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Seasonal predictions of Fire Weather Index: Paving the way for their operational applicability in Mediterranean Europe

Joaquín Bedia [a,*], Nicola Golding [b], Ana Casanueva [c,1], Maialen Iturbide [d], Carlo Buontempo [b,e], Jose Manuel Gutiérrez [a]

[a] Meteorology Group, Institute of Physics of Cantabria, CSIC-University of Cantabria, Santander 39005, Spain
[b] Met Office Hadley Centre, Fitzroy Road Exeter, Devon EX1 3PB, UK
[c] Meteorology Group, Dept. Applied Mathematics and Computer Sciences, University of Cantabria, Santander 39005, Spain
[d] Predictia Intelligent Data Solutions, S.L. I+D+i Building CDTUC Fase C, S345. Avda. los Castros s/n, Santander 39005, Spain
[e] European Centre for Medium-Range Weather Forecasts (ECMWF), Reading RG2 9AX, UK

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A B S T R A C T

Managers of wildfire-prone landscapes in the Euro-Mediterranean region would greatly benefit from fire weather predictions a few months in advance, and particularly from the reliable prediction of extreme fire seasons. However, in some cases model biases prevent from a direct application of these predictions in an operational context. Fire risk management requires precise knowledge of the likely consequences of climate on fire risk, and the interest for decision-makers is focused on multi-variable fire danger indices, calculated through the combination of different model output variables. In this paper we consider whether the skill in dynamical seasonal predictions of one of the most widely applied of such indices (the Canadian Fire Weather Index, FWI) is sufficient to inform management decisions, and we examine various methodological aspects regarding the calibration of model outputs prior to its verification and operational applicability. We find that there is significant skill in predicting above average summer FWI in parts of SE Europe at 1 month lead time, but poor skill elsewhere. These results are largely linked to the predictability of relative humidity. Moreover, practical recommendations are given for the use of empirical quantile mapping in probabilistic seasonal FWI forecasts. Furthermore, we show how researchers, fire managers and other stakeholders can take advantage of a new open-source climate service in order to undertake all the necessary steps for data download, post-processing, analysis and verification in a straightforward and fully reproducible manner.

Practical Implications

Wildfires represent a critical natural hazard in the Euro-Mediterranean (EU-MED) region (San-Miguel-Ayanz et al., 2013), causing considerable economic and environmental damages and loss of life. Estimating fire risk a few months in advance is therefore an urgent requirement, allowing fire protection agencies a timely reaction and an adequate provision of human and material resources.

Until the recent development of dynamical climate models, seasonal forecasts of fire activity relied on empirical-statistical techniques exploiting the lagged relationships between slowly-varying components of the climate system used as predictors, such as sea-surface temperatures (based on atmospheric teleconnections; Chu et al., 2002; Chen et al., 2011; Chen et al., 2016; Harris et al., 2014) or meteorological droughts (related to water content in the soils; Preisler and Westerling, 2007; Gudmundsson et al., 2014). There are also some local empirical prediction examples within the EU-MED region (see e.g. Turco et al., 2013; Marcos et al., 2015). Nevertheless, to date none of these studies, at least for the EU-MED region, has led to conclusive results on the operational applicability of seasonal forecasts, although all of them suggest a potential for their application. With this regard, recent advances in the modelling of the atmosphere–ocean coupled circulation have lead to the development of a new generation of

* Corresponding author.
E-mail address: bediaj@unican.es (J. Bedia).
1 Currently at: Federal Office of Meteorology and Climatology MeteoSwiss, Zurich CH-8058, Switzerland.

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numerical models (Global Climate Models, GCMs) producing predictions on a seasonal time horizon (Doblas-Reyes et al., 2013). In order to account for the various sources of uncertainty, a probabilistic approach based on the use of several predictions with slightly perturbed initial conditions is nowadays routinely applied, a technique known as *ensemble* prediction (Richardson, 2000; Palmer et al., 2004). The potential of such prediction systems to inform decision-makers in different economic sectors is huge, due to the provision of a large number of physically consistent variables at a sub-daily temporal scale from one to several months in advance, although their applicability is still hampered by the limited skill of such predictions in the extra-tropics (Palmer and Anderson, 1994; Manzanas et al., 2014) and the limits to accessibility and understanding by end-users (Hartmann et al., 2002; Lemos et al., 2012; Mason, 2008).

In order to ease the applicability of these products, here we present a climate service that greatly facilitates the different tasks involved in seasonal forecast application within an operational context. This climate service can be applied to a broad range of impact applications in the framework of seasonal forecast studies, although its capabilities are illustrated in this paper through a particular application in the framework of wildfire danger assessment. Its components are next briefly described:

- The User Data Gateway (UDG) is the one-stop shop for climate data access maintained by the Santander Meteorology Group, providing metadata and data access to a set of georeferenced atmospheric variables using OPeNDAP and other remote data access protocols. Its main features and its user-tailored extension for the European Climate Observations, Modelling and Services initiative (ECOMS), that coordinates the activities of three ongoing European projects (EUPORIAS, SPECS and NACLIM), are detailed in a paper (Cofiño et al., 2018). Data access and harmonization is achieved through the `loadeR.ECOMS` interface to the ECOMS-UDG (see Cofiño et al., 2018, for further details, and specific examples in the companion vignette to this paper: http://meteo.unican.es/work/fireDanger/Climate_Services_2017.html).
- `downscaleR` (Bedia et al., 2016) is an R package for empirical-statistical downscaling, with a special focus on daily data. It is fully integrated with the `loadeR` bundle and therefore it works seamlessly with the datasets loaded from the UDG. The package is available in this URL: https://github.com/SantanderMetGroup/downscaleR.
- `transformeR` (Santander Meteorology Group, 2017b) performs data post-processing tasks such as re-gridding/interpolation, principal component/EOF analysis, detrending, aggregation, sub-setting, plotting ..., being fully integrated with the above-mentioned packages. An introduction to the package and examples of application are available in the transformeR's wiki (https://github.com/SantanderMetGroup/transformeR/wiki).
- `fireDanger` (Santander Meteorology Group, 2017a) is an R package for the Implementation of the Canadian Fire Weather Index System, specially tailored to receive as input climate data structures as provided by the `loadeR` bundle, including the calculation of FWI from seasonal forecast datasets. The package is available in this URL: https://github.com/SantanderMetGroup/fireDangeR.
- `visualizeR` (Frias, submitted) is an R package implementing a set of advanced visualization tools for forecast verification. It is fully integrated (yet independent) from the R climate data structures generated by the loading functions of the `loadeR`, thus providing seamless integration with all steps of forecast data analysis, from data loading to post-processing, downscaling and bias correction and visualization. The package is available in this URL: https://github.com/SantanderMetGroup/visualizeR
- Integration with forecast verification software. As part of the ECOMS initiative, two different verification R packages have been developed: `SpecsVerification`, (Siegert, 2015) in SPECS and `easyVerification` (MeteoSwiss, 2016) in EUPORIAS, implementing verification metrics used in this application. Several bridging functions have been developed in `transformeR` for a complete integration of the above packages with the verification software.

The application of this climate service has allowed the production of the results presented in this study. A worked example covering the different components of the climate service is provided in the `fireDanger` documentation as a package vignette (also available online at http://meteo.unican.es/work/fireDanger/Climate_Services_2017.html). We show the potential for a successful application of seasonal forecast predictions for operational fire risk management in Mediterranean Europe, and in particular in the eastern area, where significantly skilful predictions have been found. Our results indicate that a moderate improvement in the skill can be achieved through the application of empirical quantile mapping (QM). Given the multi-variable nature of FWI, we advocate the application of QM on FWI directly, as computed from the raw model outputs, rather than performing a correction of its input components separately. This promising results, together with the development of new climate services facilitating the access and post-processing of seasonal forecast data to end users, pave the way for the applicability of this climate products within an operational framework in the near future.

1. Introduction

Wildfires represent the most important natural hazard in the Euro-Mediterranean (EU-MED) region, where an average of 4500 km^2 of forested and shrubland areas burn every year (San-Miguel-Ayanz et al., 2013), causing considerable economic and environmental damages and loss of life. In the context of climate analysis, the term *fire danger* refers to the assessment of the climatic factors which determine the ease of ignition, rate of spread, difficulty of control and impact of a fire. Thus, estimating fire danger a few months in advance is an urgent requirement, allowing fire protection agencies a timely reaction and an adequate provision of human and material resources.

Historically, seasonal forecasting of fire danger has relied on statistical techniques exploiting the lagged relationships between different fire statistics (number of fires, total burned area ...) and slowly-varying components of the climate system used as predictors, such as sea-surface temperatures (Chu et al., 2002; Chen et al., 2011; Chen et al., 2016; Harris et al., 2014) or meteorological droughts (Preisler and Westerling, 2007; Gudmundsson et al., 2014), at global to regional scales. There are also some local empirical prediction examples within the EU-MED region (see e.g. Turco et al., 2013; Marcos et al., 2015). However, the empirical approach poses some limitations due to the sensitivity of the statistical methods to the often short history of the observational databases and to non-stationarities in the training data.

Recent advances in the modelling of the atmosphere–ocean coupled circulation have lead to the development of a new generation of numerical models (Global Climate Models, GCMs) producing dynamical predictions on a seasonal time horizon (Doblas-Reyes et al., 2013), offering an alternative to the empirical approach. In order to account for the various sources of uncertainty, a probabilistic technique based on the use of several predictions with slightly perturbed initial conditions is nowadays routinely applied, known as *ensemble* prediction (Richardson, 2000; Palmer et al., 2004). The potential of such prediction systems to inform decision-makers in different economic sectors is huge, due to the provision of a large number of physically consistent variables at a sub-daily temporal scale from one to several months in advance, although their applicability is still hampered by the limited skill of such predictions in the extra-tropics (Palmer and Anderson, 1994; Manzanas et al., 2014) and the limits to accessibility and understanding by end-users (Hartmann et al., 2002; Lemos et al., 2012; Mason, 2008). Furthermore, the sector-specific climate impact indicators of interest for fire danger assessment differ from what climate forecasts routinely provide (Goddard et al., 2010). As a result, to date studies addressing the seasonal predictability of fire danger from GCMs are still relatively scarce in the literature (Roads et al., 2005; Roads et al., 2010; Spessa et al., 2015).

Fire weather indices are envisaged to provide a more realistic representation of the climatic conditions amenable for fires to spread (see e.g. Viegas et al., 1999 for a description of some indices applied in EU-MED). Such is the case of the Canadian Fire Weather Index (FWI, van Wagner, 1987), used in this study, calculated through the combination of precipitation and near-surface air temperature, humidity and wind speed (referred to as fire-weather variables). Beyond the daily scale on which fire-weather indices are calculated, they can be aggregated on seasonal time scales to provide a characterization of a particular season. The generation of probabilistic predictions of such indices, computed from the GCM simulations, could be highly valuable for decision-makers, helping risk managers to conduct a rapid assessment of management options in advance to the fire season. However, in most cases raw GCM outputs can not be directly used for quantitative impact assessment studies due to systematic biases of the models as compared to the observed climate, resulting in significant deviations of its statistical properties (see e.g.: Deque, 2007; Casanueva et al., 2016). In addition, their coarse spatial resolution is usually not representative of the local conditions that fire agencies are interested in, thus requiring some form of regionalization (*downscaling*). As a result, calibration techniques (often referred to as 'bias correction') are routinely applied by the impacts community as a way of correcting model biases. This already common practice in climate change applications (e.g. Christensen et al., 2008; Hagemann et al., 2011; Ruiz-Ramos et al., 2015) is for the same reasons needed in a seasonal forecasting context, although in the latter, agreed protocols for implementation are still lacking.

In this study, we use probabilistic predictions of the Canadian Fire Weather Index (FWI) from the state-of-the-art ECMWF's System 4 seasonal re-forecast (Molteni et al., 2011 S4 hereafter) in order to assess their potential for supporting operational risk management in EU-MED. We analyze the FWI forecast quality as compared to the reference observed FWI using a number of verification measures. In addition, we address the effect of Empirical Quantile Mapping (QM) techniques on the resulting forecast, as well as some methodological issues regarding the application of statistical correction techniques (and in particular QM) to ensemble forecast data for the calculation of multi-variable indices such as FWI. In particular, we test two approaches to correct the bias of seasonal FWI forecasts. On the one hand, bias correction can be performed directly on FWI (QMd hereafter, "d" stands for *direct*). On the other hand, bias correction can be performed on the model output variables before computing FWI (QMc, "c" stands for *component-wise*). This issue is analysed in a *perfect-prognosis* downscaling approach for climate change in Casanueva et al., 2014, but to date an analysis in a bias-correction framework for a seasonal forecasting application is lacking. We finally identify the regions where FWI forecasts may be successfully used as a decision-support tool for operational risk management. As companion material to this paper, we also provide worked examples of an open-source climate service readily allowing to undertake all these analyses in a straightforward manner.

2. Material and methods

2.1. The Canadian fire weather index

The FWI system uses as input daily records of four near-surface variables: last 24-h accumulated precipitation, instantaneous wind speed, relative humidity and temperature. The FWI system is calibrated for "noon local standard time" records of the instantaneous inputs (Stocks et al., 1989). Thus, we used the model and observation data verifying at 12 UTC, being the closest model output (see Bedia et al., 2012; Herrera et al., 2013 for further details on the procedure for FWI system calculation from model data, and also see the Supplementary Material for details on the 12 UTC choice). These inputs are combined through a number of empirical equations to produce six components rating the effects of fuel moisture content and wind on a daily basis, based on various factors related to potential fire behaviour (van Wagner, 1987; Stocks et al., 1989), including the moisture content of different fuel layers, wind effects affecting fire spread and a rating of the total amount of fuel available for combustion (see Wotton, 2009 for a more detailed description). These components are finally combined to produce the Fire Weather Index (FWI), a dimensionless index rating the potential fire line intensity given the meteorological conditions for a reference fuel type (mature pine stands). Despite this apparent specificity for the boreal forests of Canada, the FWI system has proven a useful fire-weather indicator in many areas of the world (Bedia et al., 2015), and in particular in EU-MED (Viegas et al., 1999; Bedia et al., 2014). As a result, FWI is nowadays the official index for the operational medium-range fire danger forecasts issued by the European Forest Fire Information System (EFFIS, San-Miguel-Ayanz et al., 2013http://forest.jrc.ec.europa.eu/effis/), being therefore natural to explore its applicability to the seasonal range in the same context.

In addition, FWI values are dependent on antecedent conditions. Some of its components tracking fuel moisture are affected by different drying rates represented as time lags, thus bearing some sort of "memory". For example, under "standard" drying conditions, the time lags of the fine fuel moisture code (FFMC), duff moisture code (DMC) and drought code (DC) components of FWI are 2/3, 15 and 53 days respectively (see Table 1 in Lawson and Armitage, 2008). As a result, FWI is initialized with default values for some of its components and there is a spin-up period until the index stabilizes. This period is usually much shorter than a month, particularly during the fire season in the study area in which snow-melt effects on soil moisture can be neglected. Thus, the effect of spin-up on lead-month 1 (LM1, used in this study) to LM3 predictions is assumed to be negligible. On the contrary, because there is no spin-up period in the reference predictions (LM0) used for the drift experiment (Supplementary Material), a certain degree of error is included in this case. However, due to the relatively fast stabilization of FWI along time (normally a few days or weeks), and given that FWI is afterwards seasonally averaged, we assume the effect of FWI spin-up to be very limited. In this case, this source of error must be added to the effect of the GCM spin-up period. The experimental setup is represented in Fig. 1. We computed FWI using the code in the R package `fireDanger` (Santander Meteorology Group, 2017a v1.0.0). Our analysis is focused on the Euro-Mediterranean area, which is the EFFIS area in which fires constitute a more serious environmental hazard. The fire season considered in this study encompasses the per-

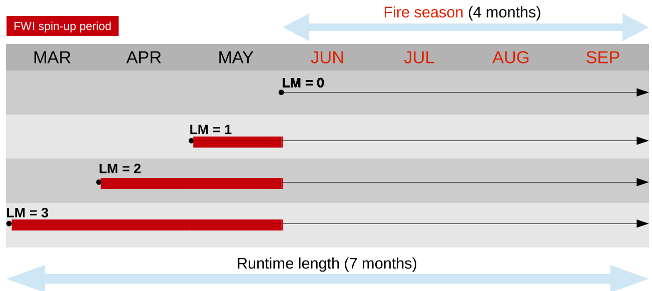

Fig. 1. Diagram of the experimental setup for FWI calculation. The black dots indicate the initialization time (1st of each month) and the arrow heads the end of the time slice used for FWI calculation (LM = *lead month*, see the final paragraph in Section 2.2 for details). The areas shaded in red correspond to the spin-up period used for FWI calculation. This period is used for calculation but not retained for data representation/analysis, as it is out of the fire season. Note that for the initialization of 1 June ($LM = 0$) there is no spin-up period. In this study, we only show results for the $LM = 1$ choice (but see Fig. A2 in the Supplementary Material).

iod June-September (JJAS). The fire season chosen is a simplification of the more detailed fire season provided by Moriondo et al. (2006) for six different Euro-Mediterranean countries/subregions, based on 3-day consecutive exceedances for selected FWI thresholds (these are given in julian days). Thus, the JJAS choice is the most precise possible time resolution to characterize the fire season in a homogeneous way for the domain selected, taking into account that seasonal forecasts are routinely issued once a month.

2.2. Seasonal forecast data

The seasonal forecast data were provided by the ECMWF System-4 (S4), a state-of-the-art, fully coupled GCM providing operational multivariable seasonal predictions at 0.758° horizontal resolution. In this study, we consider the 30-year re-forecast (or *historical hindcast*) of the model (1981–2010), composed of a 15-member ensemble and 7-month lead-time for predictions (Fig. 1). A more detailed description of the system and its performance is provided in Molteni et al., 1996; Molteni et al., 2011. The validation of the historical hindcast provides an indication of the quality of the predictions based on their past performance, aiding in the decision-making process at a later operational stage (Goddard et al., 2010; Doblas-Reyes et al., 2013). We used the S4 instantaneous outputs (12 UTC) for 2-meter temperature, northward and eastward near-surface wind components, 2-m dewpoint as well as daily accumulated precipitation. Relative humidity was computed from dew-point and surface temperature. Wind velocity was calculated from its components, while precipitation was deaccumulated as the original model outputs are accumulated from the initialization time. This was achieved in a user-transparent way by downloading the data from the ECOMS User Data Gateway (Cofiño et al., 2018) using the R-based (R Core Team, 2016) user interface of the `loadeR.ECOMS` package (Santander Meteorology Group, 2016), enabling authentication and transparent access to both original and derived variables for user-defined dimensional chunks of different seasonal forecast products (Santander MetGroup 2016, http://meteo.unican.es/ecoms-udg). The code of the conversion formulas applied to obtain relative humidity is available in https://github.com/SantanderMetGroup/loadeR/blob/devel/R/conversion.R.

Note that, according to the experimental design of the dataset used, there are seven possible lead times for each target month for the hindcast period 1981–2010; therefore, it is only possible to provide the predictions corresponding to a maximum of lead month 3 (March), as the target period (fire season, JJAS) encompasses four months (Fig. 1). For brevity, in this study we focus on the predictions corresponding to lead month 1 for the fire danger season JJAS. In addition, the predictions of the previous month (May) were also used to calculate the FWI series, in order to have a spin-up period for FWI stabilization (see Section 2.1), and then removed for the analysis. The resulting (uncorrected) S4 ensemble mean FWI climatology is displayed in Fig. 2a. Note that 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 (or LM1 in this paper).

2.3. Observational data

The Water and Global Change EU-funded project WATCH (2007–2011, www.eu-watch.org Weedon et al., 2011; Weedon et al., 2014) provides eight meteorological variables at 3-hourly time steps and as daily averages, for the global and surface at 0.5°. The latest version (WFDEI hereafter) is based on reordered reanalysis data from ECMWF ERA-Interim (Dee et al., 2011), using interpolation, elevation corrections and monthly bias correction based on the global observational dataset from the Climatic Research Unit (CRU, New et al., 1999; New et al., 2000), covering the period 1979–2012. The WFDEI is a particularly convenient dataset for FWI validation at regional to global scales, containing all the variables required for the calculation of noon-time FWI globally (Bedia et al., 2015). In this case, we considered the 12 UTC values in the whole domain for consistency with the S4 outputs (Fig. 2b). The raw model output bias is depicted in Fig. 2c.

2.4. Empirical quantile mapping approach

Quantile mapping (Panofsky and Brier, 1968 QM hereafter) is a popular calibration method to correct model biases affecting not only the mean (Fig. 2c) but also other distributional properties of

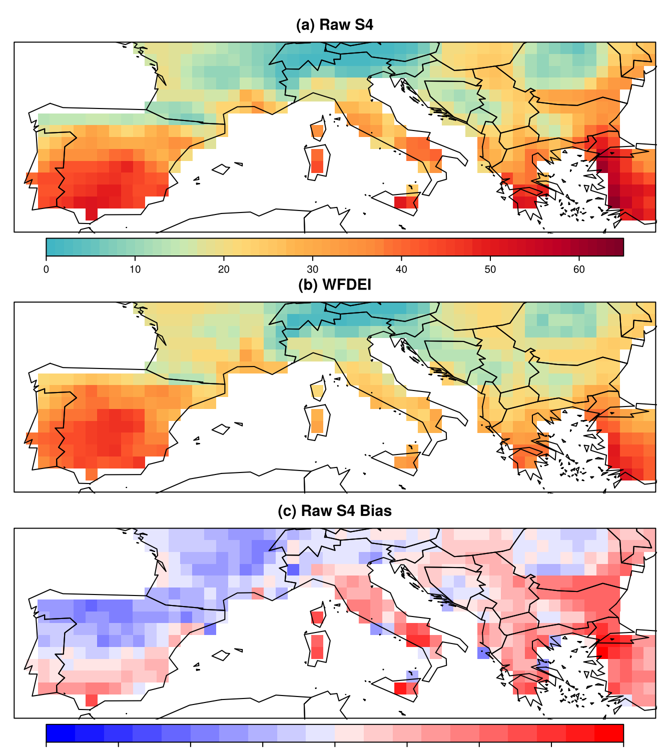

Fig. 2. a) FWI climatology (JJAS, 1981–2010) from the raw S4 model outputs (15 member ensemble mean). b) Observed FWI climatology, as depicted by the WFDEI observational dataset and c) S4 mean bias.

model outputs. In a multivariate context, QM also allows for a consistent multivariable correction (Wilcke et al., 2013), as required for the correction of the different input variables involved in FWI calculation. Several variants of QM are currently described in the literature. Here, we use the empirical QM model formulation proposed in Themessl et al., 2011, operating on the empirical cumulative distribution function (*ecdf*). QM is applied on a daily basis t and for each grid cell i independently, resulting in a corrected time series Y^{corr} using the correction function CF defined in Eq. 2:

$$Y^{corr}_{t,i} = X^{raw}_{t,i} + CF_{t,i} \quad (1)$$

$$CF_{t,i} = ecdf^{obs}_{doy,i}(P_{t,i}) - ecdf^{mod}_{doy,i}(P_{t,i}) \quad (2)$$

$$P_{t,i} = ecdf^{mod}_{doy,i}\left(X^{raw}_{t,i}\right) \quad (3)$$

CF represents the difference between the observed (*obs*) and the modelled (*mod*) inverse *ecdf* for the respective day of the year (*doy*) in the calibration period at probability P. P is obtained by relating the raw climate model output X^{raw} to the corresponding *ecdf* in the calibration period. For model calibration, *doy* is centred at lag-0 within a moving window, which is used to construct an *ecdf* for each day of the year, that helps to better describe the climatic variability for each particular day of the year. As a result, the window should be wide enough to ensure that climatic variability for each particular day is adequately represented and noise adequately filtered to provide robust estimates. The width of this moving window can vary depending on user requirements (Raisanen and Raty, 2012), typically ranging from 31 days (Wilcke et al., 2013, 2011, 2014) to 61 days (Themessl et al., 2011) and 91 days (Rajczak et al., 2016) or seasonal scales (Boe et al., 2007; Maraun, 2013). However, these previous studies are focused on climate change projections. In the particular case of seasonal forecasts, the use of a moving window can help to minimize the forecast time-dependent bias (model *drift*, see Fig. A2 in the Supplementary Information). To this aim, the window needs to be sufficiently narrow to encompass periods for which possible trends introduced by model drift can be safely neglected. As a result, in this study we apply a window width of 31 days, as a compromise between the need for a smooth daily climatology and the problem of model drift.

Different approaches to deal with out-of-range values in the calibration period (i.e. *new extremes*) have been reported in the literature in the context of QM. In this paper we use constant extrapolation of the correction value at the lowest and highest quantiles of the calibration range, i.e. all values above (below) the highest (lowest) quantile of the calibration period are corrected with the correction for the highest (lowest) quantile (as in Themessl et al., 2011). Furthermore, within the QMc approach, it is worth to note that for precipitation, QM is able to correct automatically the excess of light precipitation frequency in the models (*drizzle effect*), however a frequency adaptation is used to overcome the opposite problem (Themessl et al., 2011).

2.5. Forecast verification

Forecast verification is defined as a multifaceted quality assessment of the predictions, that need to consider besides the different aspects associated with forecast accuracy, how reliable the forecast is (Doblas-Reyes et al., 2013). As a result, there is no one single metric able to provide a complete picture of forecast quality, but a range of complementary metrics that need to be used.

2.5.1. ROC Skill Score

The area under the ROC (*Relative Operating Characteristic*) curve describes 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). In this study, we used a tercile-based probabilistic approach. For each particular grid box and member, each of the 30 years of the interannual series of predicted seasonal (JJAS) FWI were classified into three categories (i.e. whether FWI for a particular year was normal, below-normal or above-normal). Because of the nature of FWI as a fire danger indicator, the interest is particularly focused on the above-normal predictions, as high FWI values will be related with an increased severity of the fire season (Amraoui et al., 2013; Bedia et al., 2014). In particular, the forecast performance was assessed in terms of its ROC Skill Score (ROCSS) based on terciles. For each tercile, the value of ROCSS ranges from 1 (perfect forecast system) to -1 (perfectly bad forecast system). A value zero indicates no skill compared with a random prediction.

2.5.2. Forecast skill visualization

Additional visualization plots have been used for the assessment of the skill over selected sub-areas, in particular tercile plots (see e.g. Diez et al., 2011) and spread plots. For tercile plot construction, the daily FWI predictions are averaged to obtain a unique forecast series for a selected domain (it may be computed on single gridboxes as well). The corresponding terciles for the joint ensemble are then calculated to define three categories (i.e. below-normal, normal and above-normal seasonal FWI conditions). Thus, a probabilistic forecast is computed year by year by considering the number of members falling within each category. The observed terciles (the events that actually occurred) are also represented on top, allowing for a quick visual overview of observations and predictions. Finally, the ROC Skill Score (ROCSS, Section 2.5.1) is indicated in the secondary (right) Y axis.

In addition, spread plots provide an overview of observed and forecast series and the spread of the ensemble (here we use the interquartile range, IQR, as a measure of ensemble spread). The level of association between the observations and the ensemble mean was quantified by the Pearson's product moment correlation. The forecast visualization plots were generated using the R package `visualizeR` (Frias, submitted see Sec. Practical Implications).

2.6. Reproducibility of results

The results presented in this paper can be fully reproduced using the open-source code generating them. A worked tutorial with specific examples is provided as part of the `fireDanger` package documentation, also accessible in the following URL: http://meteo.unican.es/work/fireDanger/ClimateServices2017.html.

3. Results

3.1. FWI forecast verification

The first and most straightforward assessment of forecast quality consists in the validation of the raw S4 predictions against the observations. This preliminary assessment suggests skilful predictions in the eastern part of the study area (Greece, Bulgary and Turkey mainly), as well as other scattered significant ROCSS areas in France and Central Spain (Fig. 3a).

An aspect potentially altering the verification results are the GCM biases. While a shift in the mean (Fig. 2c) does not affect the ROCSS (it is calculated upon the inter-annual series variability, not on absolute values), correction methods operating on the CDF

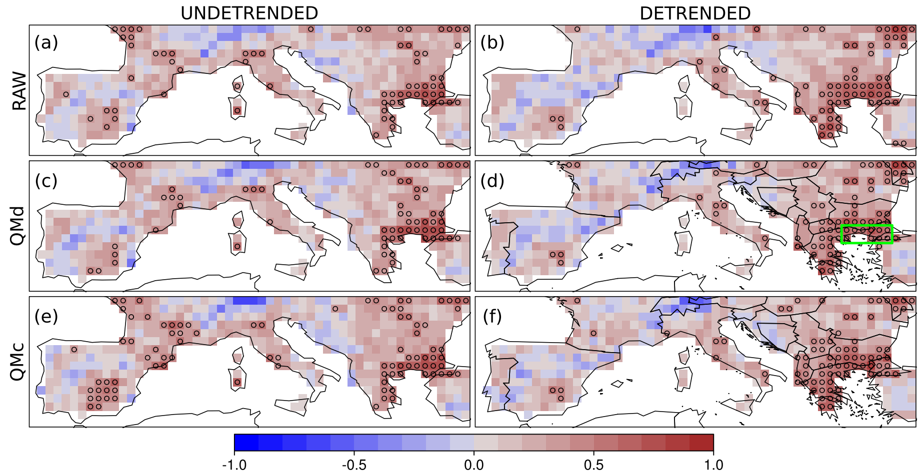

Fig. 3. ROC Skill Score of the System4 FWI predictions considering the raw (uncorrected), the QMd and the QMc–corrected predictions (rows 1 to 3 respectively). The grid boxes with significant ROCSS values are indicated by the circles (95% c.i.).

(like QM) alter not just the mean state, but also higher order moments of the distribution. Furthermore, some form of bias correction is required by end-users in order to compute threshold-dependent indicators (e.g. the frequency of days above a given threshold), or to rate fire danger potential according to categories based on absolute values, as typically issued by fire agencies. With this regard, the overall pattern exhibited by the raw S4 predictions is consistent with that of the the QM-corrected predictions (Fig. 3c/e for QMd/QMc versions respectively), with some regional differences apparent, particularly in the case of QMc in Spain.

The verification results may be altered by the trends present both in the predictions and in the verifying observations, particularly when these are of different sign and/or magnitude. This is confirmed by inspecting the results of the detrended data (Fig. 3b,d and f). These results reveal two important aspects: first, that detrending prior to verification has a remarkable effect on the verification results. While some spurious skill grid points are lost in some parts of the domain after detrending (e.g. France), the signal in the eastern region is reinforced. In addition, other residual sources of skill were consistently maintained in small areas in SE Spain and Central Italy. Secondly, both QM correction approaches were consistent and yielded equal results only after detrending. Contrarily, the undetrended versions of QMc and QMd exhibit important regional differences (e.g. in Spain). While the raw and QMd predictions did not change much after detrending and maintain the general pattern of the raw predictions, QMc proved very sensitive to this step. Thus, QMc should not be applied without detrending as it may negatively affect to the verification results. This result warns about the potential deleterious effect that the QMc approach may have on FWI trends, as analysed in Section 4.1.

3.2. Trend analysis

While the QM correction is envisaged to correct all the quantiles of the GCM (S4) distribution, trends may be still altered to some extent (Hempel et al., 2013; Maraun, 2013). Thus, first of all we look at the observed FWI trends (WFDEI), and how the different options for correction (QMd and QMc approaches) affect them.

Regarding the observed climate, the negative FWI trends described by the WFDEI dataset in the southern part of the Adriatic and the Jonian Seas are consistent with the trends previously described by ERA-Interim in this region (Venäläinen et al., 2014). The rest of the area exhibited no significant trends except for a positive trend in S and central Spain, NE Spain and S of France (consistent with those found in Bedia et al., 2012), Central Italy, Turkey and the NE corner of the study region (small fractions belonging to Moldova and Ukraine, Fig. 4).

The raw S4 predictions exhibited a markedly different trend pattern as compared to the observations, with no negative trends

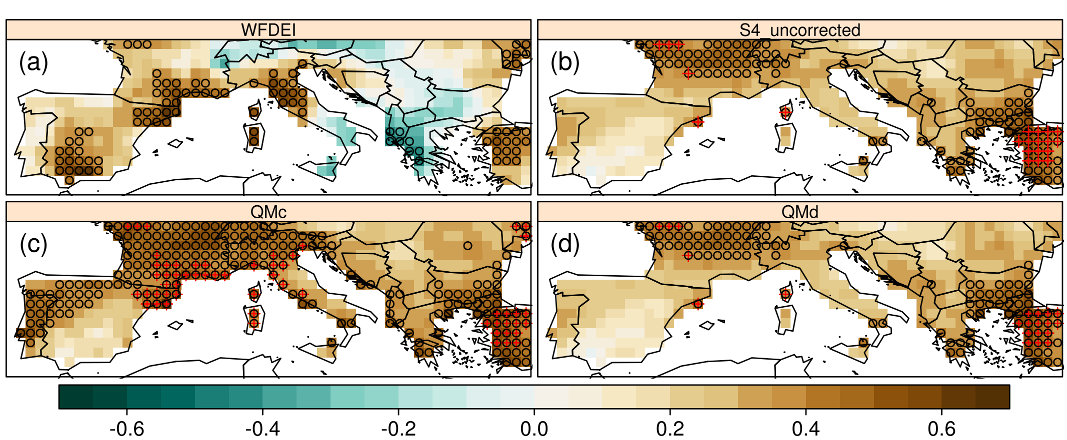

Fig. 4. Trend Maps (Mann–Kendall's Tau coefficient) of mean seasonal (JJAS) FWI, considering the 30-year period 1981–2010, according to: (a) Observed reference (WFDEI), (b) Uncorrected S4, (c) QMc S4 and (d) QMd S4. The black circles indicate significant trends (95% ci). The red crosses mark the gridboxes where there is agreement in the signs of the trends between WFDEI and S4 (and these are significant).

within the domain. The only agreement in trend sign between WFDEI and uncorrected S4 occurred in western Turkey (Fig. 4b, highlighted with red crosses). Unlike the observations, in the case of S4 most of the NW region (France), exhibited a positive FWI trend. The QMd correction largely preserved the trends described by the uncorrected forecast, although the QMc approach yielded positive trends over sizeable areas (Iberian Peninsula, France and the Alps Fig. 4c), inconsistent with the raw model output trends.

These results show that the QMd approach is able to preserve model trends, while the component-wise QMc produces spurious trends that can not be directly attributed neither to the model, nor to the observations. In addition, QMd is more straightforward and computationally cheaper than QMc, as long as correction is performed just once on the FWI series, instead than on all four input variables separately. Thus, the QMd approach is advocated, and it will be used in the presentation of the results hereafter. Nevertheless, it must be noted that QMc may still provide some benefits in the sense that the inherent biases of the GCM may affect the original uncorrected FWI to some extent, although it can be expected this error to be of minor importance provided the physical consistency of the GCM outputs. If in spite of that, QMc is eventually used for any reason, caution must be taken to perform a detrending of the data prior to verification, as already shown in Section 3.1.

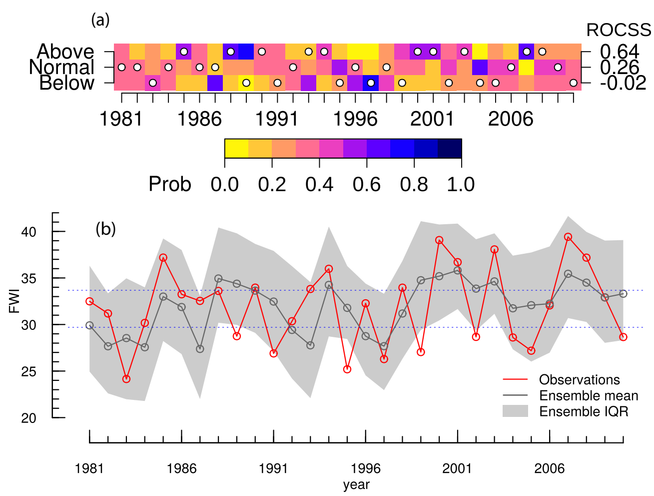

Fig. 5. Detail of forecast skill for a small area where System 4 QMd FWI predictions exhibit some degree of skill (its boundaries are indicated by the green frame in Fig. 3d). (a) Tercile validation plot. Terciles are arranged by rows. Further details for graph interpretation are given in Section 2.5.2. (b) Spread plot of forecast predictions (ensemble mean, black) against observations (red) for the same area. The ensemble spread is represented as the interquartile range (IQR) by the grey shaded area. Observed terciles are indicated by the blue horizontal lines. The correlation between the (detrended) ensemble mean (black) and the observations (red) is $r = 0.42$ (Pearson's product moment correlation, $p = 0.022$).

3.3. FWI forecast skill visualization

As previously indicated, S4 forecasts exhibit certain skill in the SE and NE extremes of the study region. In order to gain a better insight into this area, in this section we present some additional visualizations of forecast quality for a small window, encompassing grid boxes over Greece, Bulgaria and Turkey (this is represented by the green box in Fig. 3d). Here, the (spatially averaged) forecast predictions attained a ROCSS of 0.64 for above-normal (upper tercile) FWI years (Fig. 5a), suggesting a potential usefulness of S4 predictions for supporting operational decision-making in this area.

In spite of the skill in predicting above normal FWI, in generall the ensemble mean tends to underestimates the magnitude in the observations in these cases (Fig. 5b). The positive FWI trends described by S4 in this subregion (Fig. 4b and d) can be seen in the time series (Fig. 5b).

3.4. Verification of input variables

Relative humidity, temperature and –to a lesser extent– also precipitation exhibited skilful predictions over the subregion of interest shown in Section 3.3 (Fig. 6). However, the extent of signif-

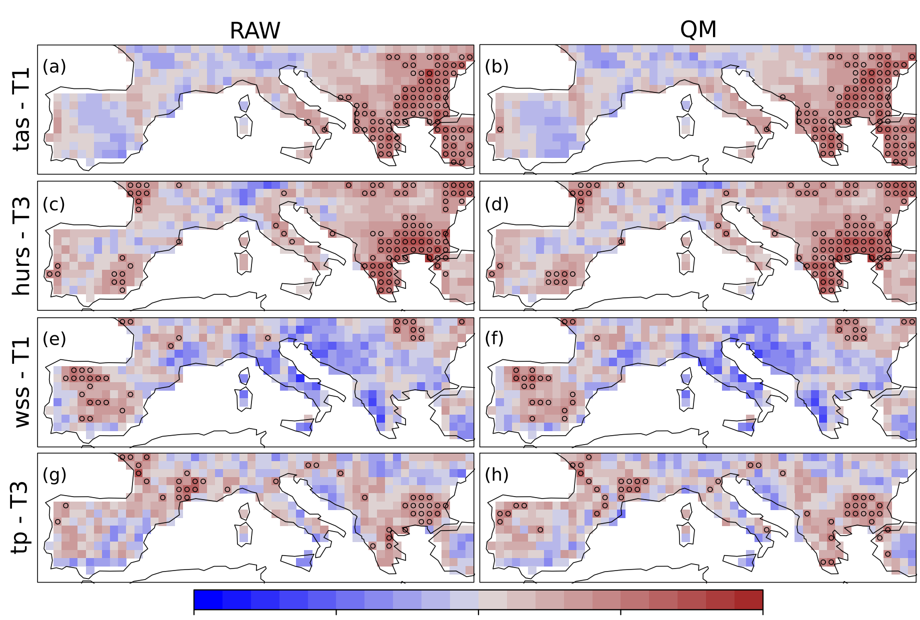

Fig. 6. ROC Skill Score of the raw (uncorrected) and the QMd -corrected S4 predictions (left/right columns respectively) of the input FWI variables (tas: surface air temperature, hurs: relative humidity, wss: wind speed and tp: total precipitation). T1 refers to the first (upper) and T3 to the third (lower) terciles of the variable. These terciles correspond to high FWI values (i.e. low relative humidity, high wind speed, high temperatures and low precipitation). The grid boxes with significant ROCSS values are indicated by the circles (95% c.i.).

icant ROCSS for temperature extends further to the north, beyond the skilful area for FWI. On the other hand, the skill of precipitation is restricted to a smaller domain between Greece, Bulgary and Turkey, and also other regions (e.g. in France) where FWI has no skill. Thus, most of the skill related to FWI predictions can be attributed to the skill in near-surface humidity predictions yielded by S4. The potential sources of predictability are discussed in Section 4.3. Like in the case of FWI (Fig. 3), the QMd and raw predictions exhibited a consistent ROCSS pattern for all the input variables (Fig. 6).

4. Discussion and conclusions

The objective of this study was to analyse the potential applicability of GCM-based seasonal FWI forecasts one month in advance in an operational context, as already consolidated and routinely issued for medium-range forecasts by the EFFIS. This requires (i), assessing the skill of such predictions for the identification of potentially dangerous years and (ii), an analysis of a suitable methodology in order to remove the inherent biases of these predictions. To this aim, we assessed different options based on a popular technique (empirical quantile mapping) for correcting FWI, and then used a number of standard probabilistic verification measures for skill assessment (ROC skill score, correlation ...), with an emphasis in the predictability of above-normal (upper tercile) FWI years, usually triggering the most dangerous wildfires (see e.g.: Camia and Amatulli, 2009).

4.1. Effect of trends

We showed that the trends present in the data are a cause of distortion of the verification metrics in certain areas. For this reason, we advocate the systematic use of detrending prior to verification in order to obtain more reliable skill estimates. Regarding the calibration of raw GCM predictions, the quantile mapping approaches tested had a significant effect on the GCM trends. While QMd preserved the original model trends, QMc significantly altered them. After detrending, no significant differences were found between both QM approaches in terms of skill assessment, but QMc yielded spurious trends and misleading verification results as compared to the original raw predictions when no detrending was performed, being QMd robust to this step. As a result, we advocate the use of QMd as a more direct and computationally less demanding approach. In addition, QMd preserves the trends present in the model outputs –irrespective of whether those trends are consistent or not with the observations–, and thus does not introduce additional uncertainty to the verification process.

As for the nature of the observed FWI trends, a strong positive trend in heat wave intensity, length and frequency has been described in the last decades in the eastern Mediterranean region (Kuglitsch et al., 2010), potentially linked to the increased fire danger conditions, as FWI extremes are highly influenced by temperature (positive relationship) and relative humidity (negative, see e.g. Fig. 2 in Bedia et al., 2012, see also Dowdy et al., 2010). The close relationship between soil-moisture deficit and hot extremes found in SE Europe (Hirschi et al., 2011) has been shown to be a major driver of the positive trends of heat waves. Furthermore, droughts are directly connected with the dynamics of summer fires in Mediterranean Europe (Gudmundsson et al., 2014; Urbieta et al., 2015; Turco et al., 2017).

4.2. Forecast quality assessment

In general, the forecast skill was poor in the domain of analysis. However, the eastern and south-eastern areas of analysis exhibited a significant degree of skill, suggesting the potential usefulness of S4 forecasts of FWI in this region for early warning of above-normal fire danger seasons. It is worth highlighting the good forecast discrimination of the relatively recent events of 2003 and 2007 in Greece (Fig. 5a; the observed FWI for each particular year is indicated by the white circles, and the colorbar indicates the proportion of ensemble members falling in the observed tercile). These events triggered important mega-fires in Greece in 2007 (mainly in the Attica and Peloponnisos regions, where there is skill; Koutsias et al., 2012) and other EU-MED countries (e.g., the fires in 2003 in Portugal; Trigo et al., 2006 with no skill though) causing several casualties and huge economic costs (San-Miguel-Ayanz et al., 2013). This particular example in Greece emphasizes the potential of seasonal predictions to improve the reaction of the European fire agencies in order to minimize the negative effects of wildfires. Notably, the relationship between FWI and burned area in eastern EU-MED has been shown to be statistically significant even at a large spatial scale of analysis (1.5° resolution, Bedia et al., 2015), further supporting the potential of seasonal FWI forecasts in this region, even at the rough scale of the GCMs, to aid in the decision-making process.

4.3. Sources of predictability

The simulations of current GCMs seem to adequately represent the soil-moisture-heat wave mechanism previously described (Section 4.1) in SE Europe (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 FWI seasons in this region (ROCSS > 0.6, Fig. 5). This is reflected by the relatively good skill attained by the seasonal predictions of near-surface relative humidity and surface air temperature (Fig. 6) that are responsible for the overall good performance of FWI predictions.

The forecast skill for above-average FWI years across the region as a whole was not improved in comparison to the forecast skill of underlying variables, but seemed to be closely controlled by the skill of humidity predictions. Further research is in progress in order to comment on the skill related to relative humidity. With this regard, 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) may prove more skilful than FWI, suggesting a potential improvement in the skill of seasonal fire danger predictions. Furthermore, some of 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).

It also remains as an open question for further research whether the skill of S4 FWI predictions could be locally improved through the use of more sophisticated downscaling techniques (e.g. *perfect-prog* methods) where long local historical records are available (see e.g. Bedia et al., 2013 for FWI downscaling of local climate change projections), or the existence of windows of opportunity related to particular atmospheric circulation patterns (e.g. ENSO events, Frías et al., 2010). The application of multi-model ensembles for FWI forecasting also offers a possibility for the improvement of the current forecast skill, although probably of limited extent in extra-tropical regions (e.g.: Doblas-Reyes et al., 2005).

Our results confirm the potential usefulness of seasonal FWI predictions, leaving the door open to the systematic incorporation of seasonal forecasts in the decision-making chain for an improved fire protection in the Euro-Mediterranean region.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cliser.2017.04.001.

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