THEME ENV.2012.6.1-1

EUPORIAS

(Grant Agreement 308291)

European Provision Of Regional Impact Assessment on a Seasonal-to-decadal timescale

Deliverable D*22.3*

Report on Validation of Climate Information Indices

Deliverable Title	*Report on validation of CIIs*	
Brief Description	*Report on validation of CIIs: Report will document the results of the WP and in particular the validation of the CIIs.*	
WP number	22	
Lead Beneficiary	*MeteoSwiss*	
Contributors	Jonas Bhend, Christoph Spirig, Irina Mahlstein, Mark Liniger (MeteoSwiss), Veronica Torralba, Isadora Ch. Jiménez (BSC), Rachel Lowe, Joan Ballester, Xavier Rodo (IC3), Sandro Calmanti, Matteo De Felice (ENEA), Christiana Photiadou (KNMI), Rita M Cardoso, Pedro M M Soares (UL-IDL), Joaquín Bedia, Jose Manuel Gutiérrez (UC), Carlo Buontempo (UKMO)	
Creation Date Version Number Version Date	13/09/2016 4 28/10/2016	
Deliverable Due Date Actual Delivery Date	31/10/2016 31/10/2016	
Nature of the Deliverable	X	*R - Report*
		P - Prototype
		D - Demonstrator
		O - Other
Dissemination Level/ Audience	X	*PU - Public*
		PP - Restricted to other programme participants, including the Commission services
		RE - Restricted to a group specified by the consortium, including the Commission services
		CO - Confidential, only for members of the consortium, including the Commission services

Version	**Date**	**Modified by**	**Comments**
1	13/09/2016	J. Bhend, C. Spirig	Initial contribution
2	25/10/2016	J. Bhend, WP22 partners	Added and edited partner contributions
3	27/10/2016	WP22 partners	Comments from internal review
4	28/10/2016	J. Bhend, M. Liniger, C. Spirig	Final edits

EUPORIAS

Table of Contents

List of Tables

List of Figures

1 Executive Summary

This report details analysis of forecast quality of seasonal forecasts of climate information indices (CIIs). CIIs are often closely related to application-relevant aspects of climatic variability such as heating degree days used to estimate the energy demand for heating. Forecasts of CIIs are challenging to produce and analyse, not least due to their probabilistic nature, the data volume and the often required daily bias correction (Mahlstein et al., 2015). As part of this WP, we have developed software tools (R packages) to facilitate download (loadeR, Santander Meteorology Group, 2016a), bias correction (downscaleR, Santander Meteorology Group, 2016b), index computation (extension to climdex.pcic, in preparation) and the validation of seasonal forecasts (easyVerification, MeteoSwiss, 2016).

Forecast skill varies considerably by CII, in space, by forecasting system, target season and lead time (time into the forecast). A newly developed interactive web-platform[1] allows users to explore this variability in forecast skill to identify opportunities for skilful and thus useful seasonal forecasts (Wehrli et al., 2016). Generally, forecasts of CIIs are at most as skilful as forecasts of the seasonal mean of the underlying meteorological variables (Bhend et al., 2016). This reduction in forecast quality, however, is moderate in most cases and thus forecasts of CIIs can be issued without major loss in skill. This implies that often the enhanced user relevance of forecasts of indices is expected to outweigh the slight reduction in forecast skill.

Seasonal forecasts for Europe are challenging and forecasts of CIIs are marginally skilful. This current report presents examples for various sectors such as hydrology, viticulture, and energy showing that it is very difficult to derive decision-relevant information from seasonal forecasts in Europe due to the lack of skill. Shorter-range forecasts on the other hand may add value thanks to their enhanced forecast quality as demonstrated with heat-related mortality forecasts (Lowe et al., 2016).

While the climatic conditions can be difficult to forecast, forecasts of impacts dependent of these conditions can have considerable value as demonstrated by forecasts of humanitarian needs for Ethiopia. Such added value is partly due to the sensitivity of the impact to large-scale long-term climatic conditions (drought) that are better predictable and partly due to the co-location of forecast skill in areas sensitive to drought. Skill of CII forecasts could also be increased through aggregation and/or spatial weighting according to context-relevant quantities, as demonstrated with the example of national averages of cooling degree days. The latter two examples illustrate that it is worth exploring the value of CII forecasts even if there is marginal skill in forecasts of the underlying variables. Implicit aggregation or weighting in the calculation of the impact variable can amplify partial skill in the underlying variables and thus exploit windows or pockets of predictability while transforming meteorological information to more user relevant quantities.

[1] https://meteoswiss-climate.shinyapps.io/skill_metrics

2 Project Objectives

With this deliverable, the project has contributed to the achievement of the following objectives (DOW, Section B1.1):

No.	Objective	Yes	No
1	Develop and deliver reliable and trusted impact prediction systems for a number of carefully selected case studies. These will provide working examples of end to end climate-to-impacts-decision making services operation on S2D timescales.	X	
2	Assess and document key knowledge gaps and vulnerabilities of important sectors (e.g., water, energy, health, transport, agriculture, tourism), along with the needs of specific users within these sectors, through close collaboration with project stakeholders.		X
3	Develop a set of standard tools tailored to the needs of stakeholders for calibrating, downscaling, and modelling sector-specific impacts on S2D timescales.	X	
4	Develop techniques to map the meteorological variables from the prediction systems provided by the WMO GPCs (two of which (Met Office and MeteoFrance) are partners in the project) into variables which are directly relevant to the needs of specific stakeholders.	X	
5	Develop a knowledge-sharing protocol necessary to promote the use of these technologies. This will include making uncertain information fit into the decision support systems used by stakeholders to take decisions on the S2D horizon. This objective will place Europe at the forefront of the implementation of the GFCS, through the GFCS's ambitions to develop climate services research, a climate services information system and a user interface platform.	X	
6	Assess and document the current marketability of climate services in Europe and demonstrate how climate services on S2D time horizons can be made useful to end users.		X

EUPORIAS

3 Detailed Report

In the following, results for a wide range of sectors in different regions are presented separately (Sections 3.1-3.7). The studies make use of a variety of CIIs targeting decision processes of the corresponding sector (Table 1). To the extent possible, all examples use the same seasonal forecasting system, the same verification metrics and the same validation protocol. This helps to intercompare the results and to derive general results.

Table 1: Climate information indices used in this report

Climate information index	Stakeholder sector	Section
Days with high and low wind speed	Energy	3.1
Extreme precipitation indices	Water transport	3.2
Growing season precipitation, hydrothermal index, cool night index	Agriculture (wine production)	3.3
Fire weather index	Civil protection, forestry	3.4
Temperature-related mortality	Health	3.5
Water balance	Agriculture	3.6
Water requirement satisfaction index	Agriculture	3.7
Cooling degree days	Energy	3.8

We conclude the detailed report with a more general interpretation of the results and an illustration of possible ways forward (Section 3.8). In this final section, we highlight the potential benefits of aggregation on seasonal forecast skill. Also, we discuss the importance of understanding the limits to predictability and being able to identify windows of opportunity for useful seasonal forecasts.

3.1 Wind speed indices for the energy sector (IC3 / BSC)

Definition of extreme wind indices

Extreme wind speed indices are useful in order to characterize the low and high wind speeds in a particular season. In this deliverable, we present one index each to assess the low wind speed (sfcWindq10nd) and the high winds (sfcWindq90nd). These are defined as:

sfcWindq10nd: percentage of time in a season with wind speed below the climatological 10th percentile (q_{10th}).

$$sfcWindq\,10\,nd=\frac{1}{n}\sum_{i=1}^{n} d_i \quad d_i=\begin{cases}0 & sfcWind_i>q_{10th}\\ 1 & sfcWind_i<q_{10th}\end{cases}$$

sfcWindq90nd: percentage of time in a season with wind speed above the climatological 90th percentile (q_{90th}).

$$sfcWindq\,90\,nd=\frac{1}{n}\sum_{i=1}^{n} d_i \quad d_i=\begin{cases}0 & sfcWind_i<q_{90th}\\ 1 & sfcWind_i>q_{90th}\end{cases}$$

The climatological 90th and 10th percentiles have been used to calculate the number of days in which some of the 4 values per day of the wind speed exceeds the 90th percentile threshold (or is below the 10th percentile threshold). Then, the frequency of days above and below the corresponding climatological percentile in a month is computed.

The methodology for the estimation of these indices was first proposed by Pepler et al. (2015) and further developed in Prodhomme et al. (2015). It has been applied for the 10m wind speed ERA-Interim reanalysis data (Dee et al. 2011) and for the ECMWF System 4 seasonal predictions (Molteni et al. 2011) at 6-hourly resolution over the period 1981-2012. The application of the methodology has been applied separately for each dataset because the percentiles in the reference reanalysis and in the predictions can be very different.

Forecast quality assessment of the wind indices and comparison with the seasonal average of wind speed

In the Deliverable 22.2 the systematic errors of the predicted indices were evaluated. The bias is slightly different for the two indices considered, with a larger bias found for the sfcWindq10nd index relative to the sfcWindq90nd. However the biases for the two indices were very low, so this suggested that bias correction is not critical for these extreme indices since they are based on relative thresholds which are computed separately for the predictions and the reference, taking into account implicitly bias correction.

A further evaluation of different aspects of the forecast quality of the two indices was provided in the deliverable 22.2. Here we have compared the forecast quality of sfcWindq10nd and sfcWindq90nd relative to the forecast quality of the average wind speed in a season (sfcWind). To better illustrate the potential benefits of these indices for the wind energy sector we have used a deterministic measure (Correlation) and a probabilistic skill score (CRPSS).

Correlation measures the linear correspondence between the observational reference and the predicted ensemble mean, which is very useful in order to identify regions where there is potential skill, which is the maximum skill that can be found for an index in a particular region. Correlation maps have been computed for the average wind speed (Figure 1a) and wind speed extreme indices: sfcWindq10nd (Figure 1b) and sfcWindq90nd (Figure 1c).

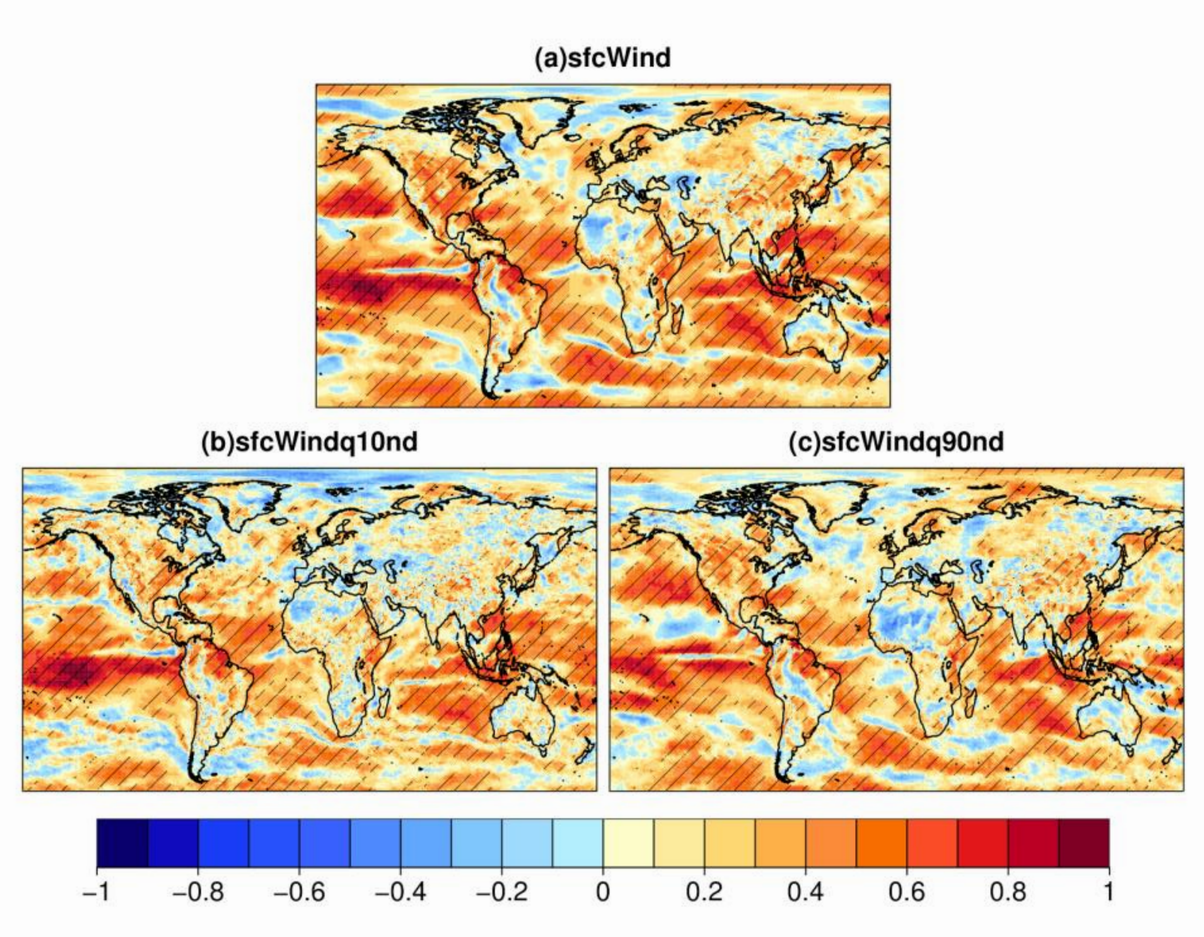

Figure 1: Correlation of forecasted ensemble mean of: (a) Average wind speed in a season (b) Number of days under the climatological 10th percentile; (c) Number of days over the climatological 90th percentile, in winter (DJF) from ECMWF System 4 and Era Interim. Forecasts with System 4 have been initialized on the 1st of November over the period 1981-2012. The hatched areas indicate where the skill is significant at the 95% confidence level (i.e. System 4 is significantly more skilful than a climatological forecast).

The three indices considered exhibit similar positive and significant correlation at a 95% level in some oceanic and tropical regions as Northern South-America, North-eastern Brazil, Western Africa and South-eastern Asia. Although the predictability of the seasonal prediction systems is limited at extra tropical latitudes, some regions such as Canada or Central US also display correlation values significantly larger than zero for the sfcWindq10nd and sfcWindq90nd indices.

The average wind speed (Figure 1a) shows significant and higher correlations in North America, Northern Europe and also in East Asia than sfcWindq10nd and sfcWindq90nd. This result illustrates the added value of the average wind speed relative to the extreme indices. However there are some regions where the extremes are more predictable than the average wind speed as in South America, Central Africa, Southern Europe or Australia where the best correlations are obtained for the sfcWindq10nd and also in Western North America or South Africa where sfcWindq90nd displays the higher correlations.

If we compare the correlations of the two extreme indices there is a better correlation for the sfcWindq90nd, however some regions as Tropical Pacific, Central Africa, Southern Europe or Australia display more predictability for the sfcWindq10 index. The differences between these two indices are an evidence of the asymmetry in the predictability of the climatological wind speed distribution relative to the six hourly wind speed values. The 10th and 90th climatological percentiles which have been used for the creation of sfcWindq10nd and sfcWindq90nd do not match the probability density function of ERA-Interim and this translates into differences in the associated percentile values.

Skilful forecasts of sfcWindq10nd and sfcWindq90nd can help users to save costs related with the vulnerabilities and risks associated with the wind extremes. Therefore, the potential skill of sfcWindq10nd and sfcWindq90nd found in some key regions for the wind industry, with a number of wind farms located there, such as North America, the North Sea or the Northeast of Brazil, could be useful to be considered in the decision making processes related with the wind energy operations.

The continuous ranked probability skill score (CRPSS) is a skill score based on the CRPS which is defined as the integrated squared difference between the cumulative forecast and observation distributions. It can be interpreted as a probabilistic generalisation of the mean absolute error which allows the evaluation of the full probability distribution.

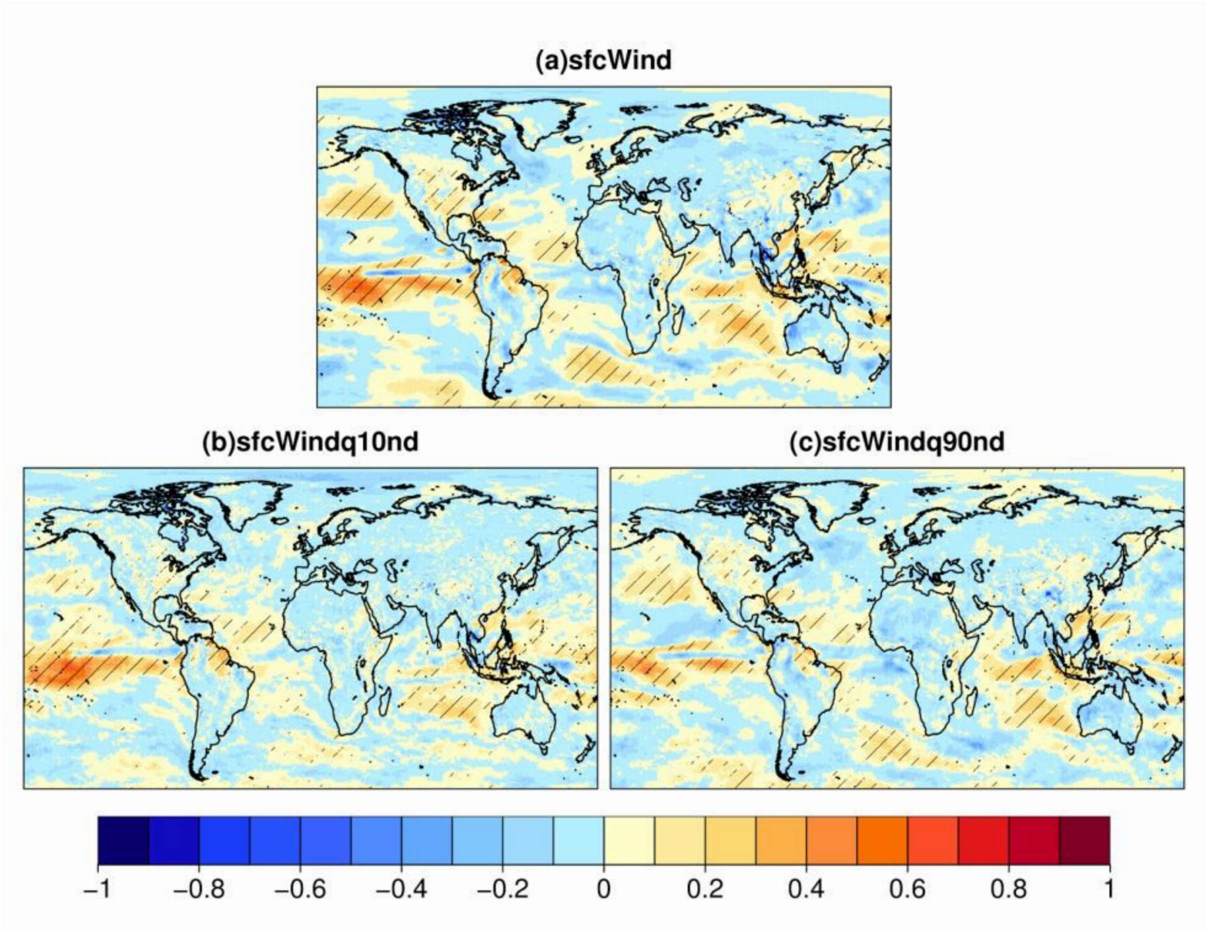

Figure 2: Fair continuous ranked probability skill score (CRPSS) of: (a) Average wind speed in a season (b) Number of days under the climatological 10th percentile; (c) Number of days over the climatological 90th percentile, in winter (DJF) from ECMWF System 4 and Era Interim. Forecasts with System 4 have been initialized on the 1st of November for the period 1981-2012. The hatched areas indicate where the skill is significant at the 95% confidence level (i.e. System 4 is significantly more skilful than a climatological forecast).

Figure 2 illustrates the agreement between the three indices with skilful regions in the tropics where the highest CRPSS skill score (up to 0.5) can be found. Northern South America and the Northeast of Brazil have particularly significant positive values of CRPSS. Some of Central US retains a positive and significant skill at the 95% confidence level for the average wind speed (Figure 2a) and the sfcWindq90nd (Figure 2c) wind speed. But nearly all other continental regions, including Europe, have not statistically significant skill scores for the three considered indices.

The differences found between correlation and CRPSS (Figure 1 and Figure 2) indicate that although the potential skill to predict the wind extremes indices is high in many regions around the world (Figure 1), the full distribution of these forecasts evaluated with CRPSS (Figure 2) does not provide extra value relative to the climatology.

Relevance of wind indices for wind energy applications

After developing two extreme indices (sfcWindq10nd and sfcWindq90nd), we have contacted users of the EUPORIAS energy prototype to identify the potential benefits of these indices for their daily activities.

The two extreme indices (defined above) consist in the percentage of time in a season with wind speeds over 90th percentile (sfcWindq90nd) and wind speeds under the 10th percentile (sfcWindq10nd). The wind energy users' feedback indicated that the definition of these indices was clear and easy to understand. Most of them were used to deal with forecasts and have enough knowledge to understand percentiles, particularly those users whose activity is focused on the evaluation of risk, e.g. energy traders. However they mentioned that the use of the "extreme" term can be misleading. Wind energy industry currently considers the extreme events such as small-scale processes which can affect the design of the turbines, for example storms. To take into account these events in their decision making processes they traditionally use weather forecasts, thus when presented extreme indices for seasonal time scales it is difficult to interpret them in the right temporal scale as they are biased by their experience. In order to clarify the difference between the seasonal prediction of the sfcWindq10nd and sfcWindq90nd and the extreme definition in the wind energy world, users have proposed more user-friendly names to be used as alternative to "extreme" such as: "outlier", "number of exceedances" or "number of exceeding threshold ".

The selected season for the illustration of the forecast quality of the wind speed indices defined in the WP22 was the boreal winter, DJF. Some users indicate that decisions in the wind energy sector are not taken for the seasons commonly used by climate scientists (DJF, MAM, JJA, and SON). They rather make their scheduling in terms of year quarters (Q4: OND or Q1: JFM), which are linked to financial calendars. These quarters or even individual months provide information directly tradeable in the energy market.

The users were also questioned about the added value of these indices compared to the seasonal predictions of wind speed that were included in the visualisation tool of the RESILIENCE prototype (http://project-ukko.net). The users mentioned that the prediction of these indices could be complementary to the seasonal predictions of the average wind speed. The information contained in project Ukko may influence their view on market prices and may lead them to take a market position on it. On the other side, information concerning the number of exceedances (10th/90th percentile) on a specific period may help them to buy an option product to hedge another position. In addition some of the users also considered the information of the indices interesting because they gave information of the number of days in a season with wind speed under/over the 10th/90th percentile, which is perceived as a higher time resolution than the average wind speed in a season.

Regarding the way in which they would like to get the information of these indices, they said that the visual format was very interesting for them but that they needed not only the visualisation but also the data. Therefore, a tabular format should be provided besides maps in order to allow the users to integrate this information in their decision making processes.

Wind energy users have also identified some potential applications of these indices related with the financial operations such as energy trading. By contrast, some of the users mentioned that these indices cannot be integrated in decision making processes related with the planning of maintenance works. The maintenance decisions are made two or three days in advance and these decisions involve many parameters besides weather and climate conditions, therefore this layer of information was not considered critical for them. Nevertheless the users also mentioned that the planning of maintenance strategies is very variable between different companies. For instance, the planning of maintenance works in offshore wind farms can potentially require information with more time in advance, and those companies could be more interested in the sfcWindq10nd and sfcWindq90nd indices.

Key Points

- Globally, there are some regions in which wind extreme indices display more potential skill than the average wind speed, but there are small differences between the two indices and the underlying variable.
- Wind energy users stated that seasonal prediction of wind speeds and the sfcWindq10nd and sfcWindq90nd can be complementary sources of information to be integrated in their decision-making processes related with the financial risk.

3.2 Precipitation indices for the water transport sector (KNMI)

Focusing on water related indices, we investigated the skill of extreme precipitation indices for the Rhine basin concerning water transport related factors. In D22.2 we concluded that no robust patterns could be found in the seasonal forecast of extreme precipitation indices such as R20mm (very heavy precipitation days), illustrating the difficulty when working with indices related to rare events. This analysis was part of the 'SOSRhine' case study where, together with the user (BFG) we could not identify potential precipitation indices/drivers of low/high flows with useful forecast skill. The predictive skill of the extreme indices was assessed after applying the necessary bias correction (available in D22.2 and D21.1). This analysis is put on hold until new hydrological simulations are available from BFG and further relevant discharge indices will be investigated.

In addition to the case study, we worked on providing the tools to generate and evaluate the ETCCDI and ECA&D indices for station and gridded data. The work on the calculation routines was done in collaboration with MeteoSwiss, where we adapted the climdex.pcic and climdex.pcic.ncdf R libraries to accommodate ECA&D, and MeteoSwiss snow related indices. These routines were also used in the CLIPC project as validation for the development of the icclim python library. A webpage on the indices calculated using E-OBS, providing thus the historical perspective and variability of the indices, is available on the ECA&D website. Following features for the webpage such as trends will be available after the homogenisation of the input data from the EUSTACE project. As the E-OBS data set is used in the bias correction of seasonal forecast, we had requests from users from South European – North African countries to provide tercile maps of the observed CII. This is related mainly to users were gridded observations are not available due to issues of data sharing and potential users could benefit from such maps in the bias correction process (this is work in progress).

Key points

- Forecast skill of indices related to extreme rainfall is not sufficient to be useful for forecasting river flows in the Rhine catchment.
- Software tools have been developed to compute an extended set of climate indices from observational and forecast data.

3.3 Viticulture indices for the wine production sector (UL - IDL / IPMA)

In the previous deliverable (D22.2) a specialized set of CII relevant for the wine producing stakeholders were calculated. Although the bias correction with quantile mapping and spread correction reduced the biases considerably, still some significant biases associated to precipitation remained. Even though the spread to error ratio, in most cases, has been brought to values near 1, the forecast skill is very limited and the skill of forecast probabilities is worse than the use of climatological frequencies as forecast. A new method of bias correction was applied to the 15 members of System 4 seasonal forecast (S4 from here onwards) (Molteni *et al.*, 2011) for the period (1981-2010) and for the European domain at 0.7º resolution. ERA Interim reanalysis was used as reference. From the seven indices in D22.2, three, which have a direct link to viticulture practices, were recomputed. As before, the seasonal forecast initialized in March (Lead Time 1) were used to derive the CII forecasts.

Table 2: Climate indices for wine production, definition and usefulness

Index	Definition	Utility
Growing season precipitation (GSP)	$GSP = \sum_{Apr}^{Sep} P$	One of the most discriminating climatic variables (Blanco-Ward et al. 2007) GSP > 600mm: excessively wet GSP <200mm: extremely dry
Hydrothermal Index (HyI)	$HyI = \sum_{Apr}^{Sep} T_{mean} \times P$	Considers both precipitation and temperature regimes for estimating the risk of downy mildew disease (Branas et al. 1946) HyI < 2500°Cmm - low HyI > 5100°Cmm - high
Cool night index (CI)	$CI = \sum_{Sep} T_{min}/_{30}$	Provides a relative measure of ripening potential, being equal to the average minimum temperature during the month before harvest (Tonietto et al. 2004) • very cool nights (CI ≤ 12°C), • cool nights (12 < CI ≤ 14°C) • temperate nights (14 < CI ≤ 18°C) • warm nights (CI > 18°C)

Bias Correction

Bias correction was attempted through the Cumulative Distribution Function-transform (CDF-t) method developed by Michelangeli et al. (2009) of the ensemble daily precipitation, maximum and minimum temperature. This approach relates the empirical cumulative distribution function (CDF) of a variable from SF to the CDF of this variable from ERA Interim. For each day, a 31 day moving window (i.e. days centred on the day of interest) is used as in Wilcke et al. (2013). A two-fold cross validation with 15 year periods is applied, thus each CDF is determined from 6975 values (15years x 31 day window x 15 members) , taking into account autocorrelation and the interannual variability of each day. In the case of precipitation, the 15 year ensemble dry day frequency is corrected to be equal to the 15 year ERA Interim climatology dry day frequency.

Forecast Quality

Growing season precipitation (GSP)

The Growing Season Precipitation, as the accumulated precipitation from April to September, i.e. the growing season, can be used as a discriminating index for vineyard distribution. Areas with GSP above 600mm are usually considered excessively humid, whereas areas with GSP bellow 200mm are extremely dry. The new method is able to reduce the bias in relation to the equidistant CDF of D22.2 (Figure 3a). The forecast presents once again a dry bias, illustrating the difficulty in bias correction of the precipitation. As before, the anomaly correlation and the ROC (Figure 3b, c and d), have similar patterns to the previous method. No improvement is detected.

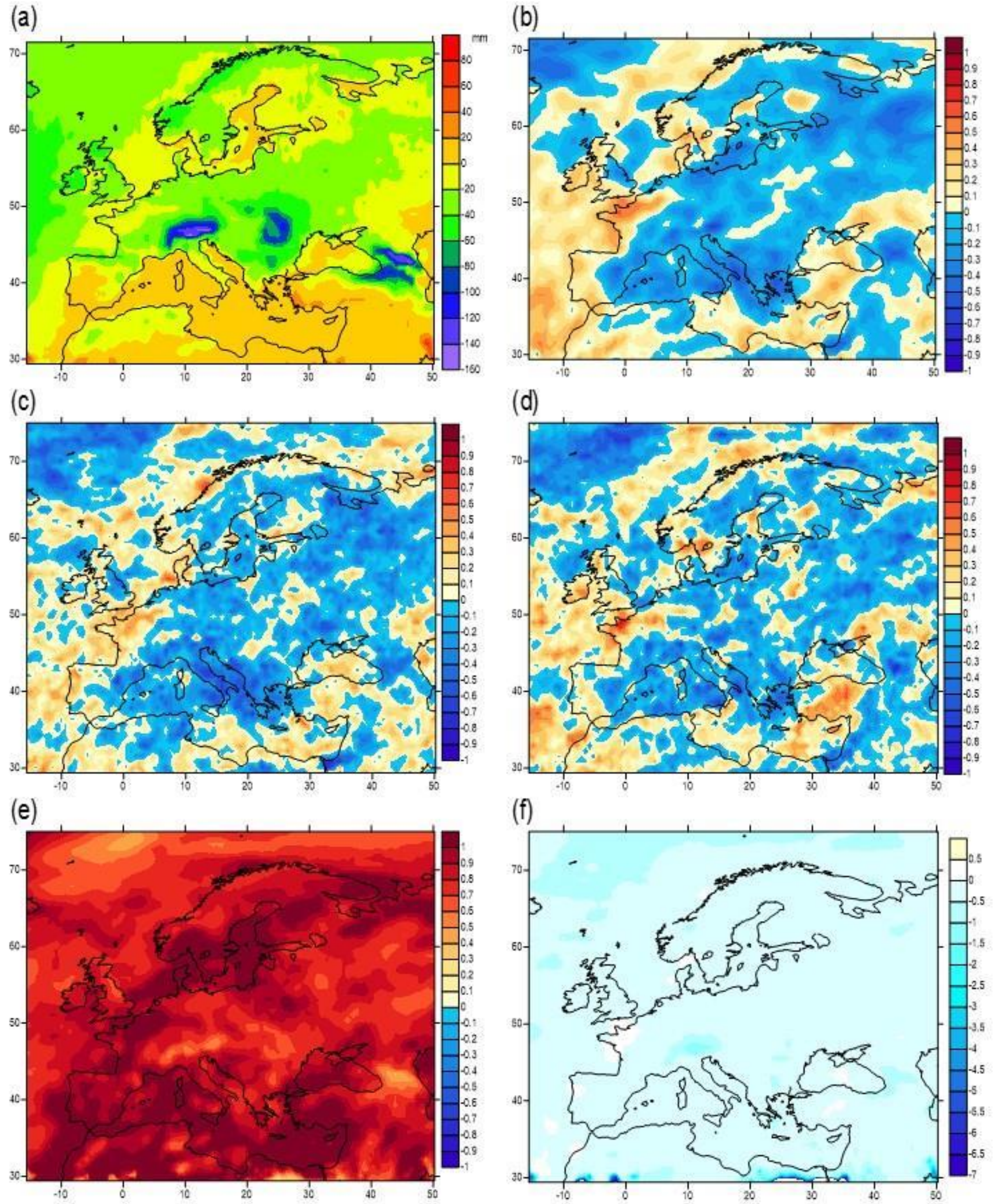

Figure 3: Growing season precipitation (a) Bias, (b) Anomaly Correlation, (c) ROCs area for the lower tercile, (d) ROCs area for the upper tercile, (e) Spread to Error ratio, (f) Continuous Ranked Probability Skill Score

The spread to error ratio (Figure 3e) displays values near 1 for most of the continent indicating that the corrected ensemble is able to represent the forecast uncertainty in several areas. The high elevation areas, like the Alps and Carpathians, the spread to error ratio is lowest indicating considerable under-dispersion/over-confidence of the ensemble, thus the ensemble is too narrow and does not represent forecast uncertainty. The continuous ranked probability skill score is improved, but remains negative (Figure 3f) implying that the skill of the forecast probabilities is worse than the use of climatological frequencies as forecast and that the lack of skill is not due to the residual biases.

Hydrothermal Index

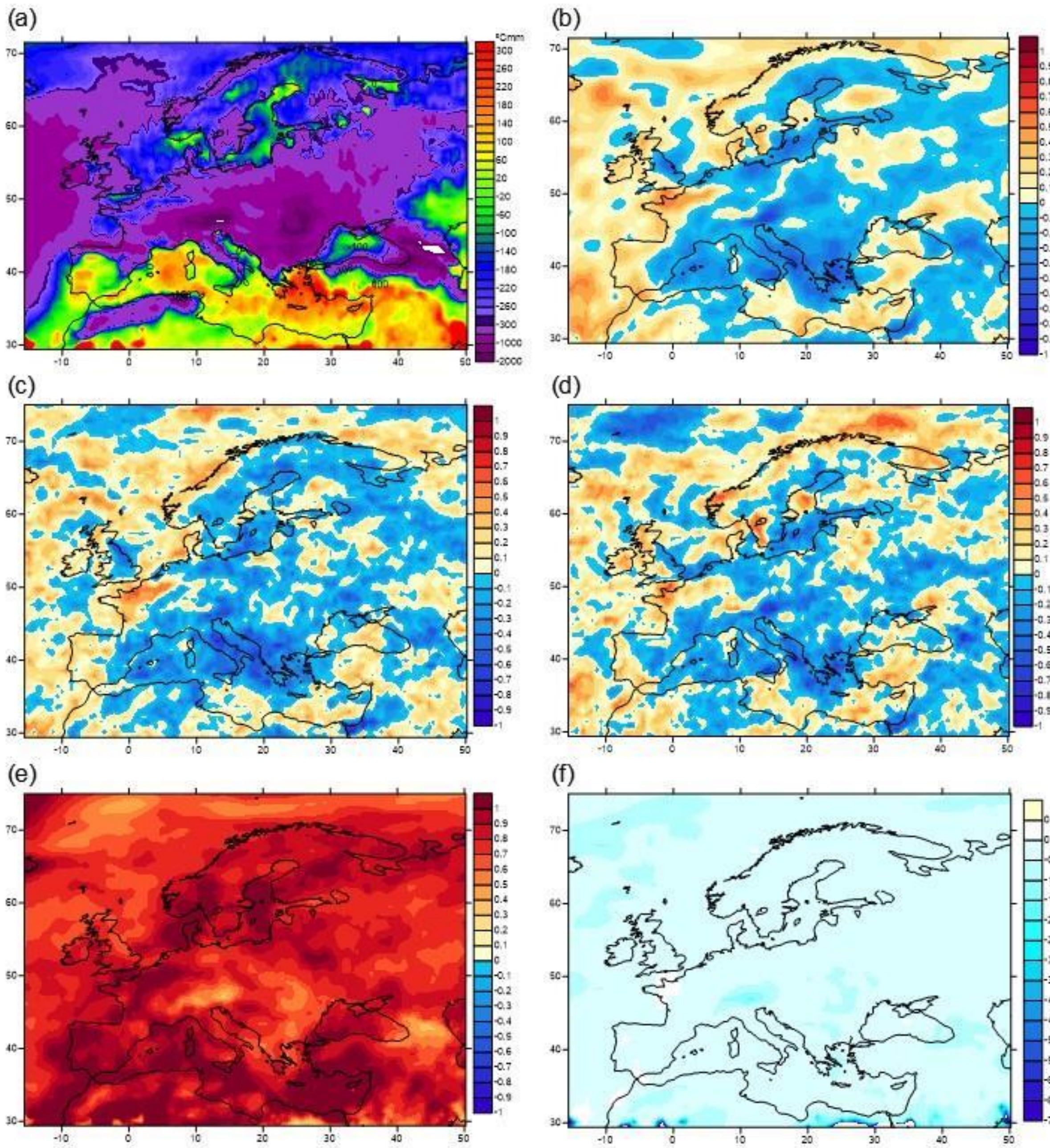

Figure 4: Hydrothermal Index (a) Bias, (b) Anomaly Correlation, (c) ROCs area for the lower tercile, (d) ROCs area for the upper tercile, (e) Spread to Error ratio, (f) Continuous Ranked Probability Skill Score.

According to Branas et al. (1946) the Hydrothermal Index can be used to determine the risk of the development of mildew. According to the climatology, all of central Europe has a high risk of mildew occurrence and only southern Greece, Sicily, Sardinia and southern Iberian Peninsula are low risk. As before, the spatial distribution of the remaining bias (Figure 4a) is analogous to the previous method, however, these biases are reduced. The anomaly correlation and the ROCs maps (Figure 4b, c and d) are very similar to the GSP anomaly correlations and ROCs, indicating that the precipitation distribution dominates the index skill. The spread to error ratio (Figure 4e) is higher with this method, but still a small under-dispersion/over-confidence of the ensemble remains, thus the ensemble is still too narrow. The continuous ranked probability skill score (Figure 4f) is negative and akin to GSP.

Cool Night Index

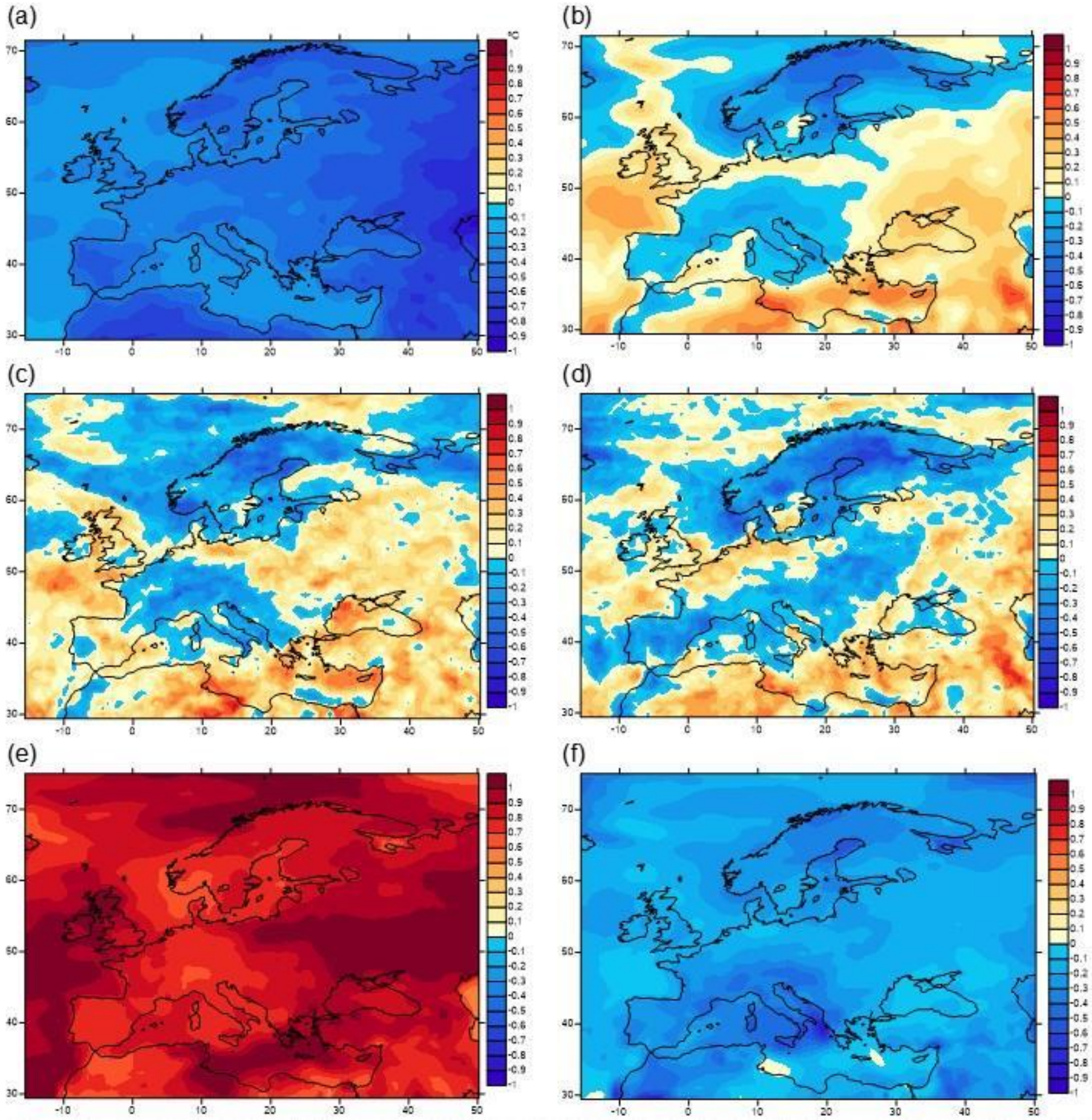

Figure 5: Cool Night Index (a) Bias, (b) Anomaly Correlation, (c) ROCs area for the lower tercile, (d) ROCs area for the upper tercile, (e) Spread to Error ratio, (f) Continuous Ranked Probability Skill Score.

The results from the CDF-t are equivalent to the equidistant quantile mapping, stressing the point the progresses in the previous indices are related to the improvement of the representation of precipitation.

Key points

- The CDF-t methodology improves the representation of the precipitation
- Forecast skill of indices relevant to viticulture is still very limited. Often forecasts based on the forecasting system perform worse than the climatological reference forecast.

3.4 Forest fire risk for the civil protection and forestry sectors (UC / MetOffice)

Introduction

While the main atmospheric surface variables affecting fire danger in a certain area are air temperature, humidity and wind speed (referred to as fire-weather variables), these are usually combined and integrated in fire-weather indices. These are multi-variable climate impact indicators (CIIs) tailored to the needs of fire prevention agencies, envisaged to provide a more realistic representation of the climatic conditions conducive to fires (see e.g. Viegas et al 1999 for a description of some indices applied in the Euro-Mediterranean, EU-MED, region). 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 seasonal predictions of such indices, computed from the GCM outputs, could be highly valuable for decision-makers, helping risk managers to conduct a rapid assessment of management options in advance of the fire season. The CII considered in EUPORIAS WP22 in the forestry and civil protection sectors is the Canadian Fire Weather Index (FWI), one of the most widely applied fire-weather indices throughout the world. Originally conceived for the boreal forests of Canada, the FWI system has proven a useful fire-weather indicator in many areas of the world (see e.g. Bedia et al 2015) and in particular in EU-MED (Viegas et al 1999, Bedia et al 2014a). 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[2], San Miguel-Ayanz et al 2013) being therefore natural to explore its applicability to the seasonal range in the same context.

In the previous deliverable (D22.2), we addressed several methodological aspects regarding the computation of FWI from seasonal forecast model outputs. Notably, we gave recommendations on how to proceed with bias correction of FWI predictions using empirical Quantile Mapping (QM hereafter), and showed the need for detrending prior to forecast verification in order to avoid spurious results. We also performed a verification of the FWI forecasts (using the System 4 seasonal hindcast) and found that there is significant skill in

[2] http://forest.jrc.ec.europa.eu/effis/

predicting above average summer FWI in parts of SE Europe at 1 month lead time, leaving the door open to the operational applicability of FWI forecasts in this fire-prone area of the Euro-Mediterranean region.

In this deliverable, we investigate the potential sources of predictability of FWI. To this aim, we perform the verification of the input FWI variables separately, in order to ascertain what variables are more related to the skilful FWI predictions. Following work by previous authors, we then hypothesize that the summer North Atlantic Oscillation (SNAO) may have an influence on the forecast skill in Eastern Europe, and perform a verification of the SNAO for the System 4 model.

Summer climate in the North Atlantic-European sector possesses a principal pattern of year-to-year variability that is the parallel to the well-known North Atlantic Oscillation (NAO, Hurrell et al 2003) in winter. This summer North Atlantic Oscillation (SNAO) is defined here as the first empirical orthogonal function (EOF) of observed summertime extratropical North Atlantic pressure at mean sea level (Folland et al 2009). It is shown to be characterized by a more northerly location and smaller spatial scale than its winter counterpart. Although of lesser amplitude than its wintertime counterpart, the SNAO exerts a strong influence on northern European rainfall, temperature, and cloudiness through changes in the position of the North Atlantic storm track (Folland et al 2009). Furthermore, and of potential relevance for fire danger conditions in the study area, SNAO significantly affects summer precipitation in the Mediterranean, particularly Italy, Greece and the Balkans (correlations of up to 0.6), as shown in Bladé et al (2012). These areas are partially coincident with the area were skilful FWI predictions were found in D22.1 and D22.2. However, Bladé et al (2012) examined whether the surface influence of the SNAO is captured by two CMIP3 GCMs (HadCM3 and GFDL-CM2.1) and found weak or non-existent correlations between the SNAO and Mediterranean precipitation. In this deliverable, we investigate whether SNAO can be skilfully reproduced by System 4, in order to gain a better understanding of the underlying processes related to the skilful FWI predictions. In addition, and provided the recent availability of the GloSea5 hindcast for the ECOMS partners through the ECOMS-UDG, we also verified the SNAO predictions of this model, provided its reported improved performance with respect to previous GCMs in capturing the NAO (Scaife et al 2014).

Our results using System 4 indicate that the skill in seasonal FWI predictions is largely coupled to its skill in the prediction of near-surface air humidity. However, neither System 4, nor GloSea5 are able to skilfully reproduce the interannual variability of SNAO, and therefore the predictability of FWI cannot be attributed to the representation of this phenomenon by the model. Interestingly, GloSea5 was able to predict the positive phase of SNAO of year 2002 with outstanding accuracy, suggesting that this year may constitute a potentially fruitful case-study for further investigation of key sources of predictability still untapped (Scaife et al 2014).

Methodology

Data and methods

Data were obtained from the ECOMS-UDG. For the sake of brevity, the interested reader is referred to previous deliverables D22.1 and D22.2, where the steps and methods used for data post-processing, quantile mapping, and verification, as well as the different open-source tools used to this aim are described. A worked, fully reproducible example of data loading, FWI calculation, bias correction and verification (considering the publicly available NCEP-CFSv2 reforecast) is also available[3].

SNAO calculation

We follow the SNAO definition by Bladé et al. (2011), as the first EOF obtained from the seasonal mean sea-level pressure (MSLP) or the months July-August in the domain defined by the corners 40° N-70° N; 90° W-30° E) calculated for the period 1950–2010. The same methodology has been used in other studies (e.g. Favà et al 2015). Here, we calculated the SNAO using a principal components analysis (PCA) from a covariance matrix of the MSLP daily anomalies in July and August, from the NCEP-NCAR reanalysis. The loading pattern of SNAO was defined as the leading EOF mode. The SNAO was calculated by projecting the leading EOF onto the MSLP daily anomalies. To this aim, we used the ‘prinComp’ and ‘grid2PCs’ functions available in the R package downscaleR v1.3-3 (Santander Meteorology Group, 2016b).

Results

FWI forecast verification

This section is a recap of previous deliverables, in order to have a complete picture of the new findings of D22.3 in a self-contained way. As already indicated in D22.2, we found skilful predictions of the upper FWI tercile in the eastern part of the study area (Greece, Bulgaria and Turkey mainly), as well as other scattered significant ROCSS areas in France and Central Spain (Figure 6). We also found that the QM correction of FWI predictions does not alter this pattern with regard to the raw (uncorrected) predictions. This enables the identification of a “region of interest” in the SE and NE parts of the study area where there is a potential for the applicability of seasonal FWI forecasts at lead month 1 (i.e., one month before the fire season, JJAS, starts).

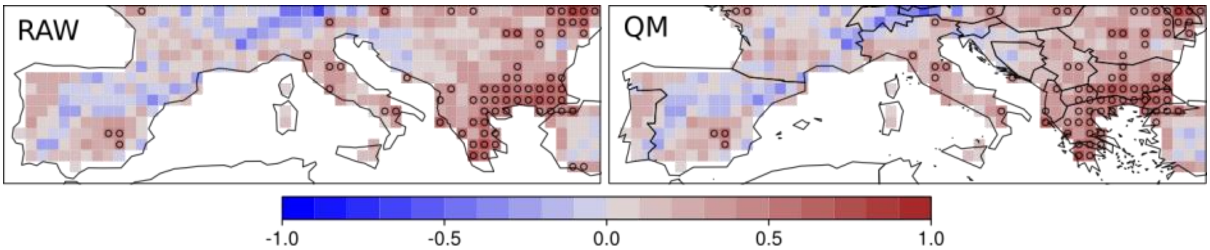

Figure 6: ROC Skill Score of the System4 (upper tercile) FWI predictions considering the uncorrected (RAW, left) and the QM-corrected predictions (QM, right). The grid boxes with significant ROCSS values are indicated by the circles (95% confidence interval).

Forecast verification of the Input FWI variables

Relative humidity, temperature and - to a lesser extent - also precipitation are skilfully predicted over the subregion of interest. However, the extent of significant ROCSS for temperature extends further to the north, beyond the skilful area for FWI (Figure 7). On the

[3] https://github.com/SantanderMetGroup/fireDanger/wiki/CS_Bedia-et-al-2016-(submitted)

other hand, the skill of precipitation is restricted to a smaller domain between Greece, Bulgaria and Turkey, and also other regions such as 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.

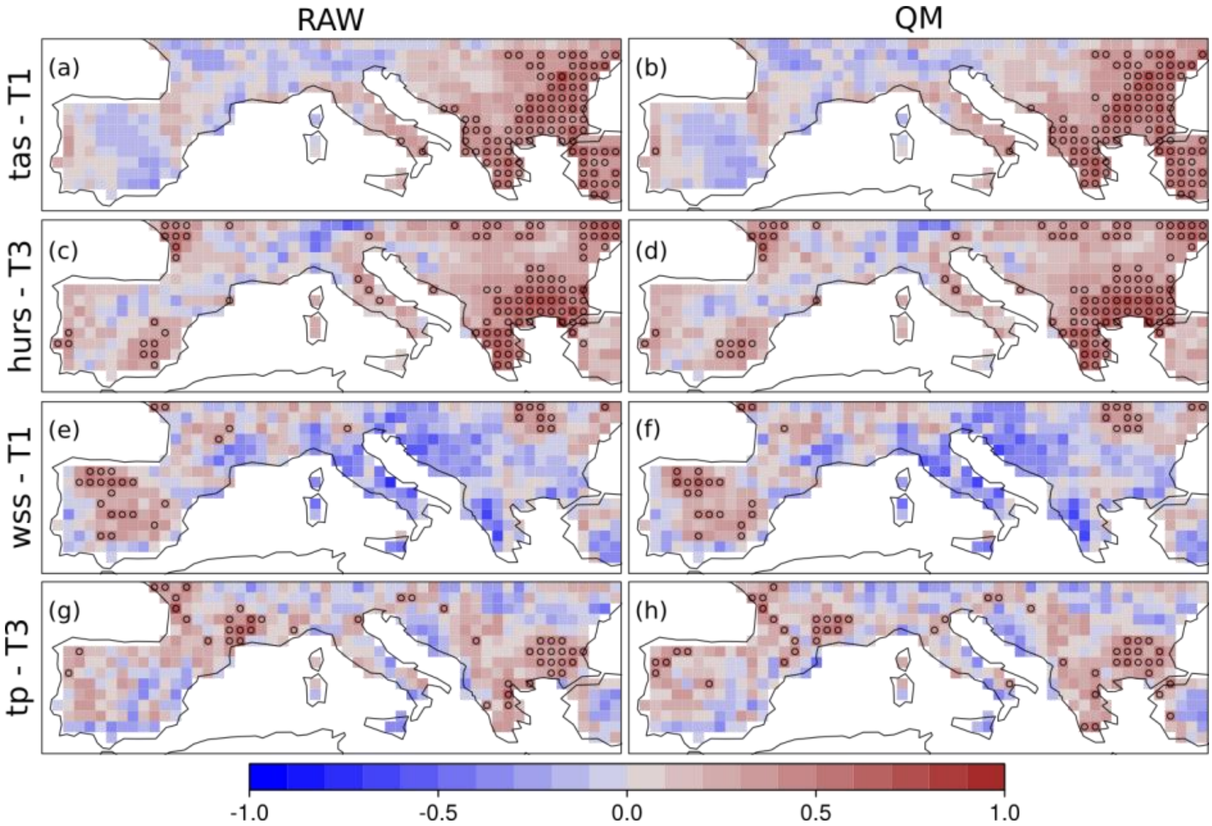

Figure 7: ROC Skill Score of the raw (uncorrected) and the QM-corrected S4 predictions (left/right columns respectively) of the input FWI variables (tas: surface air temperature, hurs: relative humidity, wss: wind speed and tp: total precipitation). T1 refers to the first (upper) and T3 to the third (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.).

Given the reported relationships between the SNAO and precipitation in the region of interest (Bladé et al 2012), we next try to ascertain whether FWI predictability could be partially linked to the predictability of SNAO.

SNAO Forecast verification

The July-August MSLP field of NCEP/NCAR Reanalysis 1 (1950-2010) and the leading EOF are represented in Figure 8. With this information, we reconstructed the normalized SNAO index for the whole reanalysis period. As an additional double-check step, we compared the NCEP/NCAR Reanalysis 1 SNAO index with the same index calculated from the Trenberth MSLP historical records (Trenberth and Paolino 1980), which yielded very similar results (Figure 9, Pearson's r=0.99).

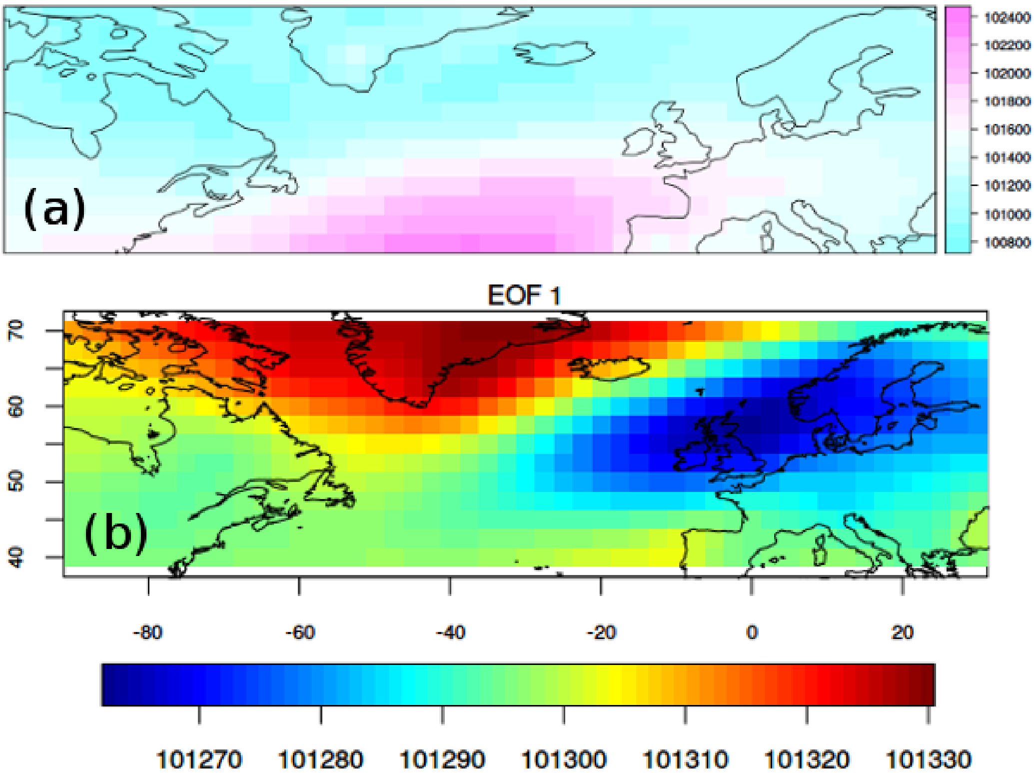

Figure 8: (a) Average mean sea-level pressure of July-August (1950-2010) as represented by the NCEP-NCAR reanalysis. (b) Corresponding leading EOF.

Using a simple correlation analysis between observed and predicted (ensemble mean) SNAO series, we conclude that there is no skill in SNAO as forecasted by System 4. This finding is in agreement with the analysis of other GCMs, as indicated in the introduction of this section (Bladé et al 2012). In the case of GloSea5 there is a slight improvement in this correlation (still far from being significant). Nevertheless, the accuracy of the GloSea5 prediction of the positive SNAO phase of the year 2002 is noteworthy, suggesting that this year may constitute a potentially fruitful case-study for further investigation of key sources of predictability still untapped (Scaife et al 2014).

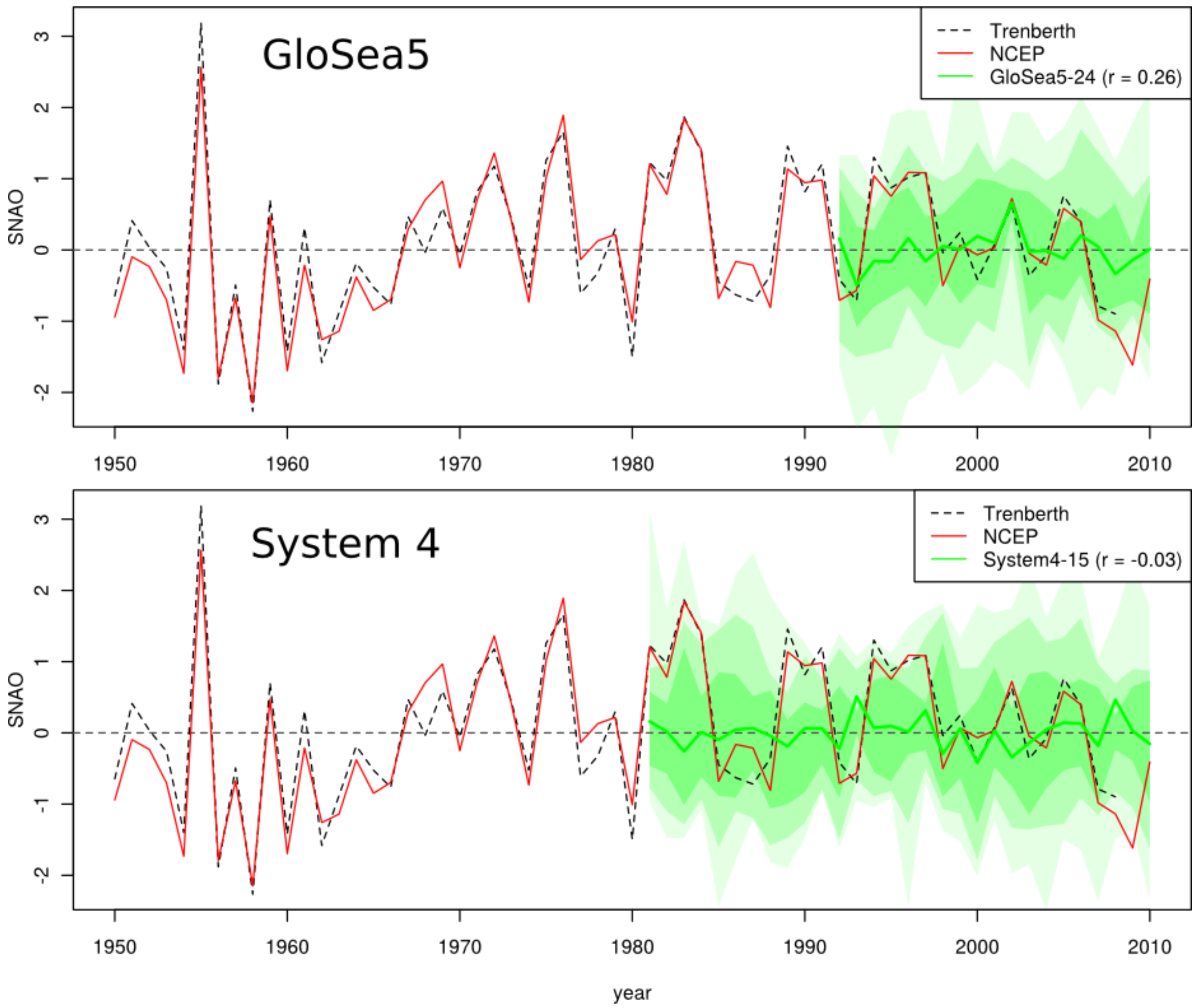

Figure 9: SNAO time series corresponding to observations (NCEP/NCAR Reanalysis 1, in red and Trenberth MSLP dataset, dashed black) and the lead month 1 predictions corresponding to GloSea5 (top) and System 4 (bottom) models. The green shading indicates, from light to darker, the envelopes formed by min-max, 10th-90th percentiles and interquartile range respectively. The green line corresponds to the ensemble mean (24 members in the case of GloSea5, 15 members in the case of System 4). Both forecasts are based on the lead month 2 predictions (initialized in May) of July-August MSLP.

Conclusions and future work

The main findings of this analysis are next briefly summarized.

- Our results using System 4 indicate that the skill in seasonal FWI predictions is largely coupled to its skill in the prediction of near-surface air humidity.
- Skill in predicting FWI cannot be linked to the predictability of SNAO, a known driver of summer precipitation in the Mediterranean. Neither System 4, nor GloSea5 are able to skilfully reproduce the interannual variability of SNAO.
- Interestingly, GloSea5 was able to predict the positive phase of SNAO of year 2002 with outstanding accuracy, suggesting that this year may constitute a potentially fruitful case-study for further investigation of key sources of predictability.

Further work currently in progress now focuses on the forecast verification of other FWI components (see van Wagner 1987), in order to better identify which components are contributing most to FWI skill. We hypothesize that FWI components more closely related with fuels and soil moisture in the upper layers (e.g. fine fuel moisture code or duff moisture code) are the main variables determining sill in FWI forecasts in the region of interest, while other components more dependent on wind such as the initial spread index may counteract by limiting the skill. Furthermore, these components are empirically known to be also closely related to fire activity as much as FWI itself (for instance in terms of total burned area or number of fires, see e.g. Amatulli et al 2013, Bedia et al 2014).

3.5 Temperature-related mortality for the health sector (IC3 / WHO)

Heat waves have been responsible for more fatalities in Europe over the past decades than any other extreme weather event. However, temperature-related illnesses and deaths are largely preventable. Reliable sub-seasonal-to-seasonal (S2S) climate forecasts of extreme temperatures could allow for better short-to-medium-term resource management within heat-health action plans, to protect vulnerable populations and ensure access to preventive measures well in advance.

In a previous study (Lowe et al., 2015), the performance of a climate-driven mortality model to provide probabilistic predictions of exceeding emergency mortality thresholds for a heat wave and a cold spell scenario in 54 European regions was evaluated. The mortality model was formulated using observed (reanalysis) apparent temperature data (Ballester et al., 2011). This observed temperature data was then used to produce spatio-temporal probabilistic mortality estimates for a heat wave and cold spell scenario. The model showed considerable skill, particularly for the heat wave scenario (1–15 August 2003), successfully anticipating the occurrence or non-occurrence of mortality rates exceeding the emergency threshold (75th percentile of the mortality distribution) for 89% of the 54 regions, given a probability decision threshold of 70% (see D22.2). The use of observed apparent temperature in the mortality model represented an upper bound to forecast skill, given a perfect climate forecast.

In a subsequent study (Lowe et al., 2016), the extent to which S2S climate forecasts could be incorporated into heat-health action plans, to support timely public health decision-making ahead of imminent heat wave events in Europe, was assessed. The observed apparent temperature data used to formulate the mortality model was replaced with sub-seasonal (Figure 10) and seasonal (Figure 11) forecast apparent temperature, at different lead times (e.g., 1 day, 4 days, 8 days, up to 3 months) to produce probabilistic mortality forecasts ahead of the 2003 heat wave event in Europe. Results were compared to mortality predictions, inferred using observed apparent temperature data in the mortality model.

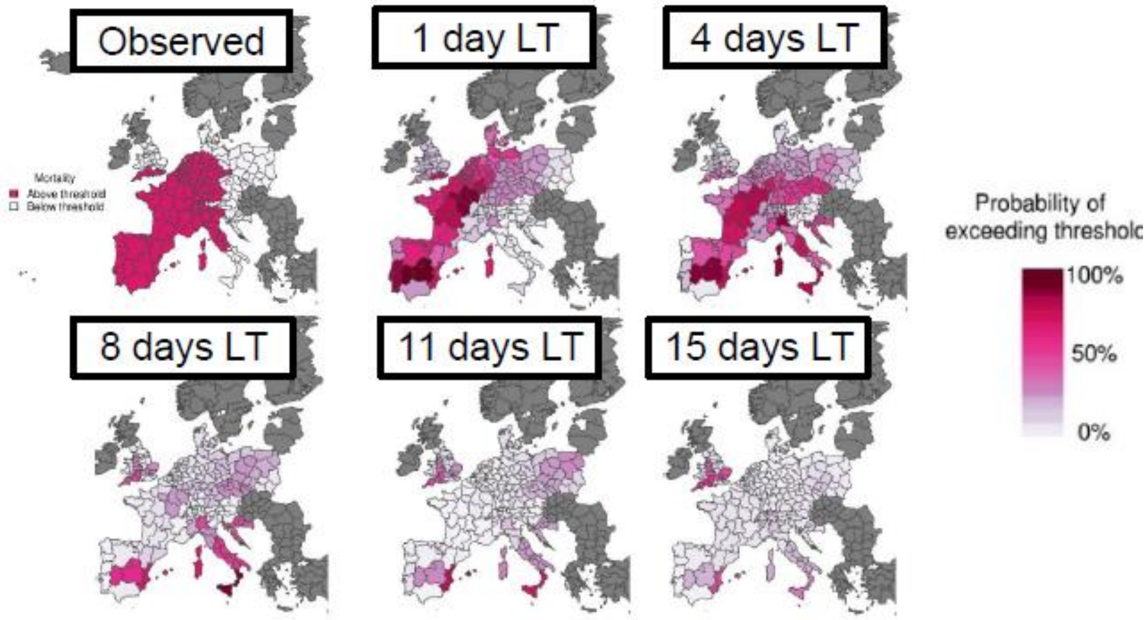

Figure 10: Binary map of observed mortality exceeding the "emergency" alert threshold (75th percentile of daily mortality distribution in the warm tail) during the heat wave scenario (1–15 August 2003), followed by probabilistic maps of exceeding the threshold using a mortality model formulated with sub-seasonal forecasts of apparent temperature at lead times (LT) of 1 day, 4 days, 8 days, 11 days and 15 days. The graduated colour bar represents the probability of exceeding the mortality threshold (ranging from 0%, pale colours, to 100%, deep colours). Most of the skill disappears in the forecasts initiated more than 4 days ahead the heat wave.

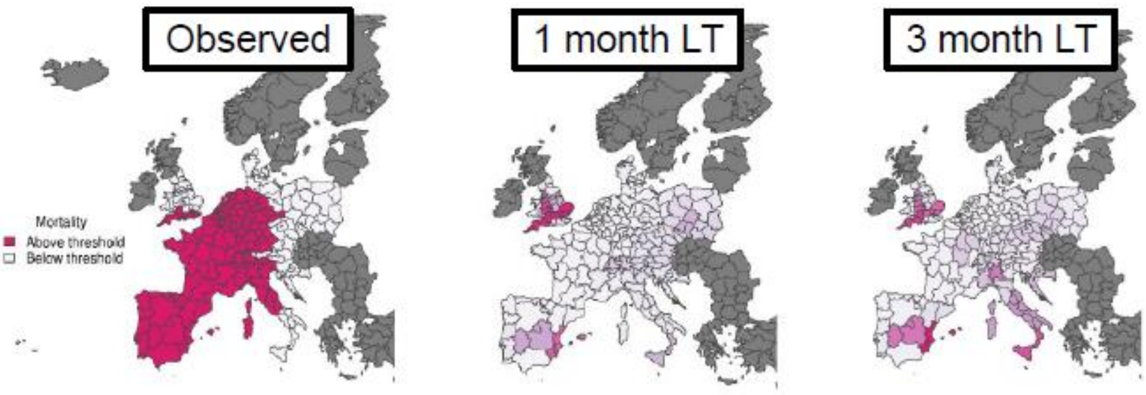

Figure 11: Binary map of observed mortality exceeding the "emergency" alert threshold (75th percentile of daily mortality distribution in the warm tail) during the heat wave scenario (1–15 August 2003), followed by probabilistic maps of exceeding the threshold using a mortality model formulated with seasonal climate forecasts with 1 month and 3 months lead time (LT). The results show no skill in the majority of regions.

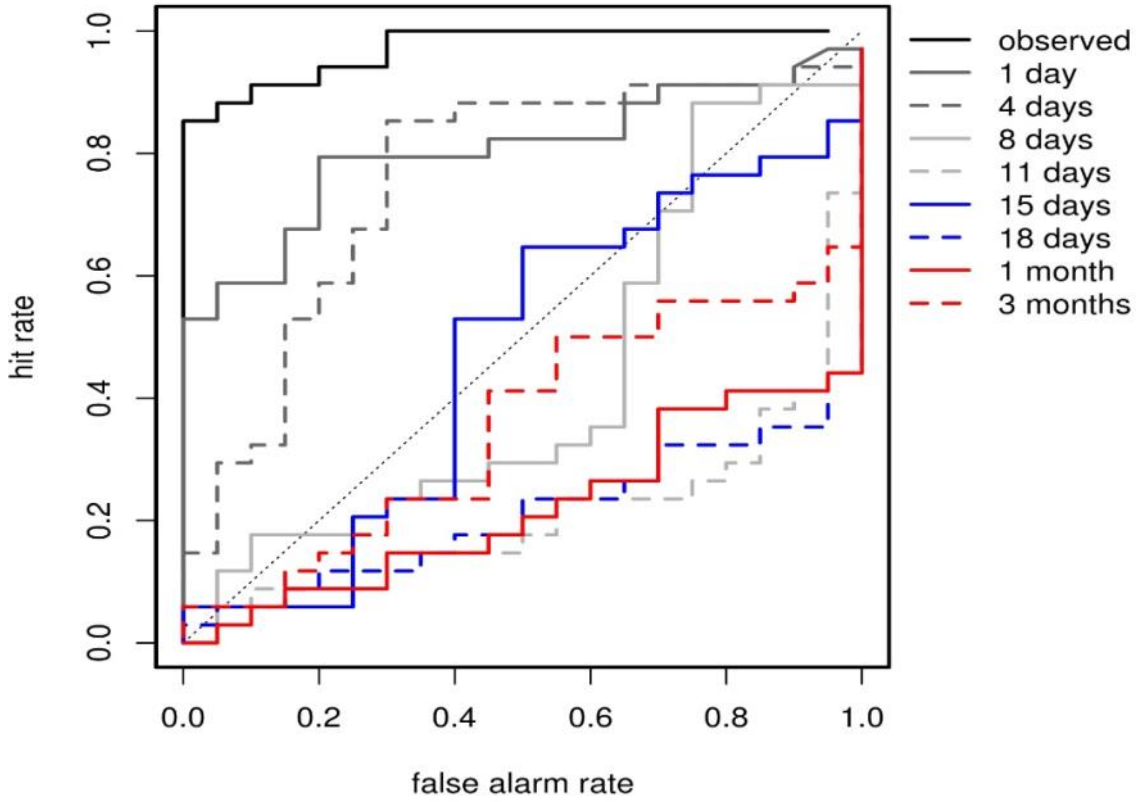

Figure 12: ROC curves for the binary event of exceeding the emergency mortality threshold of the 75th percentile in each of the 54 regions for the heat wave scenario (1–15 August 2003), using the probabilistic mortality model driven by forecast apparent temperature data at lead times ranging from 1 day, 4 days, 8 days, 11 days, 15 days, 18 days, 1 month and 3 months. The ROC curve for the mortality model driven by observed apparent temperature data is shown for reference (black curve).

In general, we found a decreasing transition in skill between excellent predictions when using observed temperature, to predictions with no skill when using forecast temperature with lead times greater than one week (Figure 12). However, even at lead-times up to three months, there were some regions in Spain and the United Kingdom where excess mortality was detected with some certainty (Figure 11). This suggests that in some areas of Europe, there is potential for S2S climate forecasts to be incorporated in localised heat–health action plans. In general, these results show that the performance of this climate service framework is not limited by the mortality model itself, but rather by the predictability of the climate variables, at S2S time scales, over Europe.

In summary, in certain areas of Europe, there is potential for longer lead-times to be incorporated into pre-existing heat-health action plans in the European Region, whilst countries yet to develop heat-health action plans could incorporate such information at the design stage. In those same attempts, countries should take into account the regional differences in both vulnerability and acclimatization. However, our results indicate that a compromise will have to be reached between user needs and the capabilities of seasonal climate forecasts over Europe, to provide skilful mortality predictions in advance of imminent extreme temperature events.

Towards a proper design of a future S2S climate forecasting system for temperature-related mortality (TRM), recognition of the variability in vulnerability and differences in adaptation capacities shown in societies across Europe should be recognized. In this respect, vulnerability to cold days, seasons and long-term winter conditions was studied in an article recently published in Nature Climate Change (Ballester et al. 2016). The link between atmospheric temperature and human mortality has been extensively characterized in the literature (Kunst et al. 1993; Ballester et al., 2011). Once the capacity of the human body to mitigate the external sources of heat stress is exceeded, risk of homeostatic failure (Kettaneh et al. 2010), disease exacerbation and death rapidly start to increase (McMichael et al. 2012). The risk of death in a society is also influenced by a number of socioeconomic factors, such as the macroeconomic situation of the country, the level of income poverty and inequality, the amount of government expenditure on education and health or simply the kind of lifestyle and habits of human individuals (Healy 2003). Housing energy efficiency and fuel poverty are additional factors associated with increased excess winter deaths and cardiovascular, respiratory and mental diseases (Marmot Review Team 2011).

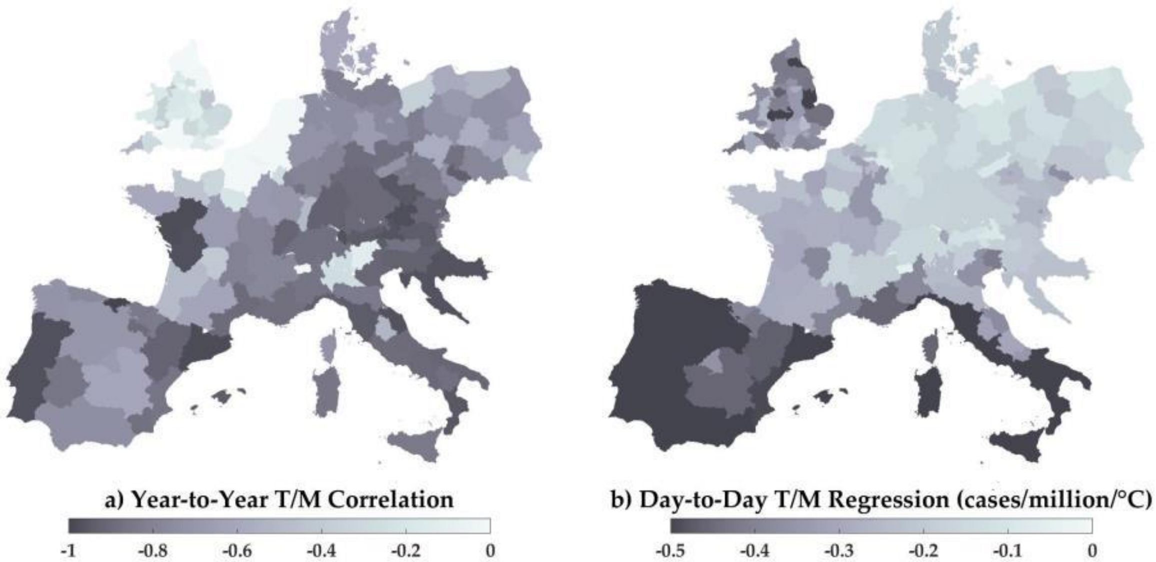

Figure 13: Year-to-year correlation between winter mean temperature and mortality (left), and regression coefficient between daily temperature and mortality in winter (in daily cases per million per ºC, right).

Our analyses resulted from the evaluation of the relationship between winter climate, influenza and numbers of deaths in a very large ensemble of NUTS2 regions representing more than 400 million people in western Europe (same as in Ballester et al. 2011). On the one hand, our study comprehensively characterized the continental picture of human sensitivity to winter conditions at different timescales, showing that the vast majority of the European regions still remain exposed to year-to-year fluctuations in winter temperatures, with higher seasonal mortality and influenza incidence during harsh winters (see in Figure 13a the correlation map between the annual time series of winter mean temperature and mortality for each of the European regions).

On the other hand, Figure 13b illustrates the so-called paradox of winter mortality, in which the highest vulnerability to cold days is found in the temperate regions of southern Europe: -1.13, -0.67 and -0.52 daily cases/million in Portugal, Spain and Italy, respectively. This apparent paradox is explained by multiple factors (Healy 2003), such as the better housing insulation in the areas with severe climatological winter conditions in central and eastern Europe. Thus, the lowest regression coefficients of daily data are found in the Netherlands, Switzerland and Germany (-0.14, -0.15 and -0.16 daily cases/million respectively). The contrast between the larger vulnerability in the southern regions and the higher degree of acclimatization in the northeastern countries is better expressed through the largely negative correlation between climatological winter mean temperatures and the regression coefficients of daily data at the regional level (-0.74, see Figure S7 in Ballester et al. 2016).

The United Kingdom exemplifies the different spatial distribution of human vulnerability at different timescales: it is the fourth country with higher day-to-day regression coefficient (-0.38 daily cases/million/°C, Figure 13b), but in contrast it is the third country with lower year-to-year correlation (-0.12, Figure 13a). The opposite situation is found in many countries in central Europe (e.g. Germany, with a year-to-year correlation of -0.85 and a day-to-day regression of -0.16 daily cases/million/°C). These results illustrate the importance of the still not well understood effect of human adaptation to environmental temperatures, which is key to have a complete description of the effectiveness of climate services and early warning systems at different timescales.

Key Points

- Heat-related mortality seems to be predictable a week in advance, with some areas of Europe showing potential for predictability over longer lead-times
- Regional differences in both vulnerability and acclimatization have to be taken into account when using climate predictions in heat-health action plans.

3.6 Water balance forecasts for East Africa (MeteoSwiss)

In addition to the analyses of CII forecasts based on single meteorological variables, we also analysed multi-variable CII forecasts. Some hope for increased skill in such multivariate indices seems justified given the physical basis of dynamical seasonal forecast systems ensuring physical consistency in the output of different meteorological variables.

In the context of food security in Eastern Africa and the LEAP prototype (also see discussion in the previous section), we investigated the provision of seasonal forecasts of the cumulative water balance at the horn of Africa based on ECMWF System 4 predictions. Drought indices based on the meteorological water balance (defined as precipitation minus potential evapotranspiration) have proven to be suitable indicators for describing drought phenomena and impacts on various timescales (Vicente-Serrano et al., 2010, Buegería et al., 2014). The most relevant time period for food security in Ethiopia comprises the months June through September, as this covers the relevant growth season of the major food crops in the area. We therefore chose the water balance over this time span as a CII, to be predicted based on the seasonal forecast issued in May.

The water balance could be computed based on a monthly basis, in principle, but we used cumulative water balances based on daily values of precipitation and potential evapotranspiration here, as we would like to capture any potential in sub-monthly variability of the forecasts, and relying on daily output also adds flexibility of choosing different aggregation periods later on, if required by users.

Daily potential evapotranspiration values were computed using the Hargreaves equation

$$EPT = 0.0023 \cdot (T_{mean} + 17.8) \cdot \sqrt{T_{max} - T_{min}} \cdot R_a$$

where Ra is the extraterrestrial solar radiation (Wm-2) approximated depending on latitude and day of year as described in Allen et al. (1996).

Bias correction of daily temperature and precipitation output was performed against the WATCH Forcing Dataset-ERA Interim (WFDEI, Weedon et al., 2011 and 2014), which also served as the reference data set for the skill analyses. Daily minimum and maximum temperatures were bias-corrected using a lead-time dependent mean bias adjustment as described in Mahlstein et al. (2015) and precipitation was processed using a quantile mapping method. In all cases, the correction factors were determined in a leave-one-out configuration.

The bias correction of the input variables proved to be important for achieving skill in seasonal water balance (WB) forecasts (Figure 14). While the bias correction didn't influence the skill of the two WB components precipitation and evapotranspiration in terms of correlation, discrimination or tercile probability predictions (not shown), the removal of the systematic biases of the two components was evidently essential to achieve some skill in their combination in form of the cumulative water balance.

Comparing the skill of the two components precipitation and evapotranspiration with that of WB predictions (Figure 14) indicates that skill of WB forecasts is largely dominated by precipitation skill. However, there are areas where WB forecast skill differs from that of precipitation. WB forecasts are more skilful in the Northern part of the domain (Sudan and Egypt) and less skilful in SW Saudi Arabia than the precipitation forecasts. Both these areas receive basically no precipitation during the season considered here, and evidently WB skill is then influenced by the respective skill in evapotranspiration.

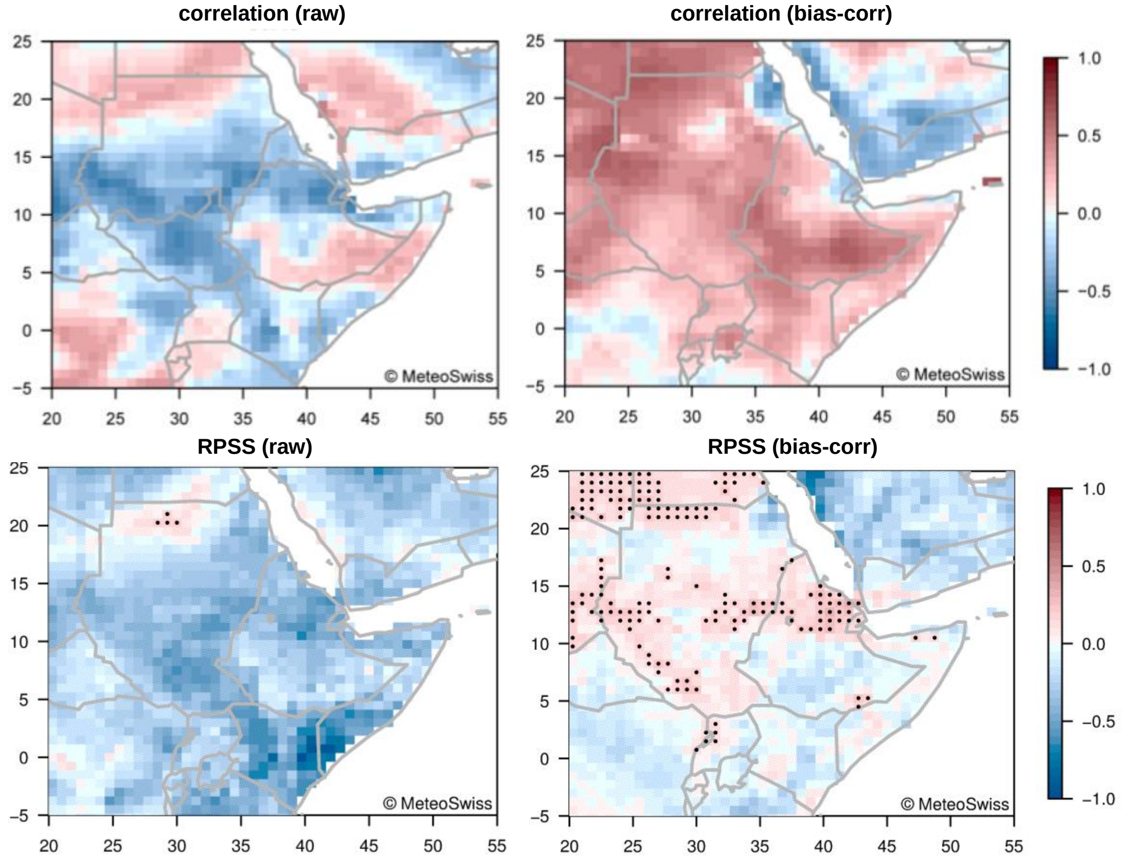

Figure 14: Correlation (top) and ranked probability skill score for tercile predictions (bottom) of cumulative JJAS water balance, left: from raw model output, right: after bias-correction of daily input variables Tmin, Tmax, and precipitation. Results based on ECMWF S4 hindcasts 1981-2012 vs WFDEI data set.

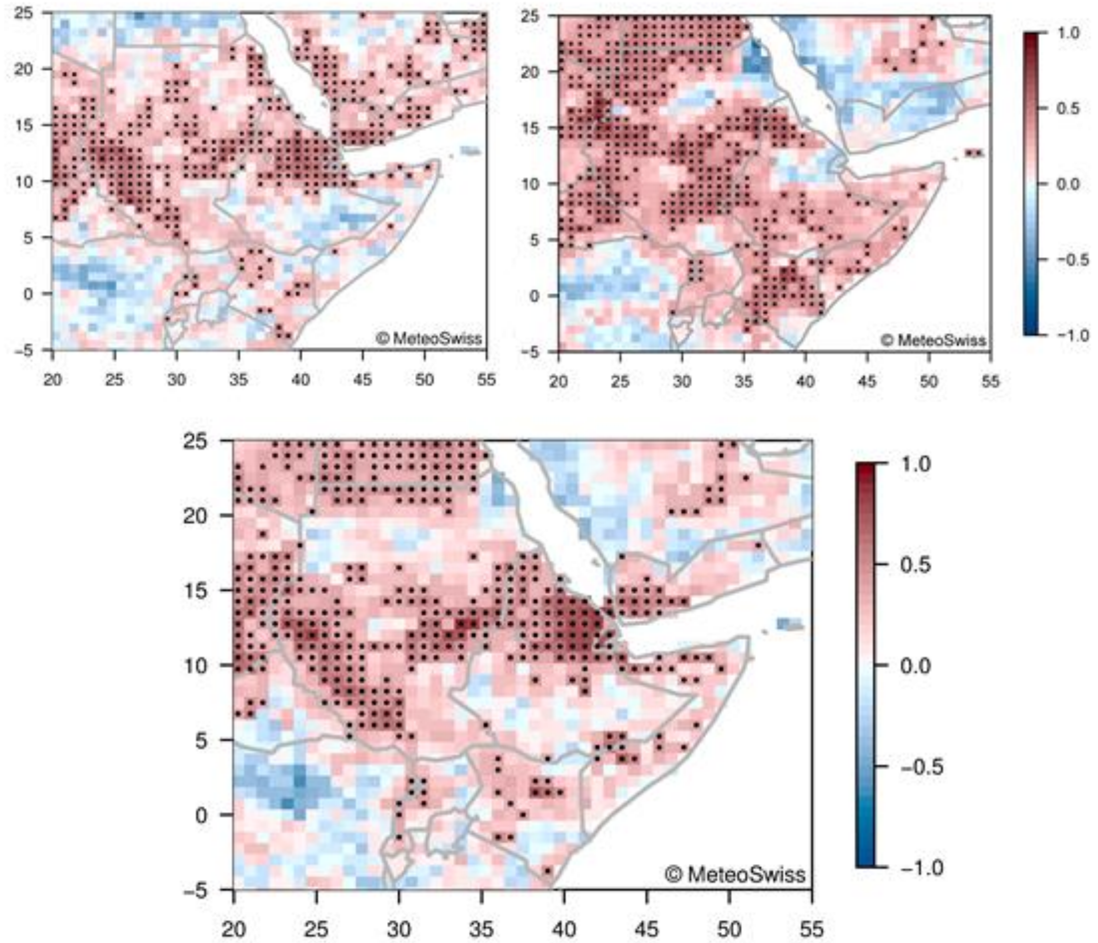

Figure 15: ROCSS for lower terciles of cumulative precipitation (top left), upper tercile of potential evapotranspiration (top right) and lower tercile of water balance predictions (bottom), JJAS forecasts issued in May.

For crop relevant areas in Ethiopia, namely the highlands, skill in WB is not increased compared to that of precipitation. Exemplary forecasts of JJAS precipitation and WB for a location in N Ethiopia are presented in Figure 16. The forecast signals for precipitation and water balance are essentially identical in this case.

Trying to generalize some of the findings in this study we conclude that carry-over of skill in underlying variables onto the multivariate CII is possible. It appears that missing skill in one of the underlying variables can only be compensated if that particular variable doesn't have a dominant influence on the multivariate CII (dominant in the sense that the variability of one variable largely determines that of the CII).

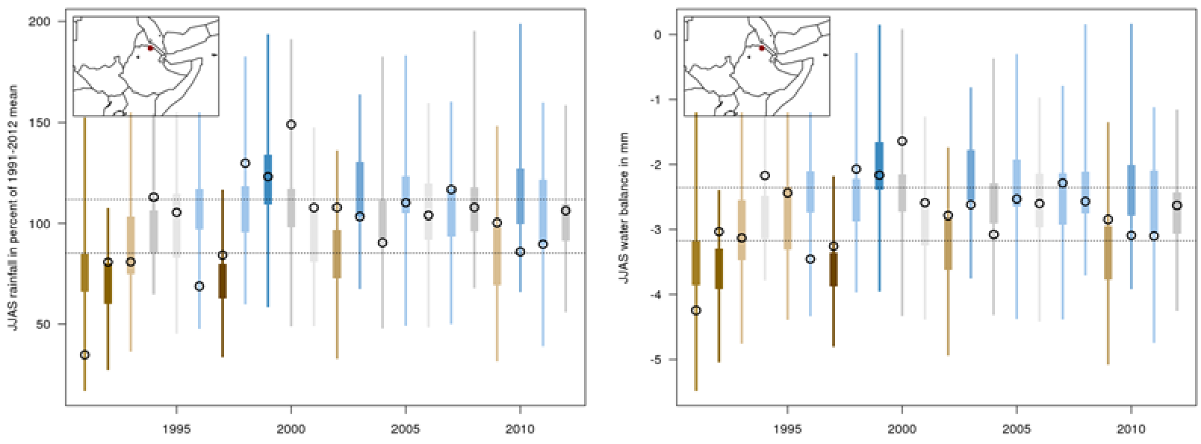

Figure 16: JJAS precipitation (left) and water balance (right) forecasts for an exemplary location in northern Ethiopia. Boxes represent the forecast distributions (ECMWF S4 hindcasts) and circles show the values of the reference data set (WFDEI).

Key point

- Carry-over of skill in underlying variables onto multivariate index is possible, implying that skill in multivariate index can be obtained despite missing skill in one of the underlying variables.

3.7 Drought and humanitarian needs forecasts for Ethiopia (ENEA)

The skill of forecasted aggregated indices of climate impact has been compared with the corresponding skill in the prediction of the underlying meteorological variables. The ECMWF System 4 ensemble forecast has been adopted as the baseline forecasting system, while the LEAP platform computes two impact indicators: the crop Water Requirement Satisfaction Index (WRSI) and the estimated humanitarian needs in terms of people affected by droughts. The analysis shows that even a mild and localized skill of the underlying forecasting system can lead to significant performance in the prediction of impact indexes and allows the production of usable climate information.

We have used seasonal forecast of rainfall over Ethiopia as the input to an existing early warning system platform (LEAP), which normally uses satellite rainfall estimates to assess the performance of the crop season and to provide an early outlook of the humanitarian needs for the country. One key objective of the activity conducted under this work package was to verify the implication of the current skill of the seasonal forecasting system for the production of aggregated indices, beyond the pure meteorological variables.

The case of LEAP is particularly interesting because there exist two layers of aggregated indices. As a first layer, LEAP uses the rainfall date to compute the WRSI, which is particularly useful for capturing water stress due to lack of rainfall for different crops. In the second step, WRSI is used as the basis to derive an aggregated estimate of the number of people that are potentially affected by droughts and need humanitarian assistance. It is therefore useful to compare the skill of forecasts of different indices ranging from the raw meteorological variables to the humanitarian needs. The skill of the forecasting system has been already analysed in the previous reports. In this report, we focus on the comparison between the raw meteorological variables and the aggregated indices.

Skill of WRSI

LEAP focuses on quantifying the impacts of droughts on livelihoods in rural areas of Ethiopia. It is therefore relevant to evaluate the performance of the forecasts, and of the associated indices, in describing dry events. The use of ROCss is particularly useful for this purpose since it allows the focus on specific classes of events.

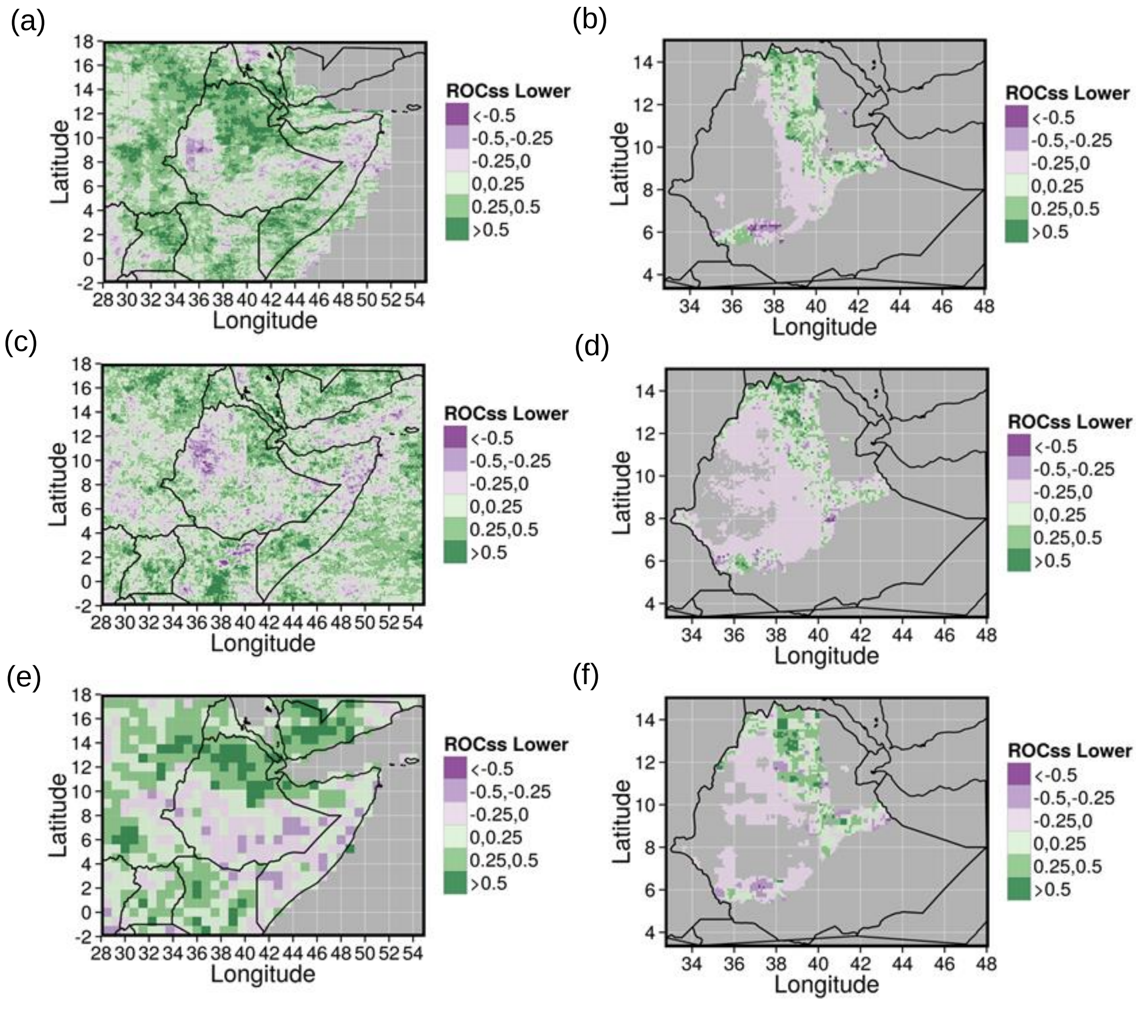

Figure 17: ROC skill scores for the lower tercile of JJAS rainfall from a 15-member ensemble hindcast from ECMWF System4 JJAS (left column) and for the corresponding LEAP WRSI (right column). The skill scores are evaluated by adopting different observational references: TAMSAT (a,b) ARC (c,d) WFDEI (e). The 1996-2012 15-member ensemble hindcast is considered for the skill analysis and for the computation of the WRSI.

Figure 17 compares the ROCss of June-September (JJAS) rainfall and the corresponding WRSI derived from the ECMWF System 4 ensemble hindcasts. In the analysis, the events in the lower tercile, reflecting dry conditions, are considered and the ensemble hindcasts for the years 1996-2012 are compared with three different observational baselines (ARC2, TAMSAT, and WFDEI).

The comparison shows significant differences in the skill scores depending on the observational baseline that is adopted as a reference. It is worth noting that TAMSAT is usually considered a more reliable observational rainfall estimate over this area (Dinku et al., 2008). Overall, the skill of the forecasting system is higher over the north, north-north east area of the country, which is also the region with the largest interannual variability of the seasonal rainfall, and therefore more exposed to the risk of drought. Over the western area, the skill is particularly low. However, this area is usually extremely wet (annual rainfall larger than 1000mm) and usually not exposed to the risk of drought. Figure 17 shows also that the corresponding WRSI preserves approximately the same pattern of positive skill as the underlying rainfall data. Note that the results presented in this section are consistent with the findings described in other sections in this report.

Skill of the needs estimate

The main scope of LEAP is to produce an outlook of humanitarian needs at national level. LEAP adopts the following model to relate drought conditions to the number of beneficiaries:

$$N = N_0 + K \cdot \left[\log\left(W_M - F\right) - \log\left(RWRSI - F\right)\right] \qquad 1$$

which uses the WRSI output from the LEAP software.

In equation 1 the parameter K is defined as:

$$K = \frac{N_R - N_0}{\log\left(W_M - F\right) - \log\left(W_0 - F\right)},$$

and the parameters are

N_0: Needs in case of optimal rainfall (chronic food insecure);
N_R: Population at risk;
W_0: Lowest observed value of RWRSI;
W_M: Optimal RWRSI;
F: Systemic failure level.

The *regional* WRSI (RWRSI) is defined as the weighted average of a woreda-level *combined* WRSI (CWRSI):

$$RWRSI = \frac{\sum_W P_W \cdot WRSI_W}{\sum_W P_W} \qquad 2$$

where the subscript W indicates the woreda, P is the corresponding population. Note that the analysis focuses only on those areas of the country that are more exposed to the risk of drought, which correspond also to the areas where hindcasts are more skilful.

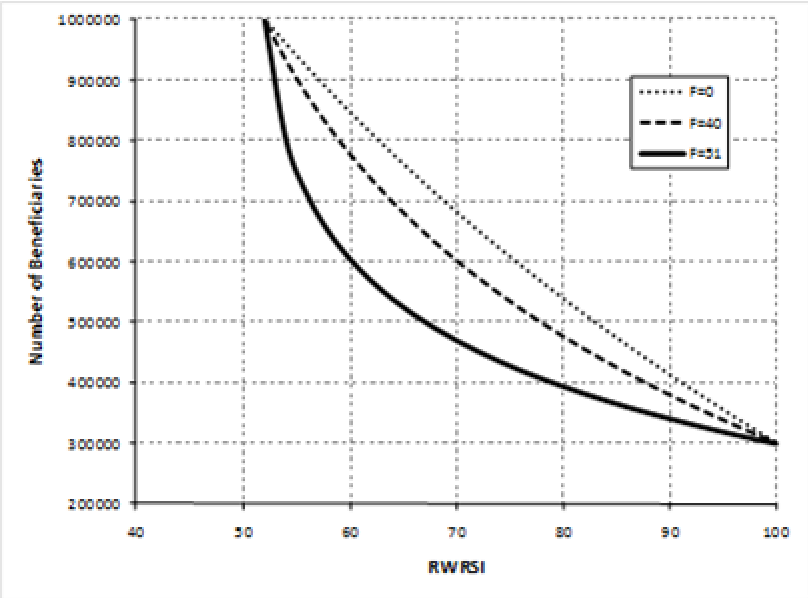

Figure 18: The log-model relation between RWRSI and the number of beneficiaries.

NOTE: The sample curves are computed by setting the following values of the log-model parameters: N_0=300000; N_R=1000000; W_0=52; W_M=100. The value of the systemic failure level F is indicated by the line style as indicated in the legend. For very low values of the parameter F, the relation between RWRSI and the Number of Beneficiaries is approximately linear.

The log-model relation between RWRSI and the number of beneficiaries has a weak slope when RWRSI is close to 100 (Figure 18). This means that with a weak water stress the number of beneficiaries in needs of assistance remains close to zero.

As RWRSI decreases, the slope of the curve increases and for RWRSI close to the regional failure level F even a small decrease in RWRSI (little additional water stress) a large increase in livelihood protection needs can be produced. The model aims at describing the failure of community based coping mechanism when the external stress (drought) strengthens.

Figure 19 compares the performance of the forecasting system based on LEAP and ECMWF System 4 in predicting the variability of the average WRSI with the performance in the prediction of the potential humanitarian needs for the country. In the figure, the observational baseline (red line) is based on the TAMSAT rainfall estimate while the ensemble hindcast is based on a 15-member subset of the global forecast.

In this case the increase in the overall skill of the forecast is remarkable. While for the average WRSI the correlation with historical records is around 0.30, the correlation of the estimated historical humanitarian needs with the corresponding hindcasts is more than 0.80.

Note that the needs estimates, based on satellite products, are usually available in September-October (end of the crop season), while needs estimates based on forecast products would be available already in May, at the beginning of the crop season. Please also note that estimated needs do not necessarily match the actual historical beneficiaries, which are identified on the basis of additional factors that might not be directly related to the occurrence of a drought (including the fact that the national Production Safety Net Programme, partially covers for the assistance to annual emergencies).

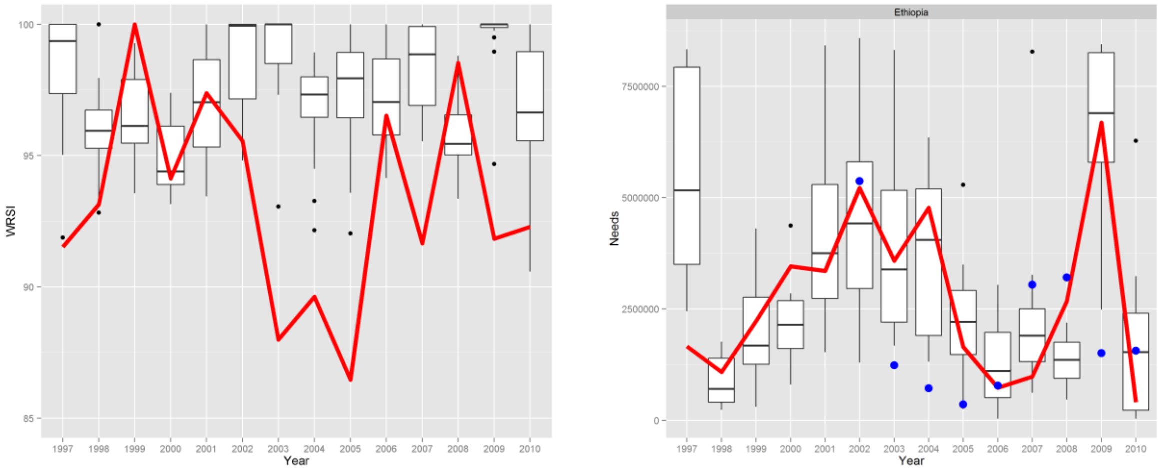

Figure 19: Hindcast WRSI (left) and needs for humanitarian interventions (right) in Ethiopia based on satellite rainfall estimates (red lines) and seasonal forecast products (box-plot). Historical actual needs are also reported (blue circles in right panel).

Three factors contribute to the increased skill of the forecast of the impact index, compared to the skill of the underlying meteorological values

First, the impact index targets a particular class of extreme events (severe rainfall deficit). Therefore, it is not strictly required that the forecast describes the full range of climate variability. For example, while floods would be linked to a more localized interplay between the intensity of rainfall and the local orography, droughts may well be captured as the consequence of larger scale anomalies in the atmospheric circulation and therefore compatible even with the coarse resolution of global forecasting systems.

Secondly, the underpinning drought indicator cumulates the effect of rainfall anomalies throughout the main crop season. Therefore, the requested skill of the seasonal forecast is on the long term, persistent anomalies that are more likely related to large scale anomalies of the climate system, such as those brought about by El Nino.

Finally, the transfer function that is adopted to convert water budget anomalies into needs for humanitarian interventions has a logarithmic shape, which enhances the effects of large deviations and smooth's out the presence of relatively small deviation from the norm. As a consequence, even a mild skill of the underlying forecasting system can lead to significant performance in the prediction of impact indexes and in providing usable climate information.

Key points

- Skill in Water Requirement Satisfaction Index (WRSI) forecasts for Ethiopia is marginal, but humanitarian needs estimates can be much more skilfully forecast
- Additional skill in humanitarian needs estimates likely results from:
- Sensitivity of needs estimate to long-term large-scale events (droughts)
- Co-location of WRSI skill in sensitive regions. That is, regions with skilful WRSI forecasts happen to be most prone to drought-related food shortages.

Planned publications

Forecasting humanitarian needs in Ethiopia. Calmanti, De Felice, Law, Bosi.

The cost-benefit of humanitarian needs outlook based on ensemble seasonal forecast. Venton, Calmanti, Bosi.

3.8 Interpretation of results and possible ways forward

The previous sections have illustrated the potential and challenges related to seasonal forecasts of indices in the various sectors considered. In the following, we discuss overarching aspects of seasonal forecasts of indices.

Building on the findings from the humanitarian needs forecasts for Ethiopia (Section 3.7), we demonstrate with an alternative set of indices how spatial aggregation with a user perspective can help to increase skill and usefulness of seasonal forecasts. Furthermore, we show that skill of forecasts of indices is closely related to the skill in seasonal averages of the underlying meteorological quantities (Bhend et al., 2016). This finding is useful to estimate expected skill in CII forecasts. For many applications, finally, it will be important to explore the space-time variability of seasonal forecast skill to identify opportunities for skilful and thus useful forecasts to be made. We have addressed this need by developing a web-based application to explore seasonal forecast skill.

Benefits of spatial aggregation

Location-specific seasonal forecasts of indices are only marginally skilful in many areas of the world and in particular in Europe. Spatial aggregation, on the other hand, may help to improve the signal to noise ratio of the predictable signal and thereby enhance forecast quality (see also discussion on the increase in forecast performance for humanitarian needs in eastern Africa presented in the previous section). Such aggregation, however, is only beneficial, if the aggregated quantity is still of relevance to potential users.

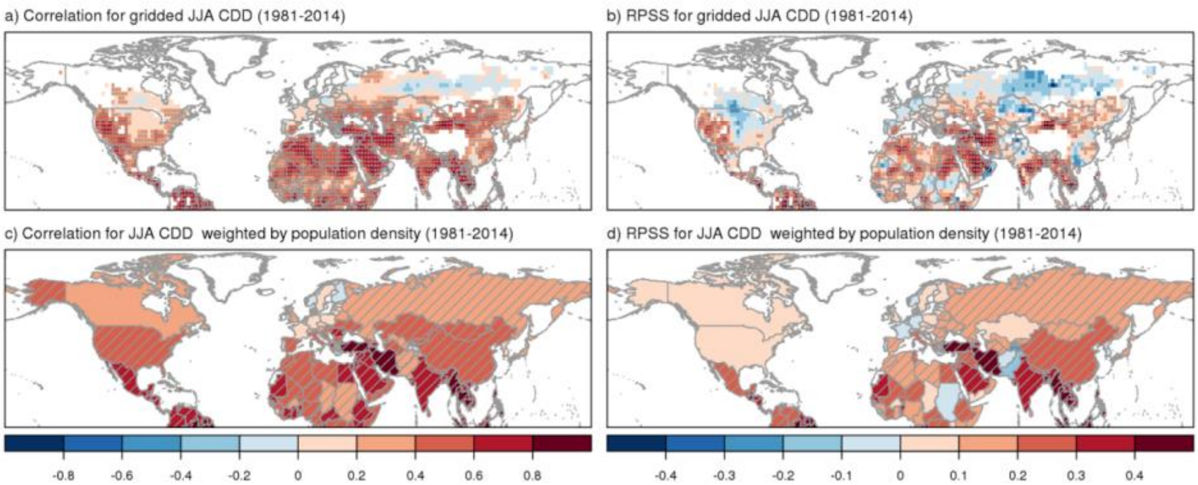

Figure 20: Correlation (a, c) and RPSS (b, d) of JJA cooling degree days (a,b) and population-density-weighted national averages of cooling degree days as a proxy for national energy demand for cooling (c,d). Stippling denotes correlations and RPSS significantly (at 5% level) larger than zero.

To exploit the benefits of aggregation on skill while preserving relevance to users, one may consider issuing forecasts of national (or regional) energy demand for cooling instead of gridded forecasts of cooling degree days (such as presented in D22.2). Here, we use the population-weighted national average of cooling degree days as a proxy for national energy demand for cooling. Correlation and RPSS of gridded forecasts of summer (JJA) cooling degree days derived from daily temperature forecasts with the ECMWF System 4 initialized in May are shown in Figure 20 (a, b). Correlation and RPSS of the national energy demand for cooling (i.e. weighted national averages of cooling degree days) are shown in Figure 20 (c, d). We use cooling degree days and national energy demand derived from daily temperature time series of ERA Interim (Dee, et al. 2011) for the period 1981-2104 for verification.

After aggregation, we find significantly positive correlation and RPSS for most countries in the northern hemisphere. In particular, we find that the area for which skilful forecasts can be issued increases (Figure 21). Figure 21 also shows that this improvement is due to the aggregation and not due to the weighting (green versus blue boxes). The weighted aggregation is here merely useful to preserve user-relevance of the derived aggregated index (i.e. national energy demand as opposed to national average of cooling degree days). In other cases such as for heating degree days (not shown) the weighting results in an additional increase in skill as population density is highest in areas with skill in heating degree day forecasts. We stress, however, that such effects are purely coincidental. We cannot think of physical reasons as to why skill in forecasts is expected to be higher in densely populated areas. In fact, the example with cooling degrees (Figure 21) illustrates the lack of a relationship between population density and forecast skill.

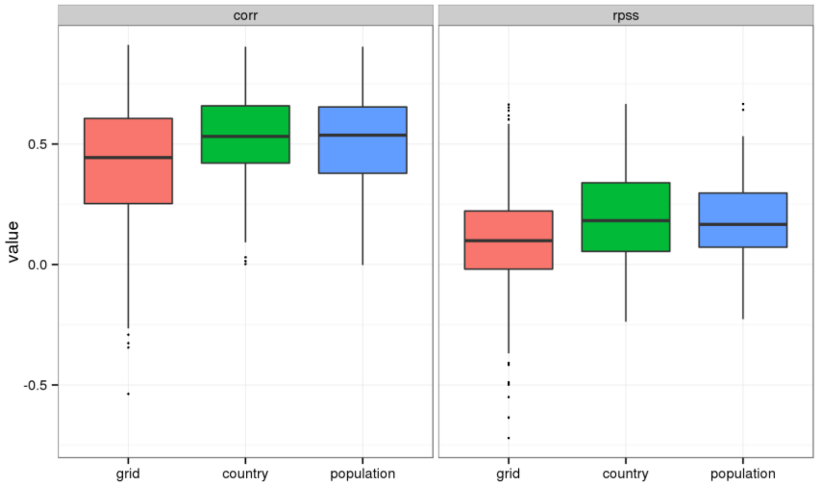

Figure 21: Area weighted distribution of correlation (left panel) and RPSS (right panel) for JJA CDD. Aggregation to the 2x2 degree grid is shown in red, aggregation to the country level (and subsequent disaggregation to the 2x2 grid) in green, aggregation to country level with weighting by population density in blue.

We conclude that the combination of both aggregation and weighting may lead to not only more skilful forecasts but also more useful forecasts providing more actionable information to users by taking into account their specific needs. It becomes evident, that a user perspective has a strong impact on the value of forecasts, an issue that has to be taken into account when designing weather and climate services.

Relationship of skill in index forecasts with skill in the underlying variable

We have analysed the relationship between skill in forecasts of climate indices and skill in the underlying meteorological variable these indices are derived of (Bhend *et al.,* 2016). With synthetic forecasts generated using a toy model, we show that skill in counts and accumulated threshold exceedances is generally reduced compared to skill in seasonal means if only seasonal variability is predictable. This reduction is strongest for skilful forecasts and for thresholds in the tail of the distribution, i.e. for indices describing rare events. Similar reductions in skill are also found in the operational forecasting system (ECMWF System 4). From the similarity of the idealized toy model results and the results from the operational system we conclude that there is little evidence of enhanced (or reduced) predictability of CIIs in excess to what can be expected due to predictability of the seasonal mean alone. Our results further suggest that skill in predicting seasonal mean quantities can be used as an estimate for an upper bound of the expected skill of forecasts of indices without having to compute and verify the forecast of indices. This finding may help to simplify stakeholder interaction and feasibility studies. Also, our findings imply that forecasts of CIIs can be issued without considerable loss in predictive skill for CIIs that describe moderately rare events. In many situations, the increased user relevance of index forecasts may thus more than compensate for the slight loss in predictive skill of such forecasts.

Interactive visualisation of skill scores

Predictive skill of seasonal forecasts varies strongly across multiple dimensions including in space, by variable or climatic index, by lead time and time of the year, and by spatio-temporal aggregation. Generally, seasonal forecasts are more skilful in the tropics than in the mid-latitudes and more skilful for temperature and related indices than precipitation. As the skill of index forecasts tends to follow closely the skill in forecasts of seasonal means of the underlying meteorological quantity (Bhend et al., 2016), skill in seasonal means of basic meteorological parameters such as temperature and precipitation can be used as an upper bound for the expected skill of forecasts of indices.

To explore the multi-dimensional variations in skill, we have developed an interactive web application (https://meteoswiss-climate.shinyapps.io/skill_metrics, Wehrli et al., 2016). This application allows the users of seasonal forecast information to browse through a comprehensive set of verification metrics for the operational seasonal forecasting system of the ECMWF (ECMWF System 4, Molteni et al., 2010). The application has been developed with a user perspective in mind in that users can select a target season and area for which they want to analyse forecast skill and compare quality of forecasts with different lead times (Figure 22).

Key Points

- Weighted aggregation with a user perspective can improve forecast quality.
- Skill in seasonal mean of underlying variable can be used to estimate an upper bound for skill in forecasts of derived (univariate) indices.
- Forecast quality varies considerably in space and time. Tools to identify opportunities for skilful forecasts may help to increase usefulness.

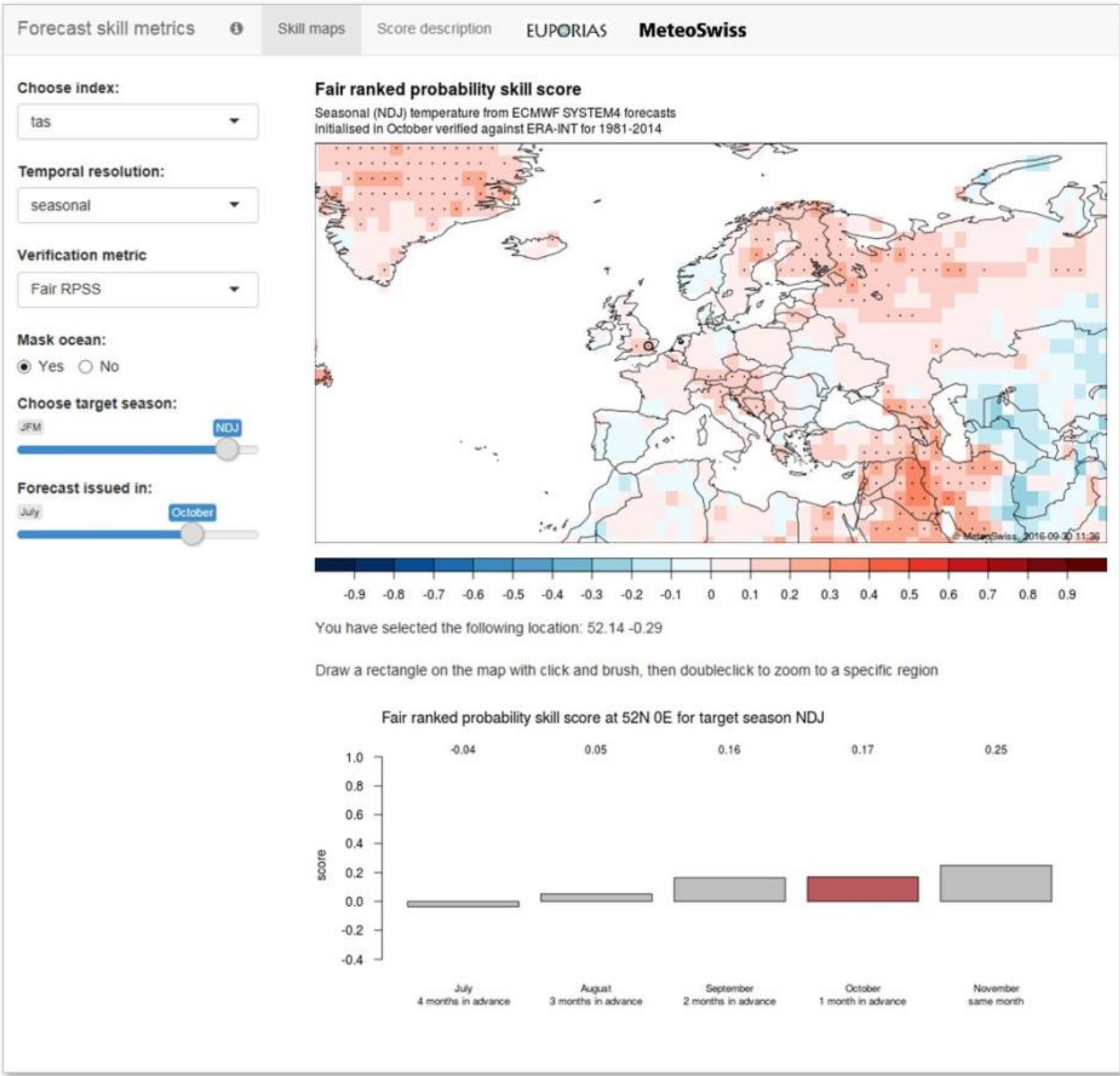

Figure 22: Screenshot of the interactive web application to explore forecast skill of ECMWF System 4 forecasts developed as part of EUPORIAS. The ranked probability skill score (RPSS) for November-January forecasts issued in October (lead month 2) is shown in the map, with a time series of RPSS for different lead times for the selected location in the south-eastern UK shown in the bottom half.

4 Lessons Learnt

Producing and assessing forecasts of climate indices is challenging (also see section on lessons learnt in D22.2[4]). In WP22, we have developed common, publicly available software tools that facilitate download, post-processing (i.e. bias correction), index computation, and verification of seasonal forecasts. The use of common tools and datasets simplifies the intercomparison and thereby the interpretation of the results. Sharing these tools is key to capacity building within the project and beyond.

Skill of seasonal forecasts is often marginal over Europe with slightly enhanced predictability of temperature-related indices in summer over southern Europe. In general, however, skill varies considerably by variable or index, forecasting system, in space and time, with forecast lead time and with spatio-temporal aggregation of the forecasts. The variability of forecast quality makes it difficult for users to identify windows of opportunity for skilful forecast. As part of EUPORIAS, we have therefore developed an interactive web application[5] for users to explore the space-time variability of seasonal forecast quality.

Skill of forecasts of CIIs is generally slightly reduced compared to seasonal means of the underlying variables these indices are derived of. This reduction in skill is strongest for skilful forecasts and indices describing rare events with thresholds at the tail of the distribution of daily values; for indices describing moderately rare events, the reduction is much less pronounced (Bhend et al. 2016). This implies that often the enhanced user relevance of forecasts of indices is expected to outweigh the slight reduction in forecast skill.

In a few cases, we have been able to demonstrate an added value of forecasts of indices. The focus on aspects of climate variability (e.g. droughts) that are dominantly large-scale and thus exhibit better predictability can lead to such improvements. Similarly, spatial aggregation can help to improve forecast quality. In contrast, small-scale and short-lived climatic events (such as intense rainfall) appear to be difficult to forecast.

Uptake of forecasts of CIIs has been found to vary strongly between different user communities. CII forecasts can be useful for communicating with a more general audience and with stakeholders from sectors with a history of using CIIs (e.g. heating degree days in the energy and insurance sectors, or growing degree days in agriculture). Conversely, stakeholders from sectors with a long tradition in impact modelling (e.g. hydrology) are more inclined to using impact forecasts. Also, impact forecasts have been shown to benefit from sources of predictability not included in the global forecasting systems (e.g. soil wetness and snow melt for forecasts of river flow, see D22.2).

While being identified as a potentially useful additional source of information, lack of forecast skill in Europe prevents CII forecasts to be usefully applied in many of the situations analysed. Shorter-range forecasts, however, have been demonstrated to be skilful in the heat-related mortality case study (Lowe et al., 2016). The focus on sub-seasonal predictions with better forecast skill may help to increase uptake and use of climate forecasts in Europe.

[4] http://www.euporias.eu/system/files/D22.2_Final.pdf
[5] https://meteoswiss-climate.shinyapps.io/skill_metrics

5 Links Built

Links to other work packages and deliverables of EUPORIAS

In WP21, tools developed as part of this work package have been used for the deliverable D21.3 on the added value of dynamical and empirical downscaling for forecasts of CIIs. D21.3 also discusses relevant results from this deliverable.

In WP43, findings from WP22 have been used to support the development of a health case study microsite: http://cmtool.euporias.eu/.

Wind speed assessments have been used to support the development of the RESILIENCE prototype in WP42. The viticulture indices and the statistical downscaling have been used in the development of the FORWINE and the rainfall indices for the SOSRhine case study in WP42.

Verification scores calculated on CIIs based on temperature and precipitation have been compared to those of soil wetness and river flow over France to build the RIFF prototype. This comparison allowed us to identify catchments with high predictability potential at the seasonal scale due to external forcing such as snow melt or aquifers. In an operational setting, tests have been conducted with real-time forecasts during summer 2016 with EPTB SGL, a dam manager on the Seine basin. CIIs were found to be useful as a complement to hydrological products to synthesize complex climate forecasts.

Technical collaborations

Results presented in this deliverable have been computed using novel forecast verification metrics developed as part of the SPECS project (Siegert, 2015) and processing tools developed in EUPORIAS. This set of tools is currently being used in other projects including the German MiKlip project on decadal predictions and Copernicus Climate Service activities. As a consequence, these tools are being developed further to suit the needs of the growing user communities.

Links to other projects

Links to the EUPORIAS partner project SPECS, led by BSC, are manifold. In addition to the technical collaboration described above, wind speed assessments have been used in WP61 of SPECS (pilot applications).

Multiple partners involved in this work package are contributing to the Copernicus Climate Change Service (C3S) project QA4Seas targeting the quality control and verification of the C3S seasonal forecasts. BSC is further leading the work package on wind power in the CLIM4ENERGY project that aims at responding to the C3S objectives, by demonstrating the added value of tailored climate information for the transitioning European energy sector.

MeteoSwiss in collaboration with FU Berlin is involved in the MiKlip 2 project CALIBRATION to development of recalibration methods for use with monthly to decadal forecasts. The experience on CII forecasting gained within EUPORIAS is also directly feeding into the development of user-tailored seasonal forecasts in the Andean region as part of the ongoing CLIMANDES project in the framework of WMO’s Global Framework on Climate Services

(GFCS). In addition, MeteoSwiss takes part in the Horizon 2020 project HeatShield to analyse heat-stress to workers and will implement an early warning system based on long-range forecasts of heat-related indices.

As part of the NACLIM project, collaboration between VITO and IC3 has been set up to test the feasibility of a TRM forecasting system adapted to urban environments. This ongoing collaboration consists in the successful adaptation of a dynamical urban climate model (UrbClim) to reproduce the urban heat island effect and the diurnal temperature ranges of the city of Barcelona.

The Earth System Services Group of the Earth Sciences department of the BSC is involved in a number of international projects and a national project called RESILIENCE. The team is a partner in two European projects within the Horizon 2020 programme: PRIMAVERA and IMPREX. PRIMAVERA aims to deliver novel, advanced and well-evaluated high-resolution global climate models tailored and actionable by sector-specific end-users such as the energy sector; and IMPREX aims to improve the prediction and management of meteorological and hydrological extremes which might have an impact on energy facilities, energy production and management. BSC also participates in an ERA-NET project called NEWA for the preparation of the New European Wind Atlas that will include seasonal and sub-seasonal wind predictions.

6 References

Allen, R. G., L.S. Pereira, D. Raes, M. Smith: Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56, FAO - Food and Agriculture Organization of the United Nations, Rome, 1998.

Amatulli, G., Camia, A., San-Miguel-Ayanz, J., 2013. Estimating future burned areas under changing climate in the EU-Mediterranean countries. Science of the Total Environment 450–451, 209–222.

Ballester, J., Robine, J. M., Herrmann, F. R., & Rodó, X. (2011). Long-term projections and acclimatization scenarios of temperature-related mortality in Europe. Nature Communications, 2, 358.

Ballester, J., Rodó, X., Robine, J.M. & Herrmann, F.R. (2016). European seasonal mortality and influenza incidence due to winter temperature variability. Nature Climate Change 6, 927–930.

Bedia, J., Herrera, S., Camia, A., Moreno, J.M., Gutierrez, J.M., 2014a. Forest Fire Danger Projections in the Mediterranean using ENSEMBLES Regional Climate Change Scenarios. Clim Chang 122, 185–199. doi:10.1007/s10584-013-1005-z

Bedia, J., Herrera, S., Gutiérrez, J.M., 2014. Assessing the predictability of fire occurrence and area burned across phytoclimatic regions in Spain. Nat Hazards Earth Syst Sci 14, 53–66. doi:10.5194/nhess-14-53-2014

Bedia, J., Herrera, S., Gutierrez, J.M., Benali, A., Brands, S., Mota, B., Moreno, J.M., 2015. Global patterns in the sensitivity of burned area to fire-weather: Implications for climate change. Agr. Forest Meteorol. 214–215, 369–379. doi:10.1016/j.agrformet.2015.09.002

Beguería, S., S. M. Vicente-Serrano, F. Reig, and B. Latorrea (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int. J. Climatol. 34: 3001–3023.

Bhend, J., I. Mahlstein, and M.A. Liniger (2016). Predictive Skill of Climate Indices Compared to Mean Quantities in Seasonal Forecasts. Quarterly Journal of the Royal Meteorological Society, accepted for publication, doi: 10.1002/qj.2908

Bladé, I., Liebmann, B., Fortuny, D., Oldenborgh, G.J. van, 2011. Observed and simulated impacts of the summer NAO in Europe: implications for projected drying in the Mediterranean region. Clim Dyn 39, 709-727. doi:10.1007/s00382-011-1195-x

Blanco-Ward D, Queijeiro JMG, Jones GV (2007) Spatial climate variability and viticulture in the Miño River Valley of Spain. Vitis 46: 63−70

Branas J, Bernon G, Levadoux L (1946) Eléments de viticulture générale. Imp. Dehan, MontpellierJackson D (2001) Climate: monographs in cool climate viticulture–2. Daphne Brasell Associates, Wellington

Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, Andrae U, Balmaseda MA, Balsamo G, Bauer P, Bechtold P, Beljaars ACM, van de Berg L, Bidlot J, Bormann N, Delsol C, Dragani R, Fuentes M, Geer AJ, Haimberger L, Healy SB, Hersbach H, Hóllm EV, Isaksen L, Kallberg P, Köhler M, Matricardi M, McNally AP, Monge-Sanz BM, Morcrette JJ, Park BK, Peubey C, de Rosnay P, Tavolato C, Thépaut JN, Vitart F (2011) The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Q. J. R. Meteor. Soc.137(656):553–597, doi: 10.1002/qj.82.

Dinku, T., Chidzambwa, S., Ceccato, P., Connor, S. J., & Ropelewski, C. F. (2008). Validation of high-resolution satellite rainfall products over complex terrain. International Journal of Remote Sensing, 29(14), 4097-4110.

Favà, V., Curto, J.J., Llasat, M.C., 2015. Relationship between the summer NAO and maximum temperatures for the Iberian Peninsula. Theor. Appl. Climatol. 1-15. doi:10.1007/s00704-015-1547-2

Folland, C.K., Knight, J., Linderholm, H.W., Fereday, D., Ineson, S., Hurrell, J.W., 2009. The Summer North Atlantic Oscillation: Past, Present, and Future. Journal of Climate 22, 1082-1103. doi:10.1175/2008JCLI2459.1

Healy JD. (2003). Excess winter mortality in Europe: a cross country analysis identifying key risk factors. Journal of Epidemiology & Community Health 57, 784-789.

Hurrell, J.W., Kushnir, Y., Ottersen, G., Visbeck, M., 2003. An overview of the North Atlantic Oscillation, in: Hurrell, J.W., Kushnir, Y., Ottersen, G., Visbeck, M. (Eds.), Geophysical Monograph Series. American Geophysical Union, Washington, D. C., pp. 1-35.

Kettaneh A, Fardet L, Mario N, Retbi A, Taright N, Tiev K, Reinhard I, Guidet B, Cabane J. (2010). The 2003 heat wave in France: hydratation status changes in older inpatients. European Journal of Epidemiology 25, 517-524 (2010).

Kunst AE, Looman CWN, Mackenbach JP. (1993). Outdoor Air Temperature and Mortality in the Netherlands: A Time-Series Analysis. American Journal of Epidemiology 137, 331-341.

Lowe, R., Ballester, J., Creswick, J., Robine, J. M., Herrmann, F. R., & Rodó, X. (2015). Evaluating the Performance of a Climate-Driven Mortality Model during Heat Waves and Cold Spells in Europe. International Journal of Environmental Research and Public Health, 12(2), 1279-1294.

Lowe, R.; García-Díez, M.; Ballester, J.; Creswick, J.; Robine, J.-M.; Herrmann, F.R.; Rodó, X. “Evaluation of an Early-Warning System for Heat Wave-Related Mortality in Europe: Implications for Sub-seasonal to Seasonal Forecasting and Climate Services”. Int. J. Environ. Res. Public Health 2016, 13, 206.

Magalhães, N. (2008) - Tratado de Viticultura - A Videira, A Vinha e o “Terroir”. 1ª. edição. Espanha, Chaves Ferreira – Publicações, S.A..

Mahlstein, I., C. Spirig, M. A. Liniger, and C. Appenzeller (2015). Estimating daily climatologies for climate indices derived from climate model data and observations. Journal of Geophysical Research: Atmospheres, 120(7), 2808-2818.

Malheiro AC, Santos JA, Fraga H, Pinto JG (2010): Climate change scenarios applied to viticultural zoning in Europe. Clim Res 43: 163−177

Marmot Review Team. (2011). The Health Impacts of Cold Homes and Fuel Poverty. https://www.foe.co.uk/sites/default/files/downloads/cold_homes_health.pdf. Last accessed in January 2016.

McMichael T, Montgomery H, Costello A. Health risks, present and future, from global climate change. BMJ 344, e1359, doi:10.1136/bmj.e1359 (2012).

MeteoSwiss, 2016. easyVerification: Ensemble Forecast Verification for Large Data Sets. R package version 0.3.0. https://CRAN.R-project.org/package=easyVerification

Michelangeli, P. A., Vrac, M., and Loukos, H.: Probabilistic downscaling approaches: application to wind cumulative distribution functions, Geophys. Res. Lett., 36, L11708, doi:10.1029/2009GL038401, 2009

Molteni F, Stockdale T, Balmaseda M, Balsamo G, Buizza R, Ferranti L, Magnusson L, Mogensen K, Palmer T, Vitart F (2011). The new ECMWF seasonal forecast system (System 4). ECMWF Technical Memorandum 656.

Pepler, A. S., Díaz, L. B., Prodhomme, C., Doblas-Reyes, F. J., & Kumar, A. (2015). The ability of a multi-model seasonal forecasting ensemble to forecast the frequency of warm, cold and wet extremes. Weather and Climate Extremes.

Prodhomme, C., Doblas-Reyes, F., Bellprat, O., & Dutra, E. (2015). Impact of land-surface initialization on sub-seasonal to seasonal forecasts over Europe. Climate Dynamics, 1-17.

San-Miguel-Ayanz, J., Schulte, E., Schmuck, G., Camia, A., 2013. The European Forest Fire Information System in the context of environmental policies of the European Union. Forest Policy and Economics 29, 19–25. doi:10.1016/j.forpol.2011.08.012

Santander Meteorology Group, 2016a. loadeR: R Package for Climate Data Loading and Manipulation. R package version 1.0-4. https://github.com/SantanderMetGroup/loadeR/wiki

Santander Meteorology Group, 2016b. downscaleR: Climate data manipulation and statistical downscaling. R package version 1.3-3. https://github.com/SantanderMetGroup/downscaleR/wiki

Santos, JA; Malheiro AC; Pinto JG; Jones GA (2012): Macroclimate and viticultural zoning in Europe: observed trends and atmospheric forcing. Clim Res 51: 89–103, doi: 10.3354/cr01056

Scaife, A.A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R.T., Dunstone, N., Eade, R., Fereday, D., Folland, C.K., Gordon, M., Hermanson, L., Knight, J.R., Lea, D.J., MacLachlan, C., Maidens, A., Martin, M., Peterson, A.K., Smith, D., Vellinga, M., Wallace, E., Waters, J., Williams, A., 2014. Skillful long-range prediction of European and North American winters. Geophys. Res. Lett. 41, 2014GL059637. doi:10.1002/2014GL059637

Siegert, S. (2015). SpecsVerification: Forecast Verification Routines for the SPECS FP7 Project. R package version 0.4-1. http://CRAN.R-project.org/package=SpecsVerification

Trenberth, K.E., Paolino, D.A., 1980. The Northern Hemisphere Sea-Level Pressure Data Set: Trends, Errors and Discontinuities. Mon. Wea. Rev. 108, 855–872. doi:10.1175/1520-0493van Wagner, C.E., 1987. Development and structure of the Canadian Forest Fire Weather Index (Forestry Tech. Rep. No. 35). Canadian Forestry Service, Ottawa, Canada.

Vicente-Serrano, S.M., S. Begería, and J. I. López-Moreno (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index, Journal of Climate, 23, 1696-1718.

Viegas, D.X., Bovio, G., Ferreira, A., Nosenzo, A., Sol, B., 1999. Comparative study of various methods of fire danger evaluation in southern Europe. International Journal of Wildland Fire 9, 235. doi:10.1071/WF00015

Weedon, G.P., Balsamo, G., Bellouin, N., Gomes, S., Best, M.J. and Viterbo, P., 2014. The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data. Water Resources Research, 50, doi:10.1002/2014WR015638

Weedon, G.P., Gomes, S., Viterbo, P., Shuttleworth, W.J., Blyth, E., Österle, H., Adam, J.C., Bellouin, N., Boucher, O., Best, M., 2011. Creation of the WATCH Forcing Data and Its Use to Assess Global and Regional Reference Crop Evaporation over Land during the Twentieth Century. Journal of Hydrometeorology, 12, 823–848. doi:10.1175/2011JHM1369.1http://dx.doi.org/10.1002/qj.2908

Wehrli, K., J. Bhend, M. Liniger, 2016. Verification of Seasonal Forecasts. Technical Report MeteoSwiss, in preparation. http://www.meteoswiss.admin.ch/home/services-and-publications/publications%20.html?topic=/content/meteoswiss/tags/topics/forschung-und-zusammenarbeit/publication/fachbeitraege