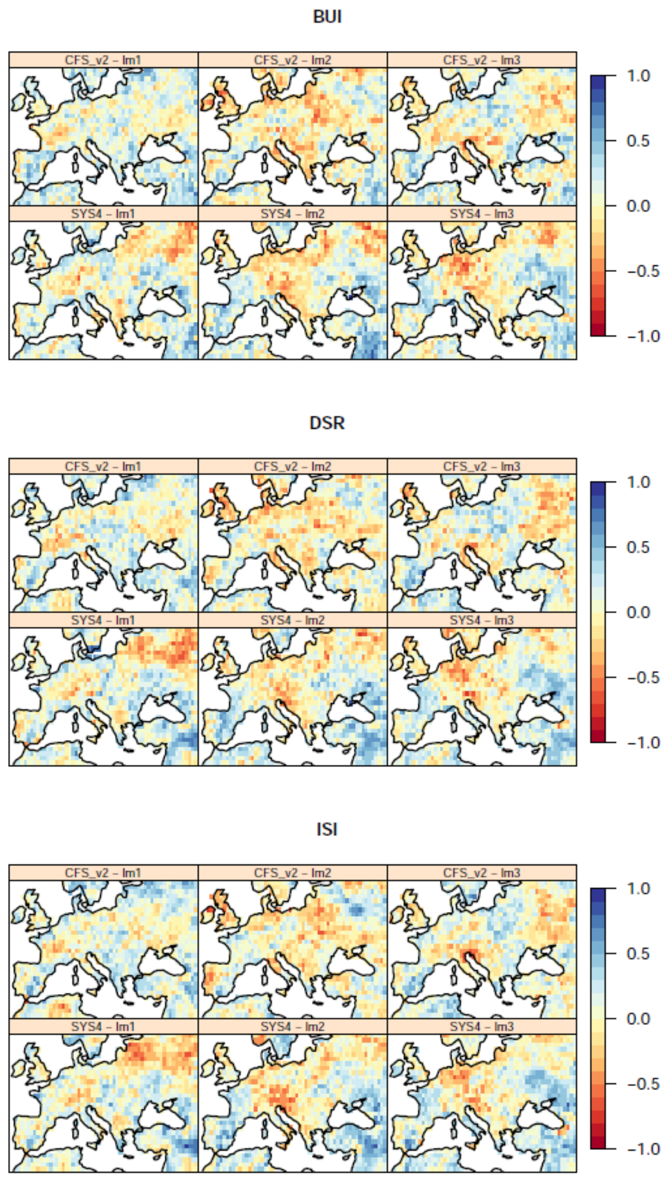

Figure A10. Same as Fig. 4 (ROC Skill Score of the upper tertile predictions), for the remaining FWI components (BUI, ISI and DSR).

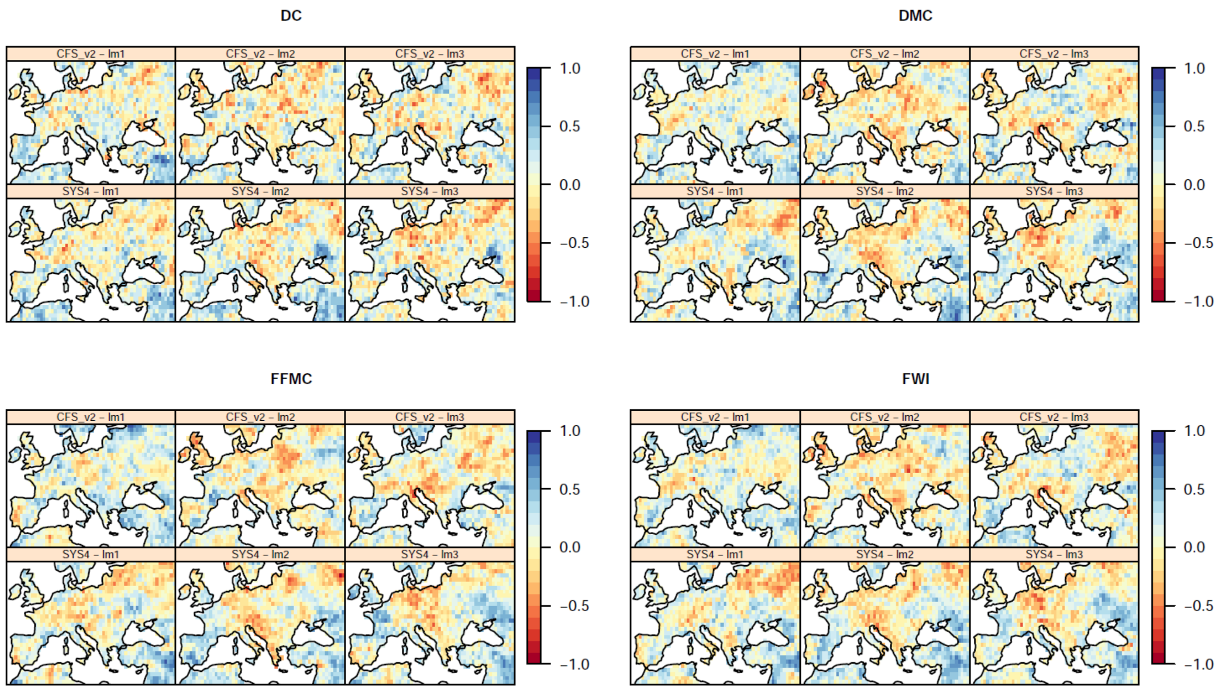

Figure A11. Same as Fig. 4 (ROC Skill Score of DC, DMC, FFMC and FWI), but considering the lower tertile (i.e., ȓbelow normalòfire danger) instead of the upper tertile.