WATExR

Climate seasonal prediction for adapting water resources to extreme events

European Research Area for Climate Services

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# Guidance document on the use of seasonal climate information of interest for the case studies.

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# 1. Introduction

The WATExR project proposes the integration of state-of-the-art seasonal climate predictions and the simulation of water quality for an efficient adaptation of water resource management to the frequency increase of extreme climatic events. Different studies have shown the potential application of seasonal climate forecasts in several sectors highly dependable on weather conditions. Agriculture has been identified in the literature as one of the main potential beneficiaries of this kind of climate forecasts for management practices and improve production (Palmer et al., 2004). However, there are other sectors that have also been recognise as potential beneficiaries of seasonal climate forecasts such as health, tourism, insurance, energy or water resources (Harrison et al., 2008b). In a water management context, seasonal climate predictions encompasses a time frame that can potentially be useful for decision-making and adaptation of water resource management. Nonetheless, the practical use of this kind of climate information in management decisions by users from different sectors is still quite limited, being the probabilistic communication of uncertainty one of the main limitations. Thus, the generation of seasonal predictions of water quality for the case studies defined in WATExR and the validation of these forecasts in the water quality sector is already a novel result of the project.

WATExR has an important climate component as an essential basis for the generation of hydrological and water quality forecasts. Most partners in WATExR are water quality modellers and stakeholders who are not familiar with seasonal climate predictions. Therefore, it is essential to provide some guidance of the characteristics and use of seasonal climate information of interest for the proper development of the project. The Meteorology Group from the University of Cantabria (UNICAN) comprises experts in climate with a wide experience in the treatment and analysis of different types of climate data. This partner is in charge of analysing the state-of-the-art climate data that best adapt to the project requirements in coordination with the partners involved in the different case studies. Following the open source philosophy of the project promoted by the European Union, the UNICAN group has developed some R packages to make easier the access to the climate data to the other partners and to perform intermediate transformations or post-processing to the data. Thus, this tool is easing the integration of seasonal climate predictions and the lake models considered in the different case studies with the guidance of the UNICAN group in coordination with the other partners.

This report presents an overall understanding of the current state of the seasonal climate forecasting: description, data available, forecast validation and uncertainty communication. The selection of the proper climate data to be used in the project is focused on the integration of state-of-the-art seasonal climate predictions and water quality simulations, which represents the main objective of the project. Particularities of the lake models considered in the different case studies defined in WATExR are considered to achieve this integration.

# 2. Seasonal climate forecast

Many sectors such as tourism, airlines, energy requirements and others rely on accurate forecasts to make management decisions. However, our society is no longer satisfied with short-range predictions, and sound long-range forecasts are more often demanded in different applications. Forecasts provide a qualitative tool for the assessment of weather and climate risk on a range of time scales from days to decades.

In this framework, seasonal climate forecast provides information on the average seasonal weather conditions which can be expected from a few months up to one year in advance (Doblas-Reyes et al., 2013).

Due to the chaotic and non-linear character of the atmosphere dynamics the trajectory obtained by the forecast system are strongly affected by slight differences on the initial conditions of the processes involved and, as a result, accurate daily predictions, as those given by the weather forecast system, are practically impossible beyond a two week period. As a result, seasonal climate forecast does not aim to predict the timing of a particular weather event with any accuracy (e.g., tomorrow it will rain 15mm in Madrid). It is only possible to predict deviations from the mean seasonal climatology some months in advance (e.g., next season will be above-, near- or below- normal if tercile-based categories are used).

The feasibility of seasonal climate prediction largely rests on the existence of slow, and predictable, variations in the soil moisture, snow cover, sea-ice, and ocean surface temperature, and how the atmosphere interacts and is affected by these boundary conditions. At seasonal time scales, the storage of heat and moisture by the ocean and the land, and the presence or absence of snow and sea ice became important factors (Doblas-Reyes et al., 2013). Predictability at this longer time-scale is influenced by components of the global climate system that change at slower rate than weather events, especially sea surface temperature (SST), which can influence the weather at some regions. The Niño-Southern Oscillation (ENSO) is a good example of a climatic phenomenon that contributes to the forecast quality on seasonal time scale (Palmer et al., 2005, Harrison et al., 2008a). A warm SST anomaly in the tropical Pacific Ocean leads to increased heat flux from the ocean to the atmosphere (coupled system). The extra latent heat release will impact the atmospheric circulation leading to climatic anomalies in remote regions of the globe (atmospheric teleconnections).

Both statistical/empirical and dynamical methods are used to generate seasonal climate predictions. The first approach is commonly based on statistical methods which relate the observed seasonal anomalies of the variable of interest (e.g., precipitation) with observed lagged SST anomalies (based on atmospheric teleconnections), usually by means of multivariate linear regression methods. The dynamical method is based on complex dynamical numerical models of the different components of the earth system. Mixed methodologies are also employed because statistical post-processing of the dynamical predictions is required by the users. Both methods are complementary because advances in statistical prediction are often associated with enhanced understanding, which leads to improve dynamical prediction, and vice versa.

In the last years, the advances in seasonal forecasting have been linked to the use of the dynamical methods based on fully coupled general circulation models (GCMs) (Troccoli, 2010). GCMs numerically solve complicated equations that describe the processes that occur in the different components of the global climate system (e.g. the atmosphere and the oceans) and their interactions. They contain a coupler module to simulate the exchanges of heat, moisture and momentum between the atmospheric and land and oceans interfaces. In the numerical process, the three-dimensional space is discretized in grid boxes with a typical horizontal resolution of about hundreds of kilometers. The equations are also simplified by making assumptions (e.g. hydrostatic approximation) and/or using parametrizations for modelling some processes at spatial scales smaller than the grid box size, which are commonly different from model to model. GCMs are in continually development in complexity due to the increase of the scientific understanding and computational resources.

Since atmospheric equations are non-linear, the time evolution of the solution is very sensitive to the initial conditions of the system. If two realizations of such a system are started from two very slightly different conditions, the two solutions will eventually diverge markedly (Lorenz, 1963). The initial uncertainty growth depends strongly on the initial conditions. The problem of the sensitivity to the initial conditions is usually overcome through the use of an ensemble of predictions. It consists of running the model several times from slightly different initial conditions. Each run is a member of the ensemble.

GCMs are not only sensitive to initial conditions, but to uncertainties in the model parameterization and numerical schemes as well (Palmer and Anderson, 1994) due to a distinct representation of the physical process. A method to take this uncertainty into account is the multi-model approach where the forecast of several GCMs is considered. multi-models generally produce more skillful forecasts due to a reduction of the ensemble error mean and a reduction of overconfidence because the ensemble spread is widened (Palmer et al., 2004, Wang et al., 2009).

A particularly valuable aspect of ensemble forecasting is its capacity to yield information about the magnitude and nature of the uncertainty in a forecast. In this case, the full set of deterministic forecasts is used for obtaining a more reliable and skilful estimate of the forecast probability.

The capability for seasonal climate predictions has been evolving in the last decades through different multi-model ensemble systems in order to obtain results not dependent on the model formulation and initial conditions. The improved collaboration between different centers and the increasing computing resources have promoted several initiatives for developing multi-model seasonal forecast systems. In Europe, the European Center for Medium–range Weather Forecasts (ECMWF) has pioneered the multi-model ensemble approach in the development of consecutive European projects (PROVOST, DEMETER, ENSEMBLES). The potential for the use of the multi-model ensemble in seasonal climate prediction was first addressed in PROVOST. These initiatives motivated the collaboration at international level in the last years in the European Operational Seasonal to Interannual Prediction (EUROSIP). The most recent initiative is the Climate Change Service (C3S) as part of the Copernicus Programme that plans to provide data from several state-of-the-art seasonal prediction systems. Out of Europe there are other institutions that produce seasonal climate forecasts using different coupled GCMs as the Climate Forecast System (CFS) from the National Centers for Environmental Prediction (NCEP) that provides real-time operational forecasts since March 2011.

The current numerical models for seasonal forecasting are not globally reliable. For each variable of interest and season of the year, their usefulness is limited to certain regions of the world, mainly the tropics due to a large extent to the seasonal predictability given by the ENSO phenomenon (Manzanas et al., 2014). Out of the tropics, the seasonal climate forecast skill might appear only conditionally, under strong phases of predictability sources such as the ENSO phenomenon (Frías et al., 2010). In most of the extratropics, the signals predicted by general circulation models are weak and do not add valuable information over a climatological forecast. Model improvements to increase their ability to accurately simulate the sources of seasonal predictability and the observed teleconnection patterns are relevant to increase the skill of the seasonal forecast systems out of the tropics.

## Particularities of the seasonal forecasting

Seasonal forecasting presents some particularities:

1) GCMs are initialized few times per month and run forward in time from six months to one year. Two terms are defined in this context: initialization time (moment in which the model is initialized) and lead-time (the time passed from the initialization moment to the beginning of the target season to be predicted).

2) Seasonal climate forecasts are intrinsically probabilistic. An ensemble of simulations is generated by using a set of slightly different initial conditions which provides forecasts with different atmospheric trajectories (members) compatible with the underlying slow variables.

Both aspects are shown in Figure 1. Each line represents the seasonal forecast generated for each member of the ensemble for two different times of initialization: January (red lines) and March (blue lines). In both cases the initialization moment to the beginning of the target season is 2 (lead-time). However, if we focused on the season lasted from May to July, forecasts from the two initializations are represented, one with lead-time 4 (in red) and another one with lead-time 2 (in blue). As shown in the figure all the members of the ensemble properly represent the annual cycle of the temperature, with increasing values in summer.

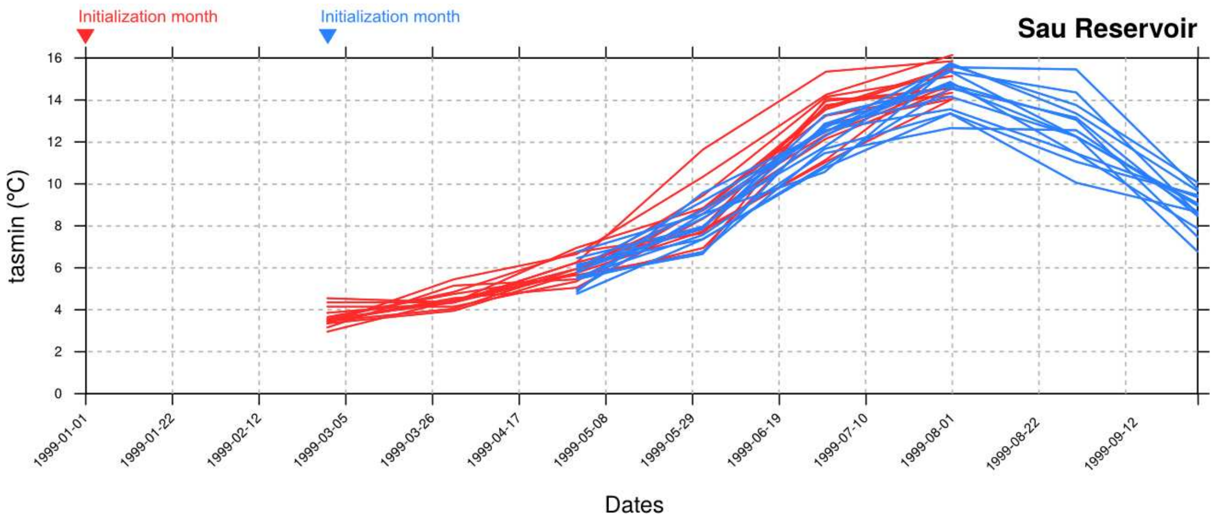


**Figure 1**. Seasonal forecasts for the initialization times of January (in red) and March (in blue). Ensemble of simulations obtained from the Climate Forecast System.

# The role of seasonal forecast verification

Despite the growing interest of climate services in seasonal forecasts and the potential value of these predictions for many sectors (hydrology, agriculture, health, etc.), there are still a number of problems which limit the practical application of this type of predictions. Obviously, a seasonal forecast in itself has no value without an indication about how much the predictions can be trusted based on past performance (Doblas-Reyes et al., 2013). Thus, the estimation of quality measures of the seasonal products is essential. Forecast quality is multi-faceted with performance measures providing complementary information on different aspects of forecast quality (association, accuracy, reliability, etc.). It should be noted that the concept of “best” or “good” forecast is subjective and can vary between users with different requirements from the predictions (Murphy, 1993). An evidence based approach for assessing forecast quality is to evaluate the performance using a paired data sample of past forecasts and observations, a process known as forecast verification (Jolliffe and Stephenson, 2003). Forecast verification provides users with information about possible skill (quality) in future forecasts. Forecasters can also provide users with probabilistic forecasts to help explicitly quantify uncertainties more dynamically. However, such probabilities are non-trivial to define from numerical model outputs (see e.g. Siegert et al., 2016; Primo et al., 2009), and can easily be misunderstood by decision-makers (Lorenz et al., 2015). For these reasons, the probabilistic communication of uncertainty in seasonal forecast products has been highlighted as a major challenge in the practical application of seasonal predictions in different economic sectors (see e.g. Mason, 2008; Lemos et al., 2012; Raftery, 2016).

A proper validation of these probabilistic forecasts requires the use of a set of complementary verification measures (Murphy, 1993) and the availability of retrospective seasonal forecasts, known as hindcast, covering a long period (ideally, over 30 years). The hindcast is used to build trust (or not) in the probabilistic forecast system issuing an actionable future forecast. A strong signal in a future forecast (i.e. very high or low probability of occurrence for an event) is useless or even dangerously misleading, if the forecast system has no skill in predicting such events, something revealed by analysing the historical hindcast performance. For this reason it is recommended to blend forecast information with the verification results of the forecast system, as an indication of its past performance. Due to the different alternative forecast systems and skill scores, and the various intermediate data processing steps involved (spatio-temporal aggregations, regriding/interpolation, bias correction …) the validation process is application-dependent and prone to error, so tailored solutions rooted on the latest research are required in order to obtain comprehensive and actionable information of model performance for particular end user applications.

Users have to deal with different types of uncertainty in seasonal forecasts. On the one hand the intrinsic uncertainty given by the probabilistic character of the forecast (which may render it non informative in some cases). On the other hand, the credibility of the forecast system, which can be estimated using forecast verification.

Communication of uncertainty and confidence of seasonal forecasts to users is one of the main limitations for the proper application of these long-range predictions in different sectors. Several strategies to address the communication challenges faced by the providers and users of this climate information were developed in the framework of the EUPORIAS project (Buontempo and Hewitt, 2018; http://euporias.eu), a project from the EU Seventh

Framework programme (FP7) focused on the provision of actionable climate information, and maximise the usefulness of seasonal-to-decadal climate information through close collaboration with end users. The user-needs survey performed in EUPORIAS revealed that users tend to favour maps and visualisations depicting forecast spread (e.g. error bars) although, there are some particularities depending on the user experience of using statistical information.

There is a lack of applications focused on the visual communication of probabilistic verification that can be easily interpreted by users and decision-makers from different sectors that are not necessarily experts on forecast verification. The experience of the UNICAN partner gained during his participation in EUPORIAS and the feedback received from seasonal forecasting and visualization experts and users from different climate impact sectors motivated the development of the visualizeR package (Frías et al., 2018) applied in this deliverable to seasonal climate forecast verification. The R package visualizeR aims at the visual communication of probabilistic forecasts together with different aspects of forecast quality (in particular accuracy and reliability) with different levels of complexity, thus targeting a wide range of users with varying expertises on statistical information or forecast verification. visualizeR goes beyond the currently existing verification tools, combining multiple verification measures in multivariate graphical displays achieving flexible verification diagrams able to effectively communicate the skill of probabilistic forecast predictions. It includes an initial set of plots that is best suited to the EUPORIAS feedback: spatial maps, time series representations and single-site displays, addressing different aspects of the forecast quality. Most of the visualizations available in the package conveniently blend the forecast quality based on the past performance of the forecasting system with the current operational forecast. These characteristics make a difference with respect to other existing probabilistic verification software packages. The code is distributed to the community through a public GitHub Repository (https://github.com/SantanderMetGroup/visualizeR), thus facilitating code sharing and collaborative development in order to optimally adapt the package to the user's needs.

As shown in section Results, VisualizeR has been used in this deliverable to forecast verification of the selected climate seasonal forecast system for the different case studies of WATExR. At the same time this tool is presented here as an example of how to visually communicate probabilistic forecasts since a similar analysis has to be also performed to the seasonal forecasts of water quality.

# 3. Climate data

The integration of seasonal climate predictions in different impact sectors (water, agriculture, energy, hydrology, …) requires data from different sources, including observations, reanalysis and seasonal predictions/hindcasts from forecasting systems. One of the main objectives of WATExR is the integration of state-of-the-art seasonal climate predictions and water quality simulations. To this end, proper climate data have to be selected from the different datasets available taking into account the requirements of the partners involved in the case studies selected in the project, shown in Figure 2.

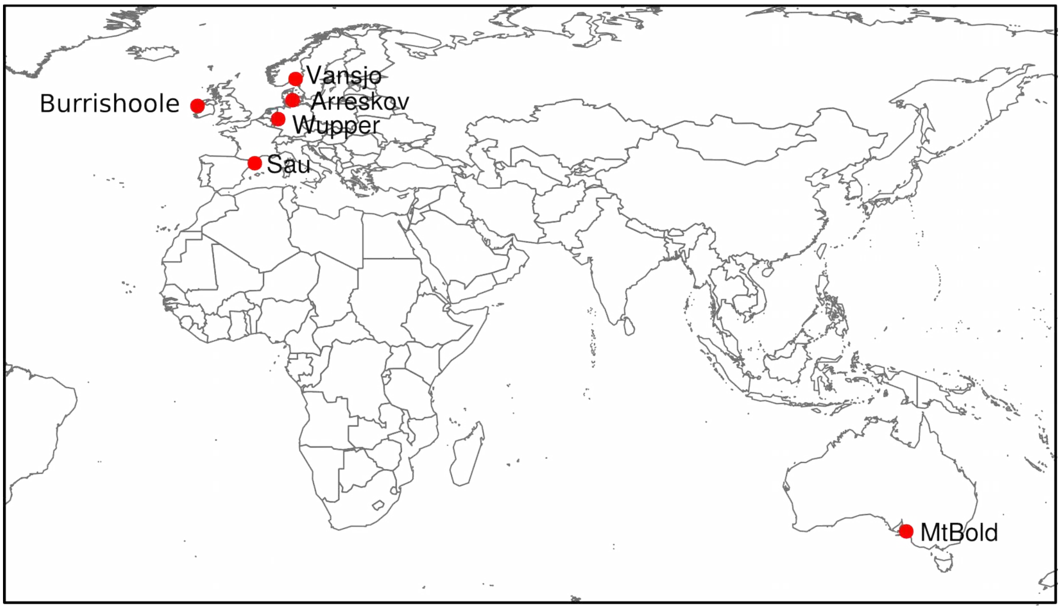


**Figure 2**. Location of the case studies included in WATExR.

A preliminary discussion about the current data available was addressed in the kick off meeting of WATExR with all the partners. Later, the UNICAN group contacted all the partners to extract more detailed information according to the particularities of the lake model to be applied in each location. The limitations found to select the different datasets required for the analysis were mainly based on the particular variables and the temporal resolution required as inputs in the different lake models. Details for each case study are shown in Table 1.

**Table 1**. List of climate data requirements for the case studies defined in WATExR (see Figure 2).

| Case Study | Country | Lake model | input meteo variables | Temporal resolution |
|---|---|---|---|---|
| Lake Arreskov | Denmark | GOTM-FABM-PCLake | Air temperature, wind speed (both U and V components), air pressure, humidity (or dew point or wet bulb temperature), shortwave radiation (optional), atmospheric longwave radiation (optional) or cloud cover | sub-daily |
| Wupper Reservoir | Germany | GLM and CEQUAL and GOTM | Air temperature, wind speed, humidity, shortwave radiation, atmospheric longwave radiation or cloud cover | Hourly or daily |
| Burrishoole Catchment | Ireland | Fish phenology (empirical model in progress) | Air temperature (°C), total precipitation (mm/d). | Daily |
| Vansjo Catchment | Norway | INCA, SimplyP, MyLake | Air temperature at 2m, total precipitation, potential evapotranspiration (mm/d), relative humidity at 2m (%), atmospheric pressure at station level (hPa), wind speed at 10m above ground (m/s), global radiation (optional), cloud cover (0-1) | Daily |

| | | | | |
|---|---|---|---|---|
| Sau Reservoir | Spain | GOTM-FABM-PCLake | Air temperature, wind speed (both U and V components), air pressure, humidity (or dew point or wet bulb temperature), shortwave radiation (optional), atmospheric longwave radiation (optional) or cloud cover | Daily |
| Mt. Bold Reservoir | Australia | GOTM-FABM-PCLake/ERGOM | Air temperature at 2m (°C), precipitation (m/s), wind speed at 10m (u and v components if possible; m/s), air pressure at sea level (hPa), relative humidity (%), cloud cover fraction (0 - 1) | 6 hourly |

In general, most of the lake models require temperature, wind (u and v components), surface pressure, humidity and longwave radiation. Few of them demand also shortwave radiation or total precipitation and just one case study ask for potential evapotranspiration. A second aspect discussed is the temporal resolution. There is a general agreement on working with daily data although, two partners stated their preference to sub-daily data. Daily and sub-daily (6 hours) seasonal climate predictions are available for most of these variables, except cloud cover and evapotranspiration. However, these two variables can be computed from others. For instance, evapotranspiration can be calculated, among other approaches, from maximum and minimum temperatures (http://www.fao.org/docrep/X0490E/X0490E00.htm). The UNICAN group has provided to the WATExR partners R functions to compute both variables. Moreover, this group has developed the R packages convertR and drought4R, the last based on the SPEI package (http://spei.csic.es/) which contain several functions to compute the needed transformations between variables. Both packages are freely available in Github (https://github.com/SantanderMetGroup/).

Taking into account the previous considerations and the licences of use of the different data available, the datasets selected at this stage of the project are the Climate Forecast System version 2 (CFSv2) from the National Centers for Environmental Prediction (NCEP) and the EWEMBI observational datasets for the seasonal climate forecast validation. The CFSv2 (Saha et al., 2011) is an ensemble retrospective seasonal climate forecast dataset with 24 members that extends along 28 years from 1982 to 2009. Beginning at January 1st, 9-month hindcasts were initiated every 5 days with 4 cycles on those days. For each calendar month, the hindcasts with initial dates after the 7th of that month were used as the ensemble members of the next month. For instance, the starting dates for the February ensemble members are the January 11th, 16th, 21st, 26th, 31st, and the February 5th. In general, there are at least 16 members having initial dates before the 1st day of the target month. The CFSv2 used in the reforecast consists of the NCEP Global Forecast System at T126 (~0.937°) resolution, the Geophysical Fluid Dynamics Laboratory Modular Ocean Model version 4.0 at 0.25–0.5° grid spacing coupled with a two-layer sea ice model, and the four-layer NOAH land surface model.

Other current seasonal climate forecasts (System4, GloSea5) were discarded at this moment due to restricted data access policy. In the near future, the plan in WATExR is to perform some analysis including the seasonal climate forecasts from the current Copernicus Climate Change Service (C3S). C3S is designed to provide data from several state-of-the-art seasonal prediction systems, among other datasets. It is defined as one of the six thematic streams of the Copernicus Programme coordinated and managed by the European Commision (http://www.copernicus.eu/). First studies about validation, bias adjustment and ensemble recalibration of seasonal climate forecasts are currently performed for the three seasonal forecasting systems available at the moment in the C3S: ECMWF-SEAS5, UK Met Office-GloSea5 and Météo France-System5. See for instance the study from Manzanas et al., (2018), as part of the participation of the UNICAN group in the Copernicus programme.

In the framework of the WATExR project, the EWEMBI (Landge, 2016) observational dataset has been considered as reference to validate the CFSv2 seasonal climate forecasts. It is also used as reference in the ISIMIP2b (Frieler et al., 2017) experiments to bias correct the GCMs. For this reason, EWEMBI will be also used in WATExR to calibrate the climate change projections analyzed in other WPs of the project. EWEMBI was developed in the project Earth2Observe "*Global Earth Observation for Integrated Water Resource Assessment*" (http://www.earth2observe.eu/) funded under the EU FP7. This project integrated earth observations, in-situ datasets and models to contribute to the assessment of global water resources using Earth Observation (EO). EWEMBI includes daily data for the meteorological variables reflected in Table 2 covering the entire globe, including land and ocean areas in contrast with previous reference datasets like WFDEI (Weedon et al., 2014). It covers the period 1979-2013 at 0.5ºx0.5º spatial resolution. Table 2 includes all the meteorological variables demanded for the different case studies (Table 1) and also those required for the computation of other variables such as the evapotranspiration that requires maximum and minimum temperatures.

The main shortcoming of this dataset is its medium-low spatial resolution (0.5ºx0.5º) and, for some case studies or extreme events of interest for the project, the temporal resolution (daily). However, the variables available allow the analysis of a great diversity of events, covering the high climatic variability of Europe.

**Table 2.** List of the EWEMBI variables (see Table 1 in Frieler et al., (2017)).

| Variable | Description | Units |
|---|---|---|
| tas | Daily Near-Surface Air Temperature | K |
| wss | Daily Near Surface Wind Speed | m/s |
| ps | Daily Surface Air Pressure | hPa |
| hurs | Daily Near Surface Relative Humidity | % |
| huss | Daily Near Surface Specific Humidity | kg/kg |
| rlds | Daily Surface Downwelling Longwave Radiation | W/m2 |
| rsds | Daily Surface Downwelling Shortwave Radiation | W/m2 |
| pr | Daily Precipitation | kg/m2s |
| prsn | Daily Snowfall Flux | kg/m2s |
| tasmax | Daily Maximum Near Surface Air Temperature | K |
| tasmin | Daily Minimum Near Surface Air Temperature | K |
| vas | Daily Northward Near-Surface Wind | m/s |

| | | |
|---|---|---|
| uas | Daily Eastward Near-Surface Wind | m/s |

# Data access

The process of climate data retrieval is in general a time consuming task due to the allocation of data files in different data providers, or the inhomogeneity in the temporal and/or spatial resolution across the different data sources. These steps are in some cases very technical and require different specialized tools entailing multiple specific choices that are often insufficiently documented in practical applications (Iturbide et al., 2019). Depending on the case and the expertise of the data user, the difficulty of carrying out such processes remain as an important factor hampering the full exploitation of available climate data to generate actionable information leading to an “usability gap” (Lemos et al., 2012).

In the last years the UNICAN group has developed climate4R (Iturbide et al., 2018), an R-based climate services oriented framework that integrates a number of R packages implementing harmonized (one single vocabulary) data access (loadeR and loadeR.ECOMS packages, Cofiño et al., 2018), data collocation including regridding, temporal aggregation, subsetting, etc. (transformeR package, Bedia and Iturbide, 2018), bias adjustment and downscaling (downscaleR package, Bedia et al., 2018), as well as blended visualization of probabilistic forecasts and quality measures, (visualizeR, Frías et al., 2018). All the packages are available through the SantanderMetGroup public GitHub Repository (https://github.com/SantanderMetGroup/).

The access to local and remote (OPeNDAP) data sources, such as the Santander User Data Gateway (UDG) is simplified with climate4R. The UDG is a THREDDS-based service from the Santander Climate Data Service including a wide catalogue of datasets (observations, reanalysis, climate change projections) popular in impact studies. For instance, climate predictions can be accessed using the workhorse function loadECOMS() from the loadeR.ECOMS package (an extension of loadeR) with intuitive arguments to unequivocally specify the data subset requested. Thus, for instance non-expert users do not need to worry about how the different ensemble members have been generated and their possibly different starting dates since just one argument is used for this function to specify the number of members to retrieve. The advantages of this R interface lie not only in its user-friendly arguments to specify complex data requests, but also in the possibility of performing flexible on-the-fly temporal aggregations (from sub-daily to daily) best suited to the particular needs of each user.

The UDG service has been adapted to the WATExR needs including new datasets of interest such as the seasonal climate forecasts or selected variables of relevance to the water sector. The access to the UDG has been opened to the WATExR community to easily access the different datasets selected for the project. Climate4R eases the data access process and also allows the application of some common transformation and post-processing steps such as regridding, temporal aggregation, subsetting of bias correction among others.

Figure 3 shows an example of daily time series loaded from the Santander UDG using the climate4R framework. It presents the visualization of a subset of the obtained data (year 2000) for the WATExR project, for one of the variables (minimum temperature) and two of the case studies, the first located in Europe (Sau reservoir) and the second in Australia (Mt

Bold reservoir). The black time series correspond to the EWEMBI observational data and the red ones to the CFSv2 (the red shadow informs about the multi-member spread). Finally, the months written in blue indicate the initialization month of each season (DJF, MAM, JJA and SON), separated by blue vertical lines. Here we can see that the minimum temperature (tasmin ºC) of CFSv2 is positively biased with respect to EWEMBI.

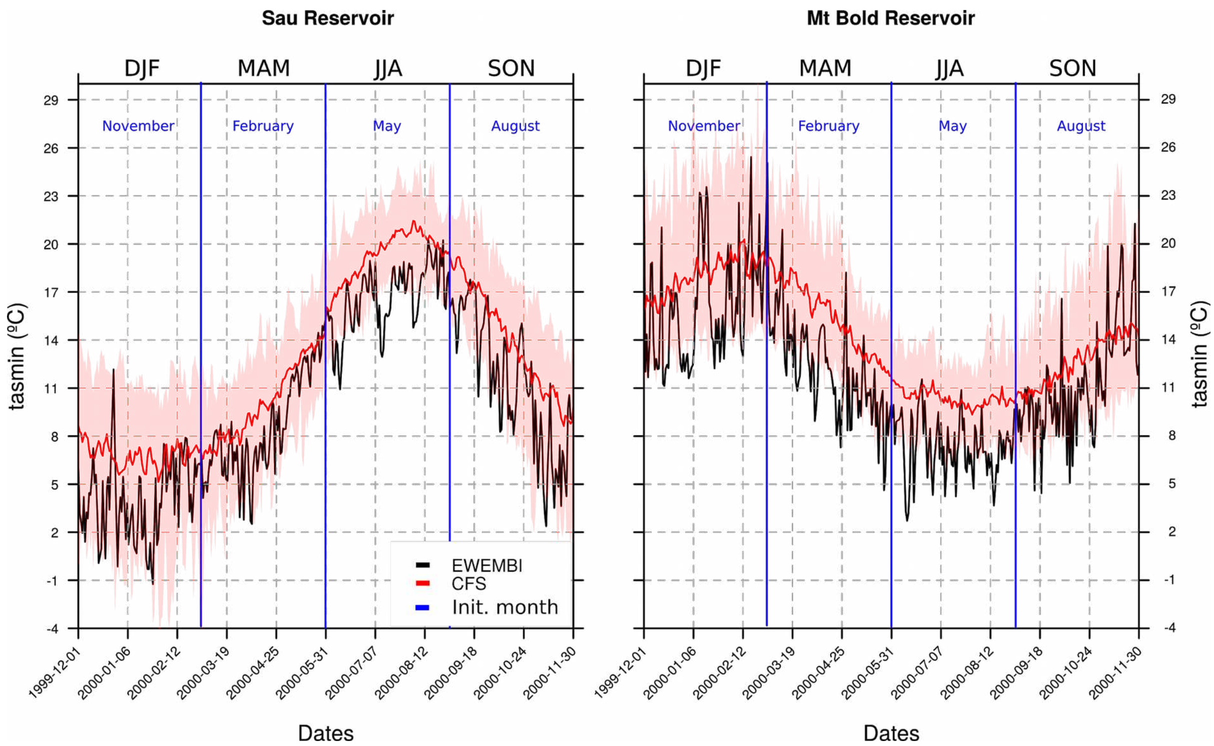


**Figure 3.** Seasonal climate forecast (red shadow) and observations (black line) of minimum temperature for the Sau (left) and Mt Bold (right) reservoirs. Red line corresponds to the ensemble mean. Months in blue indicate the initialization month of each target season (DJF, MAM, JJA and SON), separated by blue vertical lines.

# 4. Bias Correction

GCMs used for seasonal forecasting contain important systematic biases and drifts with respect to observational data (Doblas et al., 2013). For instance, the minimum temperature (tasmin) of CFSv2 is positively biased with respect to EWEMBI as depicted in Figure 3. Thus, the direct use of climate model outputs in impact studies is a risk when the statistical properties of the model data are assumed to be similar to those from the local observations (Christensen et al, 2008). Therefore, a calibration process is necessary before using these data in real applications. Bias correction methods are trained over a representative historical period (typically 30 years), and then applied to correct model outputs for a test (historical or future) period. Due to their simplicity and straightforward application, these methods have become very popular during the last decade and have been used in numerous recent papers covering different forecast temporal horizons (Iturbide et al., 2019). In this work, we used the Empirical Quantile Mapping (EQM) method, already used and tested in the VALUE initiative (Gutiérrez et al., 2018). The EQM method is applicable to any kind of variable (see, e.g., Wilcke et al. 2013) and consists in calibrating the empirical predicted Cumulative Distribution Function (CDF) by adjusting, for a control period, the model quantiles towards the observed ones (Déqué, 2007):

$$Y_{eqm} = eCDF_{obs}^{-1}(eCDF_{model}(Y))$$

In this case, the EQM method was applied using a monthly calibration window (30 days) and a 2-weekly correction window, so that each 15-day time interval (target days) is corrected considering a wider time step for calibration (30 days) centered in the target days. This particular configuration of the method corresponds to the acronym EQMs in Gutiérrez et al. (2018) and is implemented in the downscaleR package (Bedia et al., 2018). As a result, we obtained calibrated time series for each member of the seasonal forecast (Figure 4) for each variable and case study. Note that once the bias correction is applied the calibrated ensemble covers, more or less, the observed values and, then, it can be used as input for the impact models (e.g. lake or watershed model).

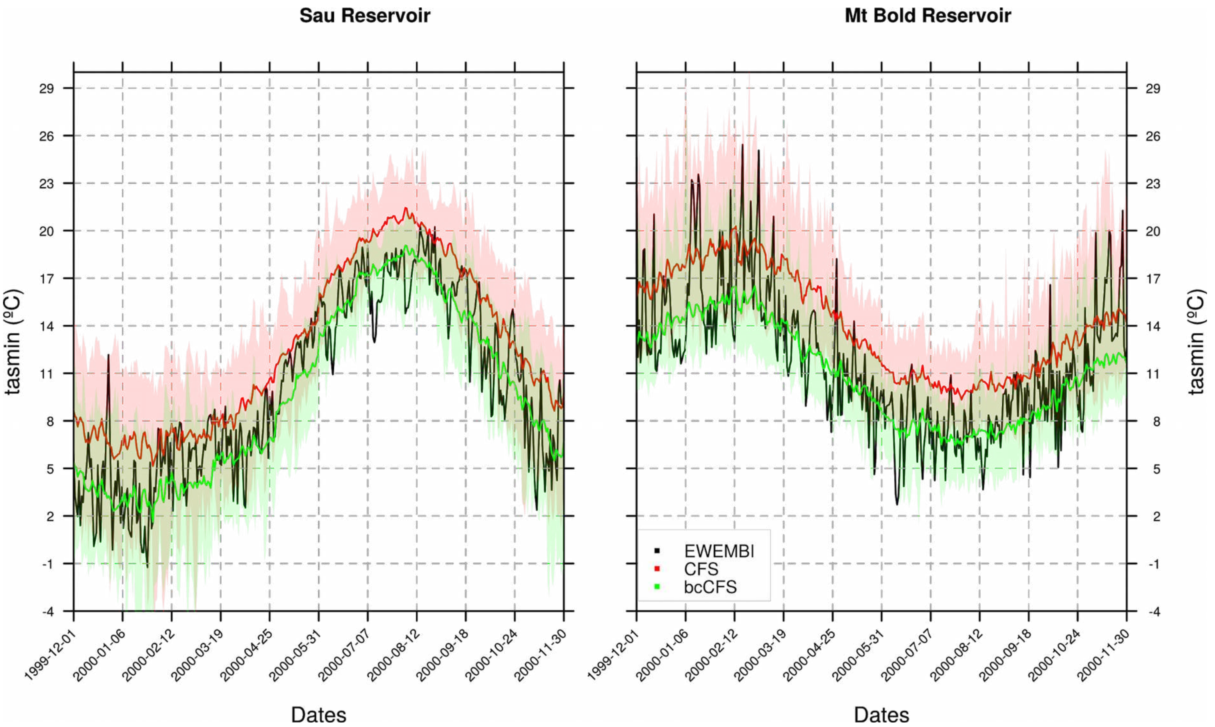


**Figure 4.** Raw (red) and calibrated (green) seasonal forecast (shadows) and observations (black line) of minimum temperature for the Sau (left) and Mt Bold (right) reservoirs. Red and green lines correspond to the mean of the corresponding ensemble (shadow).

# 5. Results

As described in previous sections, seasonal forecasting is a problem of probabilistic nature. The resulting ensemble of simulated weather realizations (ensemble members) allows estimating the likelihood of different events/indices related to the seasonal average weather.

The information most commonly provided at seasonal time scales is the probability of the next season being above, within and below normal conditions. Terciles computed from a long hindcast are used as thresholds to identify these conditions. This definition includes a normal category in the middle allowing to clearly differentiate events above/below normal in contrast to the consideration of only two categories (above/below). Moreover the number of categories is appropriate according to the hindcast period currently available (usually ~30 years, i.e. n=30). In case of quintiles, some categories may be even almost empty leading to non-robust skill estimates.

In order to assess the seasonal forecast quality, a hindcast of past forecasts is required, CFSv2 in this case. It extends along 28 years from 1982 to 2009. Past observations covering the same period as the hindcast are also required as reference to assess the forecast quality. That is, to know whether the event forecast occurred or not. EWEMBI datasets are considered here.

We have selected here the tercile plot to show the performance of the forecast system along the historical period. This type of plot have been already used in several recent works (Manzanas et al., 2017; Oguto et al., 2016) and is one of the visualizations implemented in visualizeR. This package has been used to produce the tercile plots in Figures 5, 6, 7 and 8. The shading of each square represents the probability of each tercile for each year. Darker shade depicts higher probability in this case given by the seasonal forecast (CFSv2). White dots indicate the observed tercile from the EWEMBI dataset. Thus, observed terciles with high probability values indicate good performance, while mid-low probabilities indicate the opposite. Therefore, tercile plots provide a direct, intuitive assessment of forecast quality. The tercile plot from visualizeR also includes a summary score to quantify the forecast quality of each category, the Relative Operating Characteristic skill score (ROCSS). ROCSS measures forecast discrimination for binary events, in this case associated to the occurrence of each tercile. This score is commonly used to evaluate the skill of probabilistic systems (Jolliffe and Stephenson, 2003) and is the only probabilistic numerical summary recommended by the WMO's Lead Centre for Long-Range Forecast Verification System (http://www.bom.gov.au/wmo/lrfvs). The values of ROCSS range from 1 (perfect forecast system) to -1 (perfectly bad forecast system). A value zero indicates no skill compared to a random prediction. Significant values with a 95% confidence are marked with an asterisk in the plots. This visualization might help in building the end user understanding of skill scores, given that they are presented along with the actual past forecasts and occurrences of the event.

In order to properly isolate the uncertainty and predictability sources in the model chain - from the direct output of the seasonal forecast to the calibrated product to be used as input for the impact model, - we have applied the same evaluation process to each step reflecting the added value introduced by each part of the process (climate model, bias correction method, etc..). This has been done for each variable and case study (Table 1), obtaining a detailed analysis of the skill (ROCSS) given by the climate information (see Table 3). For the sake of brevity, only the tercile plots showing the results obtained for the minimum temperature for the Sau and Mt Bold reservoirs are shown (Figures 5, 6, 7 and 8), although the same has been applied for the rest of variables and case studies. The final step, which is not an objective of this deliverable, is to consider the output of the impact model obtained with the calibrated climate information and apply the same evaluation in order to be able to compare the results obtained in each step of the model chain.

# Validation of Seasonal Forecast

In spite of the bias of the climate model most of the signal, in terms of skill and predictability, is present in the direct output of the model, so this component should be evaluated in order to isolate the added value associated to the calibration process.

The performance of the CFSv2 is here analysed for each case study and variable of interest. Results are shown for each season: winter (DJF), spring (MAM), summer (JJA) and autumn (SON). In all cases we have considered lead-time 1.

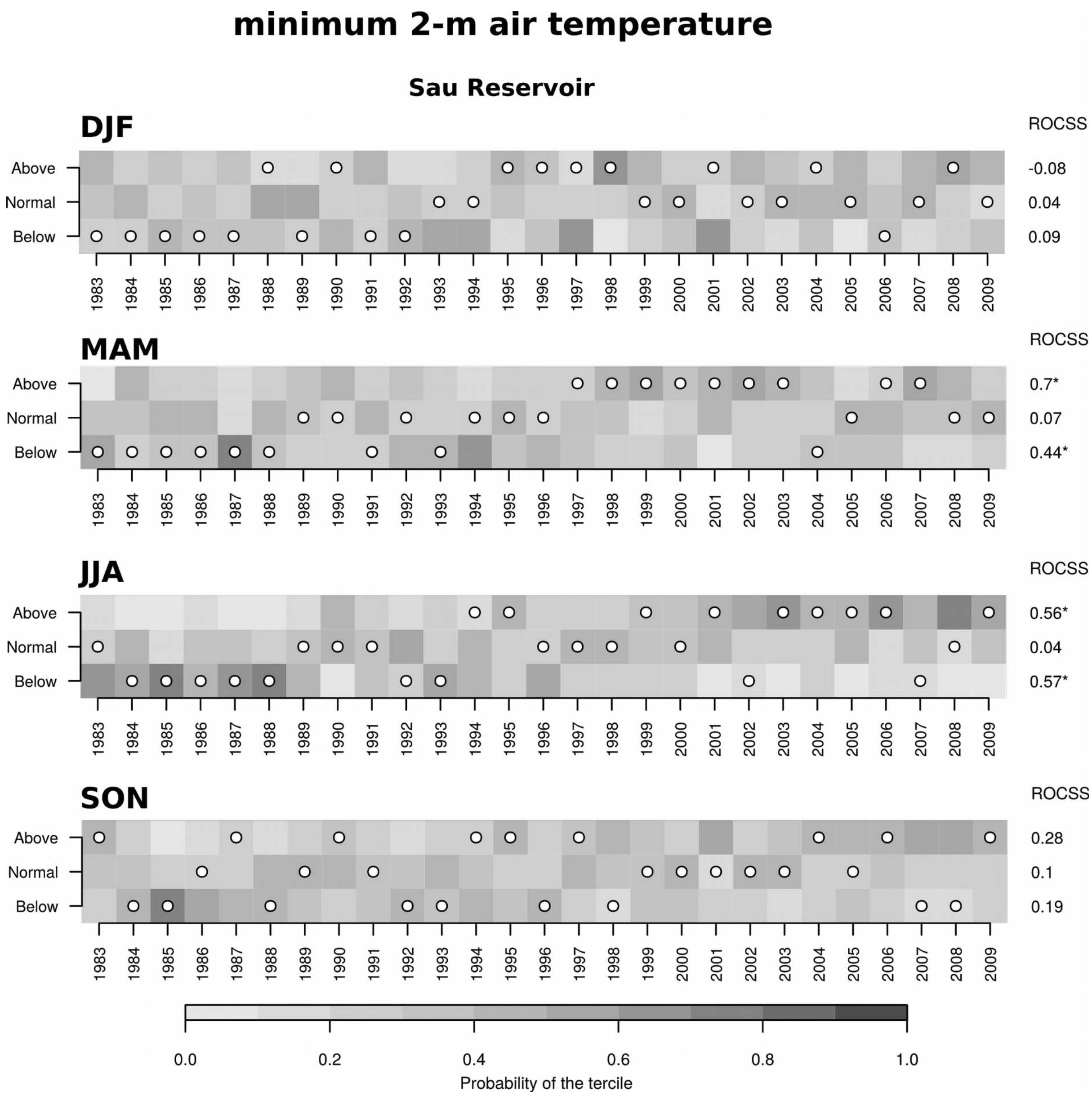


**Figure 5.** Tercile plot of the Sau reservoir for each season (rows). The grayscale shows the probability of each tercile given by the ratio between the number of members falling in each tercile and the total number of members. White dots show, for each year, the observed tercile. The asterisk indicates statistically significant ROCSS values.

Regarding the Sau reservoir and minimum temperature (Figure 5), the agreement between the observed and the most probable terciles is not remarkable for most of the seasons/years, leading to a poor performance of the seasonal forecast system for this case study and variable. In general, there is not a clear signal for any year or season as the three terciles are more or less equi-probable with some exceptions in spring and summer. A slight positive discrimination capability is obtained in spring and summer, especially for the upper tercile (significant ROCSS value of 0.7.) in spring (MAM). In those cases, the positive trend of the minimum temperature is captured to some extent, from the lowest tercile in the first years, to the highest tercile in the last part of the period.

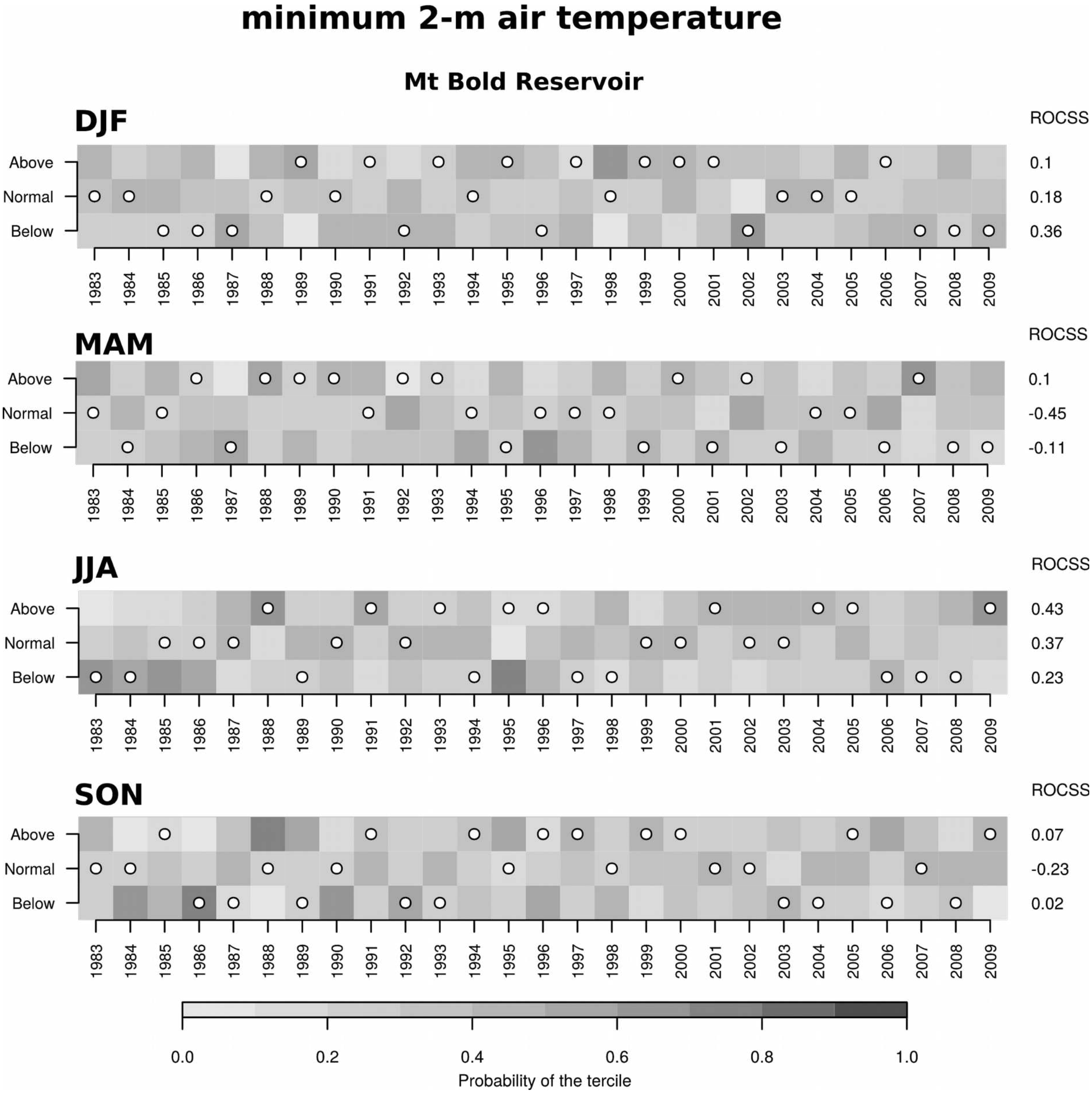


**Figure 6.** Same as Figure 5, but for the Mt. Bold reservoir.

According to the literature (Manzanas et al., 2014), it is known that the signal and predictability in Europe is very weak and in some cases it is restricted to some windows of opportunity related to the ENSO events (Frías et al., 2010). Manzanas et al. (2014) found some predictability at seasonal time scales for the precipitation over the region around

Indonesia and Northern Australia. The Mt. Bold case study, in Australia, was included in WATExR in order to explore how the seasonal forecast works in a region with, in principle, stronger signal than Europe. However, as shown in Figure 6, results for the minimum temperature in this particular location reflect a lack of signal for all seasons.

## Validation of Calibrated Seasonal Forecast

Figures 7 and 8 show the tercile plots for the bias-corrected seasonal forecasts by applying the EQM method to the raw output of the climate model. As could be inferred from the analytical expression of the method considered, the tercile structure is preserved by the calibration method so the differences of the validation measures are due to the cross-validation approach used to apply the calibration method. According to these results, in spite of the usability of the calibrated data for impact studies the predictability of both raw and calibrated data is the same.

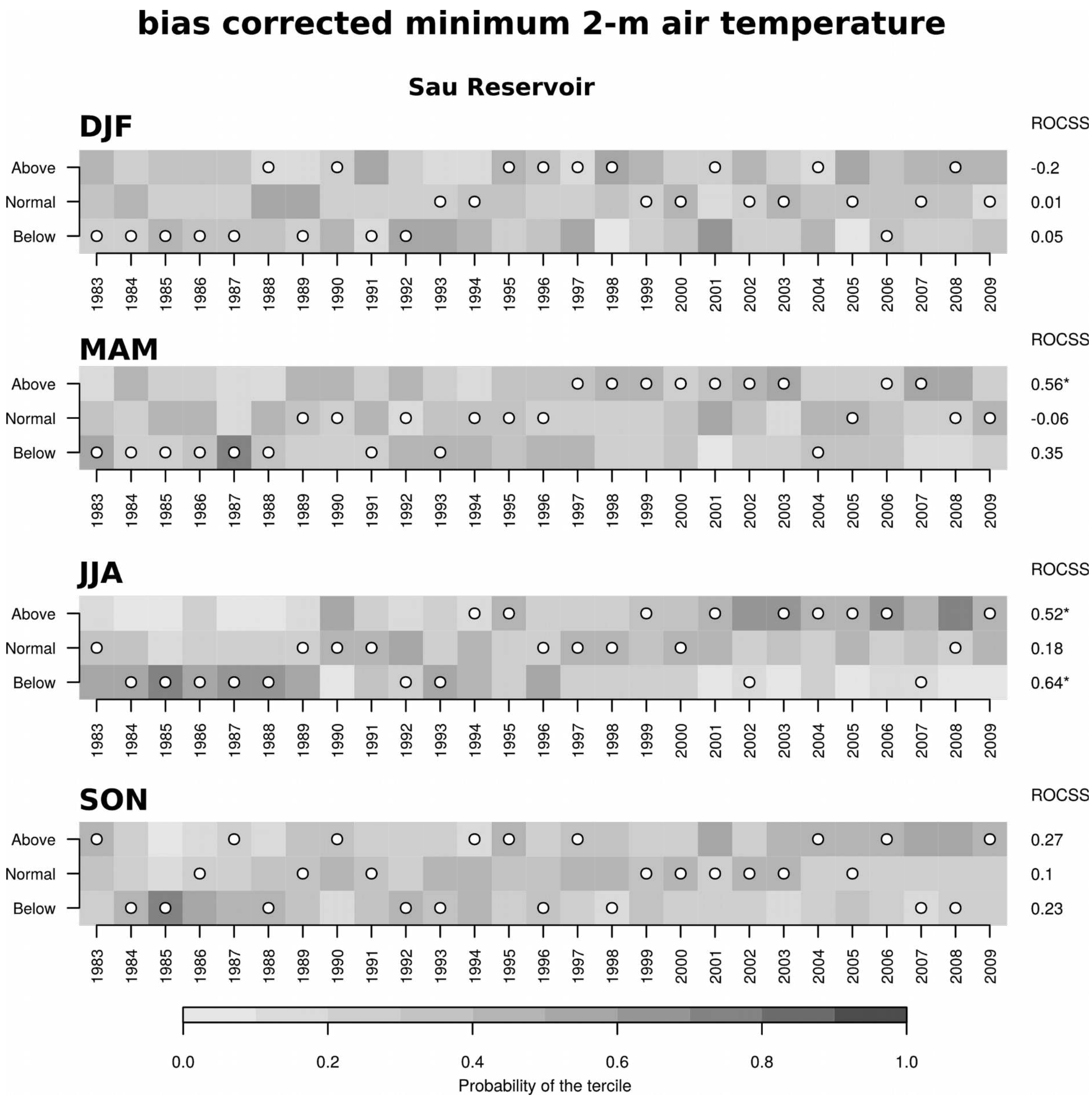


**Figure 7.** As Figure 5, but for bias corrected minimum temperature.

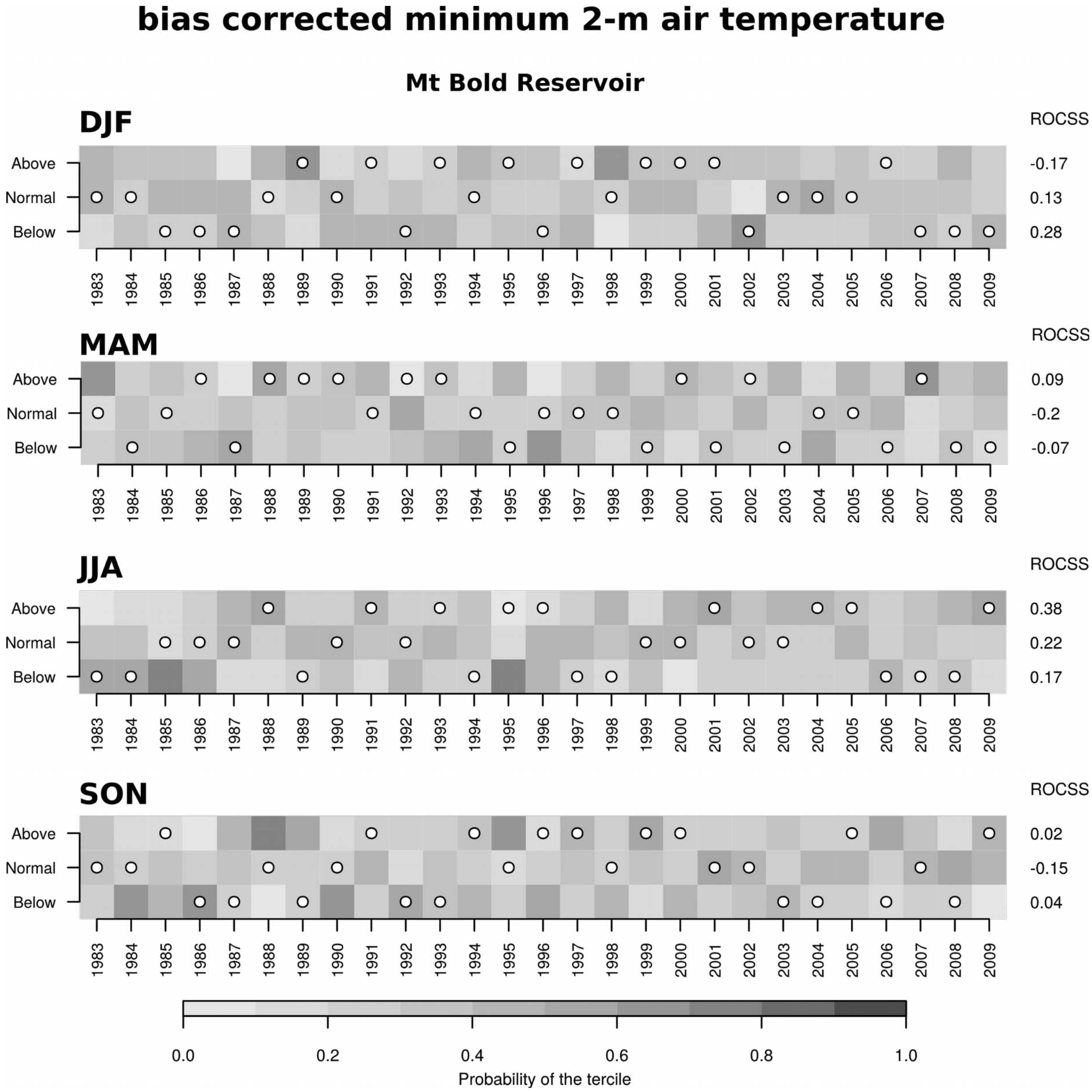


**Figure 8.** As Figure 6, but for bias corrected minimum temperature.

Table 3 summarizes the results for all variables, case studies, seasons and terciles. Similarly to the minimum temperature and the two case studies considered in the previous figures, the results shown in Table 3 reflect a low discrimination capability of the seasonal forecast, with few statistically significant ROCSS values, highlighted in green in the table. The highest ROCSS values are obtained for temperature variables, being the precipitation the variable with lower performance.

**Table 3.** ROCSS for the selected meteorological variables, case studies, seasons and terciles. The asterisk indicates statistically significant ROCSS values.

| Variable | Lake | Season | Below | Normal | Above |
|---|---|---|---|---|---|
| hurs | Burrishoole Catchment | winter | 0.28 | -0.17 | 0.35 |
| | | spring | -0.14 | -0.08 | 0.39 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.24 | -0.23 | 0.25 |
| | | autumn | 0.21 | 0.03 | 0.05 |
| | Lake Arreskov | winter | 0.05 | 0.06 | -0.36 |
| | | spring | 0.32 | 0.26 | 0.56* |
| | | summer | 0.19 | 0.37 | -0.15 |
| | | autumn | -0.24 | 0.28 | 0.17 |
| | Mt Bold Reservoir | winter | 0.46* | 0.12 | 0.07 |
| | | spring | -0.01 | 0.01 | -0.1 |
| | | summer | -0.01 | -0.02 | -0.12 |
| | | autumn | 0.08 | -0.26 | -0.28 |
| | Sau Reservoir | winter | -0.02 | 0.21 | -0.06 |
| | | spring | 0.15 | -0.08 | -0.07 |
| | | summer | 0.36 | -0.22 | 0.22 |
| | | autumn | 0.6* | -0.07 | -0.2 |
| | Vansjo Catchment | winter | -0.11 | 0.14 | -0.14 |
| | | spring | 0.24 | 0.08 | 0.53* |
| | | summer | 0.29 | 0.03 | 0.2 |
| | | autumn | -0.19 | 0.23 | 0.12 |
| | Wupper Reservoir | winter | -0.01 | -0.17 | -0.11 |
| | | spring | -0.07 | 0.04 | 0.12 |
| | | summer | -0.1 | 0.09 | 0.53* |
| | | autumn | 0.33 | -0.23 | 0.54* |
| pr | Burrishoole Catchment | winter | 0.17 | 0.2 | 0.14 |
| | | spring | -0.19 | -0.12 | 0.25 |
| | | summer | -0.35 | -0.06 | 0.07 |
| | | autumn | 0.19 | -0.05 | -0.02 |
| | Lake Arreskov | winter | 0.18 | 0.18 | 0.03 |
| | | spring | -0.22 | 0.01 | -0.05 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.22 | -0.36 | -0.09 |
| | | autumn | -0.29 | -0.08 | -0.15 |
| | Mt Bold Reservoir | winter | 0.07 | -0.06 | 0.37 |
| | | spring | -0.04 | -0.06 | -0.09 |
| | | summer | 0.01 | 0.06 | 0.15 |
| | | autumn | 0.23 | 0.07 | 0.07 |
| | Sau Reservoir | winter | 0.41 | -0.02 | -0.02 |
| | | spring | -0.14 | -0.1 | -0.25 |
| | | summer | 0.36 | -0.19 | 0.25 |
| | | autumn | 0.06 | -0.03 | 0.12 |
| | Vansjo Catchment | winter | -0.23 | -0.14 | -0.18 |
| | | spring | 0.23 | 0.01 | -0.04 |
| | | summer | 0.05 | -0.31 | 0.06 |
| | | autumn | -0.05 | 0.04 | 0.12 |
| | Wupper Reservoir | winter | -0.05 | 0.22 | -0.06 |
| | | spring | -0.15 | -0.27 | 0.19 |
| | | summer | 0.19 | -0.19 | 0.35 |
| | | autumn | -0.44 | -0.25 | -0.07 |
| ps | Burrishoole Catchment | winter | 0.1 | -0.21 | 0.33 |
| | | spring | -0.19 | -0.62 | -0.4 |
| | | summer | -0.3 | 0.27 | -0.37 |
| | | autumn | 0.33 | 0.14 | -0.06 |
| | Lake Arreskov | winter | -0.22 | -0.2 | 0.46* |
| | | spring | 0.2 | 0.12 | -0.01 |
| | | summer | -0.18 | -0.1 | -0.04 |
| | | autumn | 0.29 | 0.02 | -0.18 |
| | Mt Bold Reservoir | winter | 0.1 | 0.17 | 0.43 |
| | | spring | 0.3 | -0.23 | 0.15 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | -0.03 | -0.53 | 0.42 |
| | | autumn | 0.31 | 0.2 | 0.57* |
| | Sau Reservoir | winter | 0.33 | -0.01 | 0.54* |
| | | spring | 0.66* | 0.48* | 0 |
| | | summer | 0.04 | -0.07 | 0.06 |
| | | autumn | -0.17 | -0.36 | 0.15 |
| | Vansjo Catchment | winter | -0.37 | -0.01 | 0.18 |
| | | spring | 0.45* | -0.23 | -0.43 |
| | | summer | 0.05 | -0.1 | -0.04 |
| | | autumn | 0.15 | -0.15 | 0.23 |
| | Wupper Reservoir | winter | 0.51* | 0.04 | 0.31 |
| | | spring | -0.07 | 0.06 | -0.3 |
| | | summer | -0.13 | 0.15 | -0.14 |
| | | autumn | -0.17 | -0.11 | -0.31 |
| rlds | Burrishoole Catchment | winter | 0.09 | 0.07 | -0.1 |
| | | spring | 0.19 | -0.12 | 0.13 |
| | | summer | 0.3 | 0.17 | 0.28 |
| | | autumn | 0.43 | -0.49 | 0.48* |
| | Lake Arreskov | winter | 0.14 | 0.25 | 0.21 |
| | | spring | -0.2 | -0.04 | 0.04 |
| | | summer | -0.01 | 0.52* | 0.18 |
| | | autumn | -0.07 | -0.02 | -0.03 |
| | Mt Bold Reservoir | winter | -0.37 | -0.2 | 0.04 |
| | | spring | -0.01 | -0.1 | 0.07 |
| | | summer | -0.17 | -0.12 | 0.07 |
| | | autumn | 0.16 | 0.2 | 0.02 |
| | Sau Reservoir | winter | 0.15 | 0.15 | 0.22 |
| | | spring | 0.35 | -0.31 | 0.48* |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.55* | 0.02 | 0.5* |
| | | autumn | 0.3 | 0.22 | 0.01 |
| | Vansjo Catchment | winter | 0.03 | -0.26 | -0.06 |
| | | spring | -0.25 | 0.09 | 0.06 |
| | | summer | 0.7* | -0.46 | 0.25 |
| | | autumn | 0.36 | -0.12 | -0.22 |
| | Wupper Reservoir | winter | 0.18 | -0.04 | -0.19 |
| | | spring | 0.09 | 0.19 | -0.02 |
| | | summer | 0.62* | -0.05 | -0.12 |
| | | autumn | -0.01 | 0.41 | 0.24 |
| rsds | Burrishoole Catchment | winter | 0.17 | -0.2 | -0.33 |
| | | spring | -0.05 | -0.34 | 0.1 |
| | | summer | 0.33 | 0.14 | 0.1 |
| | | autumn | 0.23 | 0.36 | 0.68* |
| | Lake Arreskov | winter | 0.05 | 0.15 | 0.28 |
| | | spring | 0.23 | 0.1 | 0.06 |
| | | summer | 0.27 | -0.08 | -0.3 |
| | | autumn | -0.2 | -0.37 | -0.06 |
| | Mt Bold Reservoir | winter | 0.02 | -0.01 | 0.17 |
| | | spring | -0.04 | -0.44 | -0.35 |
| | | summer | 0.02 | -0.35 | -0.28 |
| | | autumn | 0.09 | -0.26 | 0.3 |
| | Sau Reservoir | winter | 0.5* | 0.07 | 0.41 |
| | | spring | 0.2 | 0.2 | -0.19 |
| | | summer | -0.49 | -0.11 | -0.09 |
| | | autumn | 0.19 | 0.17 | -0.04 |
| | Vansjo Catchment | winter | -0.32 | 0.15 | 0.15 |
| | | spring | 0.41 | 0.07 | -0.11 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.19 | -0.15 | 0.09 |
| | | autumn | 0.21 | -0.03 | -0.22 |
| | Wupper Reservoir | winter | -0.45 | -0.38 | 0.03 |
| | | spring | 0.09 | 0.42* | -0.04 |
| | | summer | 0.1 | 0.05 | 0.1 |
| | | autumn | -0.25 | 0.01 | 0.05 |
| tasmax | Burrishoole Catchment | winter | 0.25 | 0.04 | 0.68* |
| | | spring | 0.34 | -0.38 | 0.4* |
| | | summer | 0.6* | -0.02 | 0.05 |
| | | autumn | 0.38 | 0.36 | 0.53* |
| | Lake Arreskov | winter | 0.36 | 0.27 | 0.18 |
| | | spring | 0.65* | -0.01 | 0.56* |
| | | summer | 0.34 | 0.2 | -0.06 |
| | | autumn | 0.27 | -0.46 | 0.38 |
| | Mt Bold Reservoir | winter | 0.38 | -0.02 | 0.02 |
| | | spring | -0.27 | 0.06 | 0.21 |
| | | summer | 0.18 | -0.48 | -0.09 |
| | | autumn | 0.51* | 0.28 | 0.4 |
| | Sau Reservoir | winter | 0.05 | 0.2 | -0.09 |
| | | spring | 0.28 | -0.13 | 0.21 |
| | | summer | 0.51* | 0.31 | 0.51* |
| | | autumn | 0.12 | 0.01 | 0.1 |
| | Vansjo Catchment | winter | 0.47* | 0.06 | -0.04 |
| | | spring | 0.31 | -0.2 | 0.54* |
| | | summer | 0.35 | 0.25 | 0.09 |
| | | autumn | 0.4 | 0 | 0.21 |
| | Wupper Reservoir | winter | 0.24 | 0.19 | 0.19 |
| | | spring | 0.53* | 0.12 | 0.41* |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.37 | -0.09 | 0.14 |
| | | autumn | -0.09 | 0.17 | 0.59* |
| tasmin | Burrishoole Catchment | winter | 0.19 | 0.1 | 0.42 |
| | | spring | 0.49* | -0.23 | 0.36 |
| | | summer | 0.61* | 0.57* | 0.7* |
| | | autumn | 0.64* | 0.51* | 0.56* |
| | Lake Arreskov | winter | 0.38 | 0.1 | 0.15 |
| | | spring | 0.36 | -0.05 | 0.33 |
| | | summer | 0.37 | 0.2 | 0.13 |
| | | autumn | 0.09 | 0.01 | 0.21 |
| | Mt Bold Reservoir | winter | 0.28 | 0.13 | -0.17 |
| | | spring | -0.07 | -0.2 | 0.09 |
| | | summer | 0.17 | 0.22 | 0.38 |
| | | autumn | 0.04 | -0.15 | 0.02 |
| | Sau Reservoir | winter | 0.05 | 0.01 | -0.2 |
| | | spring | 0.35 | -0.06 | 0.56* |
| | | summer | 0.64* | 0.18 | 0.52* |
| | | autumn | 0.23 | 0.1 | 0.27 |
| | Vansjo Catchment | winter | 0.35 | 0.17 | -0.1 |
| | | spring | 0.09 | 0.14 | 0.24 |
| | | summer | 0.43* | 0.27 | 0.29 |
| | | autumn | 0.36 | -0.2 | 0.46* |
| | Wupper Reservoir | winter | 0.33 | 0.14 | 0.02 |
| | | spring | 0.67* | 0.01 | 0.33 |
| | | summer | 0.49* | 0.2 | -0.03 |
| | | autumn | -0.27 | 0.07 | 0.16 |
| tas | Burrishoole Catchment | winter | 0.13 | -0.14 | 0.58* |
| | | spring | 0.56* | 0.27 | 0.32 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.67* | 0.05 | 0.29 |
| | | autumn | 0.72* | 0.67* | 0.44* |
| | Lake Arreskov | winter | 0.43* | -0.06 | 0.15 |
| | | spring | 0.49* | 0.08 | 0.7* |
| | | summer | 0.33 | 0.16 | -0.04 |
| | | autumn | 0.1 | -0.09 | 0.41* |
| | Mt Bold Reservoir | winter | 0.17 | 0.06 | 0.01 |
| | | spring | -0.26 | -0.05 | 0.02 |
| | | summer | 0.23 | -0.04 | 0.19 |
| | | autumn | 0.33 | 0.19 | 0.22 |
| | Sau Reservoir | winter | -0.02 | 0.52* | -0.12 |
| | | spring | 0.25 | 0.12 | 0.48* |
| | | summer | 0.58* | -0.1 | 0.41 |
| | | autumn | 0.24 | -0.39 | 0.22 |
| | Vansjo Catchment | winter | 0.51* | 0.11 | -0.07 |
| | | spring | 0.17 | -0.2 | 0.48* |
| | | summer | 0.33 | 0.49* | 0.25 |
| | | autumn | 0.36 | -0.46 | 0.3 |
| | Wupper Reservoir | winter | 0.26 | -0.1 | 0.06 |
| | | spring | 0.67* | 0.31 | 0.51* |
| | | summer | 0.51* | 0.11 | -0.16 |
| | | autumn | -0.07 | -0.37 | 0.23 |
| uas | Burrishoole Catchment | winter | -0.28 | -0.28 | 0.23 |
| | | spring | -0.2 | 0.15 | 0.2 |
| | | summer | 0 | 0.49* | 0.48* |
| | | autumn | 0.1 | -0.09 | 0.3 |
| | Lake Arreskov | winter | -0.12 | -0.41 | 0.26 |
| | | spring | -0.25 | -0.35 | 0.32 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | 0.28 | 0.01 | -0.15 |
| | | autumn | -0.42 | 0.17 | 0.04 |
| | Mt Bold Reservoir | winter | 0.15 | 0.22 | 0.16 |
| | | spring | -0.35 | 0.23 | -0.2 |
| | | summer | 0.12 | 0.12 | 0.19 |
| | | autumn | 0.4 | 0.03 | 0.34 |
| | Sau Reservoir | winter | -0.16 | -0.23 | -0.01 |
| | | spring | -0.23 | -0.25 | -0.09 |
| | | summer | 0.44* | 0.49* | 0.08 |
| | | autumn | -0.34 | -0.6 | -0.01 |
| | Vansjo Catchment | winter | 0.29 | -0.16 | 0.17 |
| | | spring | -0.06 | -0.05 | 0.18 |
| | | summer | 0.02 | 0.61* | -0.09 |
| | | autumn | 0.16 | 0.11 | -0.19 |
| | Wupper Reservoir | winter | -0.16 | -0.4 | 0.23 |
| | | spring | -0.3 | -0.26 | 0.03 |
| | | summer | 0.08 | -0.1 | 0.06 |
| | | autumn | 0.1 | -0.14 | 0.04 |
| vas | Burrishoole Catchment | winter | -0.01 | -0.25 | -0.22 |
| | | spring | -0.02 | -0.09 | 0.06 |
| | | summer | 0.14 | 0.09 | -0.19 |
| | | autumn | -0.65 | -0.48 | -0.27 |
| | Lake Arreskov | winter | 0.22 | 0 | -0.39 |
| | | spring | -0.16 | -0.62 | -0.31 |
| | | summer | -0.05 | 0.17 | 0.09 |
| | | autumn | 0.35 | 0.19 | 0.3 |
| | Mt Bold Reservoir | winter | 0.28 | 0.13 | 0.24 |
| | | spring | 0.13 | 0.04 | 0.17 |

| | | | | | |
|---|---|---|---|---|---|
| | | summer | -0.14 | 0.38 | 0.16 |
| | | autumn | 0.09 | -0.16 | 0.21 |
| | Sau Reservoir | winter | -0.35 | -0.2 | -0.19 |
| | | spring | -0.23 | -0.16 | 0.12 |
| | | summer | 0.25 | 0.32 | 0.6* |
| | | autumn | 0.23 | -0.04 | 0.12 |
| | Vansjo Catchment | winter | 0.06 | 0.02 | -0.15 |
| | | spring | 0.25 | 0.37 | -0.2 |
| | | summer | 0.14 | 0.23 | 0.12 |
| | | autumn | 0.61* | 0.02 | 0.14 |
| | Wupper Reservoir | winter | 0.2 | -0.15 | -0.47 |
| | | spring | 0.1 | 0.35 | 0.38 |
| | | summer | 0.15 | 0.31 | 0.28 |
| | | autumn | 0.16 | 0.4 | 0.53* |

# 6. Conclusions and discussion.

This document presents a guide about the use of seasonal climate information of interest for the different case studies defined in WATExR. The particularities of this kind of forecasts and the relevant role of the verification and the calibration of the data have been highlighted along the manuscript as an initial step to integrate these long term predictions as input in the different lake models.

According to the interactions with the other partners, at this stage of the project seasonal climate forecasts from the CFSv2 has been selected taking into account the spatial and temporal resolution of this dataset and the open access to the data. On the other hand, EWEMBI observational data has been considered as reference to assess the seasonal forecast quality of the CFSv2. As expected, the skill of this probabilistic system is low at the extratropical latitudes considered being restricted to particular seasons, variables, regions or terciles. It is planned for the near future of the project, to perform some experiments taking into account the state-of-the-art seasonal prediction systems from the C3S after the verification process that is currently being developed as part of the Copernicus programme.

Several tools developed in R by the UNICAN group and integrated in the climate4R framework have been adapted and presented to the other partners to easily access the different types of data, make transformations and calibrations to the data or visualize probabilistic forecasts and quality measures in an agreed format. In particular these visualizations tools can be considered as a starting point for the probabilistic visualization that should be done with the impact model outputs.

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