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Seasonal-to-decadal timescale

Deliverable D23.4

Report summarising predictability of impact parameters for water sector

EUPORIAS

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1. Executive Summary

Water resources, water security and water safety are of great importance to society, and the ability to predict these at time scales from weeks to years has great potential for pro-active water resources management (drinking water, irrigation, cooling water, hydropower, etc.) and disaster preparedness (floods and droughts). Forecasts possess no intrinsic value. They acquire value through their ability to influence the decisions made by users of the forecasts. (Murphy 1993). Thus, their skill in forecasting, in the current context, hydrological anomalies is necessary but not sufficient for societal value. In WP23 a suite of existing hydrological models (table 2) has been implemented for the first time in a S2D framework to explore their potential for hydrological forecasts in terms of skill and performance in Europe. Their potential to eventually influence basin management is the subject of a different EUPORIAS WP.

Previous findings and discussions in WP23 led to a common modelling strategy and workflow:

- aim of the multi model exploration here is to achieve an optimal model performance in the various settings chosen; not a strict model intercomparison
- to explore the potential of S2D hydrological prediction, skills will not only be assessed against observed discharges, but also against 'synthetic observations' obtained from a reference run. This circumvents some model limitations stemming from e.g. non-modelled basin modification through dams and reservoirs, and relaxes the need for model calibration.
- a set of sensitivity experiments is needed to assess the effect of different forcings (e.g. SYSTEM4, GLOSEA5, CFS20), but also the effect of performing bias corrections or not.
- similarly sensitivity experiments are needed for different initialisation approaches, important for hydrological forecasting as hydrological systems exhibit considerable memory caused by soil and groundwater reservoirs as well as snowpacks (see D23.3)
- harmonisation of approach, climatology, S2D forcing and common case studies does facilitate the exchange of experiences and the search for causalities for (the lack of) predictive skill (especially relevant for the closely related WP31).

The model suite comprises three pan-European (EHYPE, VIC, LPJml), one national (ISBA-MODCOU) and one basin scale model (SIMRISK) to allow the assessment of various modelling approaches and physiographic settings.

Key model development achievements

For all hydrological models presented in the following (EHYPE, LPJml, ISBA-MODCOU), the seasonal forecasts have been evaluated so far against synthetic observations only, that is against the simulation results of the same model forced by WFDEI.

A new version of EHYPE was developed and used in EUPORIAS, calibrated for 870 stations in Europe on a full set of flow signatures using the DEMCC optimisation algorithm. As a result a good performance is achieved over the entire European domain for WFDEI forced simulation.

Seasonal hydrological forecasts with EHYPE show deterministic skill: ensemble mean daily discharge volume of the hindcast compares well to the reference across large parts of the European domain for short lead times. This is particularly clear in northern Europe. However, skill deteriorates as a function of lead time, especially so in the summer months. Central Europe and the Mediterranean region exhibit less skill. Also here, skill is dependent on the lead time; however the skill seems to be better in the summer period compared to the other seasons. Probabilistic skill with respect to discharge anomalies from EHYPE remains to be analysed.

The SAFRAN-ISBA-MODCOU hydro-meteorological suite performed hindcasts for the low flow period in France, summer to autumn, a period of high interest for EPTB Seine-Grands Lacs, in charge of the management of the great lake-reservoir upstream over the Seine basin. Deterministic predictive skill scores (temporal correlation between ensemble mean and reference) for all the months show a correlation higher than 0.7 for many river stations over the Seine basin up to August and still higher than 0.5 in September, while elsewhere it is rarely higher than 0.3 after June. Probabilistic skill scores (Brier Scores – BS, ROC areas for Below Normal flows, BN) confirm this rapid decrease in most of the basins right from the month of June, but the Seine basin is still the most predictable area. The part of the predictability coming from the Seasonnal forecast against the Initial conditions is evaluated using a comparison of Brier scores caculated on the one hand with seasonal forecast results and on the other hand with climatology. For EPTB two integrated indicators describing the drought severity are more relevant: the number of days below the “vigilance” threshold, and the volume below this threshold. Both perform quite well.

The LPJml model does show considerable deterministic skill (Kuiper Skill Score 0.8-0.9) in reproducing AN/BN flows for many GRDC stations across Europe, suggesting good potential for predicting flow anomalies, despite some biases in large parts of Europe (both WFDEI and SYS4 forced), mostly negative in springs more variable in late summer. Probabilistic skill for spring are good (BS<0.2) for AN and BN events of lead month 1 in large areas of Europe. These gradually detoriate up to lead month 4, especially in NE Europe, though certain areas in SE Europe retain some skill. MAM ranked probability skill scores (RPSS) also suggest considerable skill across most of Europe for short lead times, retracting to NE Europe for longer lead times. Overall, BS are slightly worse in late summer than in spring and vary surprisingly little with lead time, and significant RPSS levels seem to be confined to Northern Scandinavia, the Eastern Mediterranean and a few isolated but persistent ‘hotspots’ in the Swiss Alps and parts of the Iberian peninsula. Of a few individual basins analysed to date the Rhone shows some skill (AROC scores) for both MAM and JAS flows for shortest lead times only. The Danube and Göta Älv exhibit more skill for longer lead times in MAM, while for the Ebro JAS low flows are predicted with some skill.

VIC performance to date has been assessed deterministically only; probabilistic analysed awaiting completion of full SYS4 ensemble simulations. VIC forced by WFDEI exhibits high correlations but positive biases for mean flows (especially in the Mediterranean), negative biases for low flows (especially in Fennoscandia) and considerable positive biases (>20%) for high flows everywhere. Anomaly correlations for a month ahead are generally quite OK throughout the year. For longer lead times strong seasonal differences exist with skill occurring mostly in spring / early summer with lead times up to 3-4 months.

These seasonal hydrological predictions are used for dam inflow (mostly in winter) and drinking water demand (mostly in summer) forecasts in Spain. Correlations between NAO and dam inflow suggest a potential for seasonal prediction here. After validation against local inflow data for a dam in the upstream Ebro catchment the EHYP simulations reported before were chosen as input for the SIMRISK dam management support tool. From the limited analyses till present, the SIMRISK model results do not significantly benefit from using seasonal predictions for the catchment considered, as almost no differences in reservoir volume in reservoir, or demand-deficit exist between the simulations done with the predictions and done with climatology). For water demand, for each trimester of the year, regression between air temperature and water demand have been developed. Then CFS and SYS4 hindcasts were used to ‘predict’ water demand. Some potential in water consumption prediction was demonstrated, more so with SYS4 than in CFS.

For all results presented it should be noted that seasonal hydrological forecasting skill does not always have a direct dependency to the seasonal climatic forecasting skill. Hydrological processes have longer memory (i.e. snow accumulation/melting processes, processes in lakes and wetlands etc.), which also affect the skill in the system. How important climatic forecasting skill is relative to initialisation skill in the present set of model frameworks (EHYP, VIC, LPJml, SAFRAN-ISBA-MODCOU) remains to be analysed, as discussed in D23.3 (‘Report on initialisation of impacts models for seasonal predictions’). In addition, hydrological forecasting skill is masked by the human influences to the natural system, i.e. regulation of reservoirs, particularly at regions downstream of the reservoir.

The work will be continued in WP31 where we will analyse the reasons for (lack of) skill for a number of common case studies / events, analysing propagation of skill and uncertainty through the respective modelling chains. Also the relative benefit of multi model ensemble forecasts as opposed to that of any single model will be analysed, using already agreed protocols. It will further contribute to 2 climate services prototypes developed in WP42. Finally, these results will be confronted with progress in the wider, global community organised in the HEPEX programme.

2. Project Objectives

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

Table 1 Project wide EUPORIAS objective as addressed in this WP.

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.	Yes	
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.		No
3	Develop a set of standard tools tailored to the needs of stakeholders for calibrating, downscaling, and modelling sector-specific impacts on S2D timescales.	Yes	
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.		No
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.		No
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.		No

3. Introduction

Following the EUPORIAS DOW, one of the main tasks of WP23 is the development of the underpinning hydrological impacts models that will be used within the sector specific products. Their development has been based on the existing impact models available within the consortium, more than one model for each sector, i.e. five structurally different hydrological models see table 2. The skill of the models has been assessed with respect to their accuracy for key sector specific variables e.g. high/low river-flow events. Seasonal hindcasts have been evaluated with respect to their accuracy for key, sector specific variables; decadal hindcast have not been analysed till present. The specific factors limiting or enhancing the skill in the model chain, i.e. non-linear error propagation, are being and will be assessed in collaboration with WP31 in space and time scales and comparison of skills between related models will reveal respective weaknesses and strengths, systemic uncertainties, and possibly provide guidance for skill weighted multi models forecast ensembles.

These off-line hydrological impact models have been configured to be driven by S2D ensemble forecasts to generate ensembles of high-resolution surface data. As much as possible common climate input and output data-streams have been developed for models addressing the same sectors (e.g. for all hydrological models). This should ease the burden on WP21 and to provide researchers and sectorial stakeholders with consistent outputs from multiple models, thus providing multi model ensemble based estimates and associated uncertainties (WP31).

We have defined a limited set of common cases to be analysed by each contributing partner in addition to specific cases that will be addressed individually. Outputs and experiences will be made available to RT4 and case studies for developing dedicated services.

Table 2 Overview of hydrological models implemented in a S2D framework in WP23

model	**partner**	**resolution / domain**	**processes included**	**calibrated**
EHYPE	SMHI	~15km[1], Europe	land use (CORINE), reservoirs (GrAND), irrigation (GMAI), lakes & wetlands (GLWD)	yes, parameter calibration on 870 stations
VIC	WU	0.5^o, Europe	land use (FAO/WISE,)	no
LPJml	WU	0.5^o, Europe	land use (HYDE), reservoirs (GrAND), irrigation (GMAI), lakes (GLWD)	no
SAFRAN-ISBA-MODCOU	MeteoFrance	8km, France	land use (ECOCLIMAP), groundwater (BDRHF)	yes, output calibration (post processing)
SIMPA	CETaqua	1km, Spain		
SIMRISK	CETaqua	-, reservoir	reservoir management	

[1] EHYPE is not grid based, but semi distributed/sub-basin based (average sub-basin area 215 km^2

The predictive skill of river runoff for a number of European catchments using river routing models have been assessed on seasonal timescales, based on the comparison between hindcast simulations and high-resolution observations, both real (i.e. GRDC) and synthetic (simulations with the same models forced by observed meteorology). Both high flow (i.e. flood) events and low flow periods will be analysed in the present report. Verification points have been chosen to represent various climatologies, soil-types, land uses, altitudes and catchment scales within Europe.

In particular the model's abilities to capture flood and drought indices that are of interest to the stakeholders have been assessed. The skill of the predictions have been and will be further assessed using the tools (such as tercile probability, outer quintile, reliability diagrams, ROC scores, etc., commonly used by GPCs) that have been developed by the meteorological community to assess the skill of ensemble prediction systems.

Analysis of model output may reveal regions where the hydrological responses are comparable with one another. For these functionally similar areas, the physical/climatological factors that are responsible for the variations in skill observed in the different regions will be analysed and where possible model improvements will be suggested.

4. Progress summary

4.1 Development and application of the HYPE model for seasonal hydrological forecasting at the pan-European scale (SMHI)

EHYPE impact model description

The Hydrological Predictions for the Environment, HYPE, model is a semi-distributed rainfall-runoff model capable of describing the hydrological processes at the basin scale (Lindström et al., 2010). The model represents processes for snow accumulation and melting, evapotranspiration, soil moisture, discharge generation, groundwater recharge, and routing through rivers and lakes. HYPE simulates the water flow paths in soil which is divided into three layers with a fluctuating groundwater table. In addition, parameters are more linked to physiographical characteristics in the landscape, such as Hydrological Response Units (HRUs) linked to soil type and depths and vegetation. Elevation is be used to get temperature variations within a sub-basin to influence the snow conditions. The model requires information on terrain, soil and land use, lakes and reservoirs and irrigation as input, which, in this application, has been obtained from the global sources.

Irrigation in HYPE is simulated based on crop water demands calculated either with the FAO-56 crop coefficient method or relative to a reference flooding level for submerged crops (e.g. rice). The demands are withdrawn from rivers, lakes, reservoirs, and/or groundwater within and/or external to the sub-basin where the demands originated. The demands are constrained by the water availability at these sources. After subtraction of conveyance losses, the withdrawn water is applied as additional infiltration to the irrigated soils from which the demands originated.

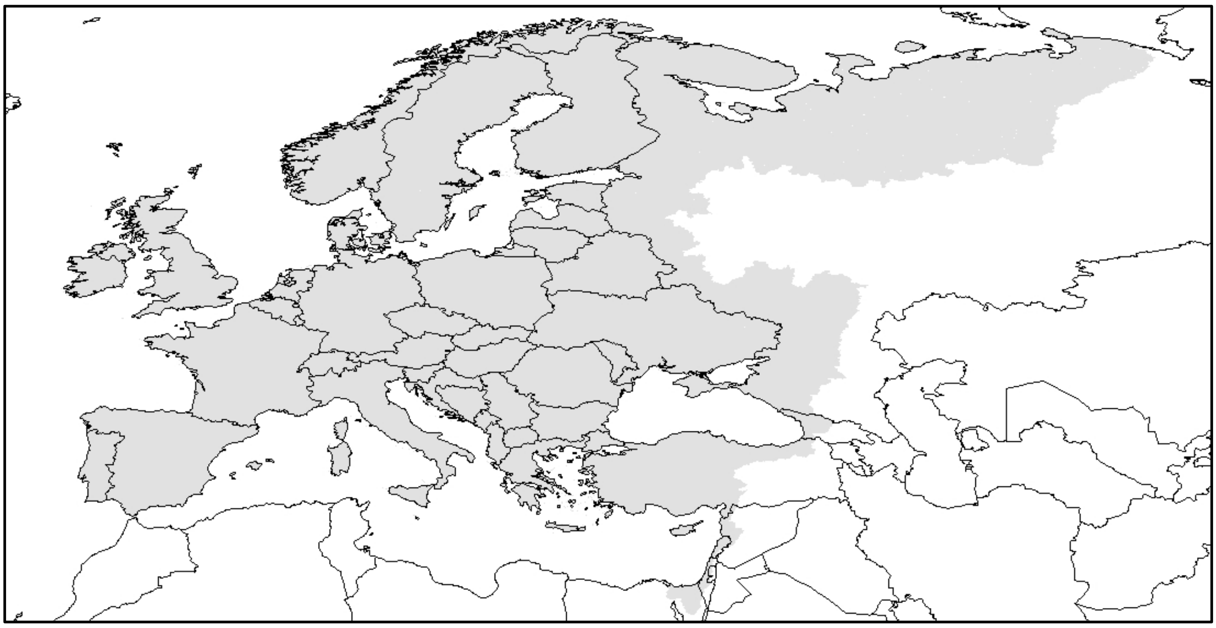

Figure 1 Domain of the EHYPE model.

Table 3 Data sources and characteristics of the EHYPE setup.

Characteristic/Data type	**Info/Name**	**Provider**
Total area (km^2)	8.8 million	-
No. of sub-basins	35408 (mean size 215 km^2)	-
Topography (routing and delineation)	hydroSHEDS (15 arcsec)	Lehner et al. (2008)
Soil characteristics	Harmonised World Soil Database (HWSD)	Nachtergaele et al. (2012)
Land use characteristics	CORINE	Bartholomé et al. (2002)
Reservoir and dam	Global Reservoir and Dam database (GRanD)	Bernhard et al. (2011)
Lake and wetland	Global Lake and Wetland Database (GLWD)	Lehner & Döll (2004)
Irrigation	Global Map of Irrigation Areas (GMIA)	Siebert et al. (2005)
Discharge	GRDC, EWA and others (2690 stations)	http://www.bafg.de/GRDC
Precipitation	WFDEI (0.5^o x 0.5^o)	Weedon et al. (2011)
Temperature (mean, min, max)	WFDEI (0.5^o x 0.5^o)	Weedon et al. (2011)
Snow cover area	GlobSnow	Weedon et al. (2011)

The HYPE model setup for the pan European region (8.8 million km^2; see Figure 1) is currently improved. The model has a spatial resolution of 35408 sub-basins, i.e. in average 215 km^2 and is referred to as EHYPE v3.0. The model runs at a daily time step.

Model setup

The model is setup based on global available datasets, which are listed in Table 3. Forcing data (daily mean precipitation and temperature) are based on the WATCH-ERA INTERIM (WFDEI) product.

Initialisation of the model

The EHYPE hydrological model needs initial conditions (level in surface water, i.e. reservoirs, lakes and wetlands, soil moisture, snow depth) that are obtained by driving the model using "observations" (in here the output of the model forced by WFDEI) for a spin-up period. The model can further run using pre-calibrated model parameters (Donnelly, Andersson et al. 2015). The protocol used for the forecasts is presented in Figure 2 on the next page.

Model evaluation

The aim is to develop an impact model directly been useful to the end-users; hence an adequate model performance in terms of discharge and other hydrological variables is important. EHYPE v3.0 was calibrated using observed discharge stations, in-situ data and satellite data. We note that we also aim to improve the representation of WFDEI forcing data (i.e. precipitation and temperature) in the model in order to adequately estimate the sub-basin mean fluxes. The difference between WFDEI and E-HYPE spatial resolution could result into under- / over-estimation of extremes; hence different spatial interpolation methods were investigated and their corresponding runoff is assessed.

Results on model performance with regard to flow signatures are presented in Figure 3. Overall a good performance is achieved over the entire European domain. Analyses of the spatial performance pattern and its relation to physiographic-climatic characteristics point towards limitations of the current model setup and requirements for improvements (e.g. regulation of reservoirs).

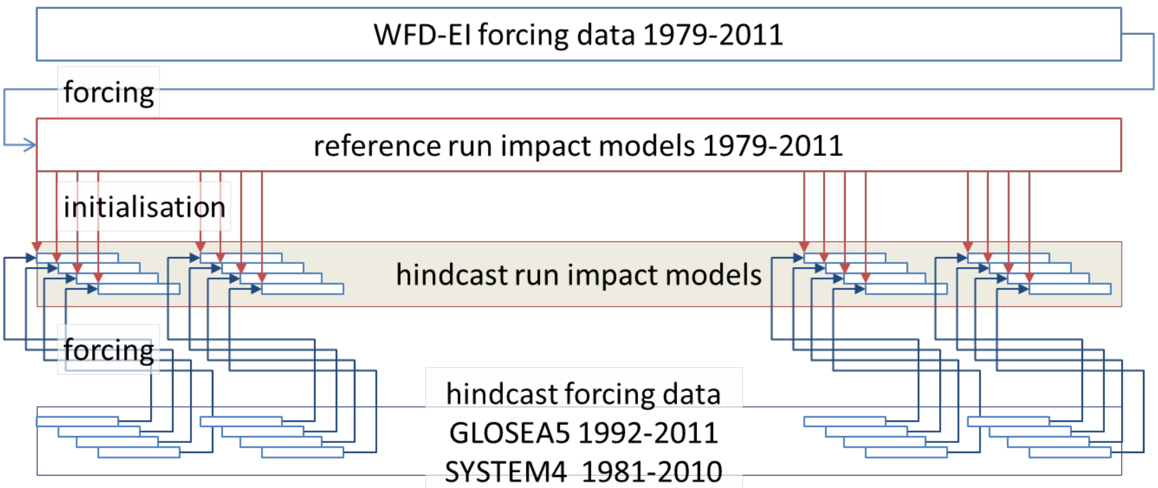

Figure 2 Protocol for seasonal impact model forecasts within WP23/31.

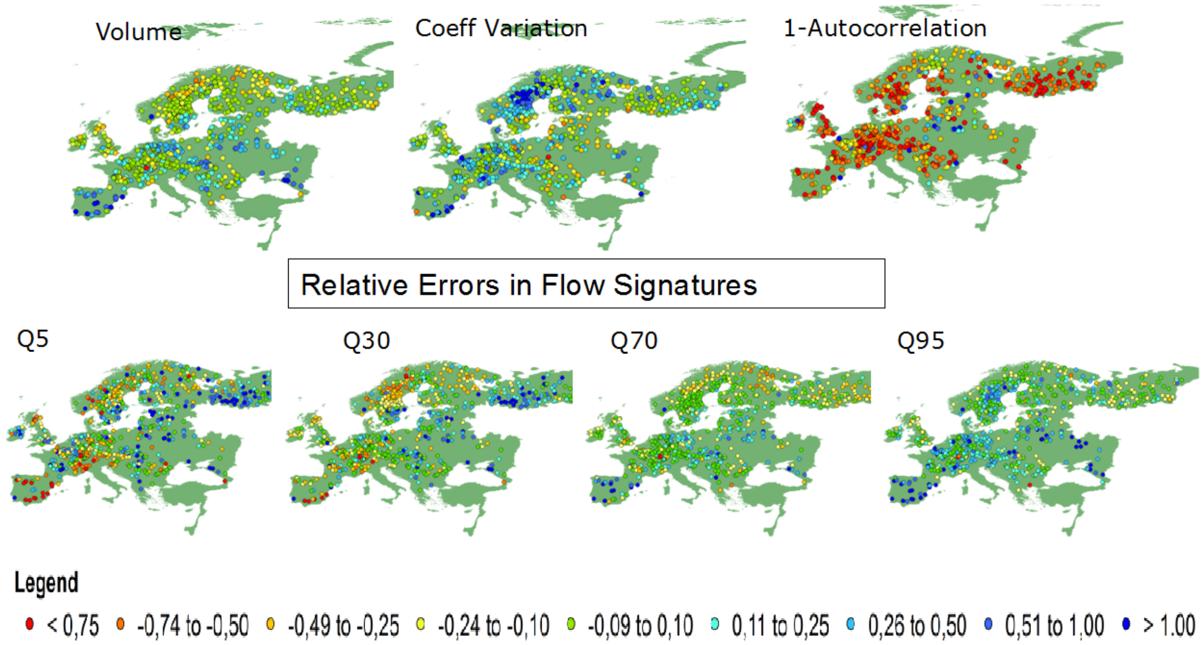

Figure 3 Spatial performance based on various flow signatures (volume, coefficient of variation, autocorrelation, and flow percentiles 5th, 30th, 70th and 95th).

Seasonal hydrological forecasts

The skill of seasonal hydrological forecasts was analysed in about 1200 locations around Europe. The objective was to assess the potential to represent the monthly average discharge (hence focus mainly on representing the volume of water) for different lead times (i.e. 0, 2, and 4 months ahead of the initialization) and for all 15-ensemble members. The *beta* metric is used here (Gupta et al., 2009):

$$beta = 1 - \sqrt{(\beta - 1)^2}$$

β is defined as the ratio of the daily mean of the forecasts over the daily mean of the "observations" (the output of the model forced by WFDEI); note that the range of values for each term varies between -∞ and 1 with 1 being the optimum.

Figure 4-6 shows the spatial variability of *beta* for all months for lead months 0, 2, and 4 respectively. Overall, a good skill is achieved for lead month 0 particularly over the northern Europe. The performance seems to deteriorate in the Mediterranean region in the autumn period. As expected the skill is further deteriorated with increased lead month. This is particularly emphasized over the central Europe and Mediterranean region. Less precipitation occurs during the summer months in these regions, which could result in the generally good skill over these months. Note that the runoff response in the Mediterranean is generally rain-fed. The skill over the north Europe is good particularly over the winter period. The response of the northern European basins is controlled by snow accumulation/melting processes. Consequently the skill of the seasonal temperature forecast could be a key control in these regions. It is interesting that the skill is deteriorated in the summer months during which snow melting has occurred and basin response is mainly controlled by rainfall; see Figure 5 and 6.

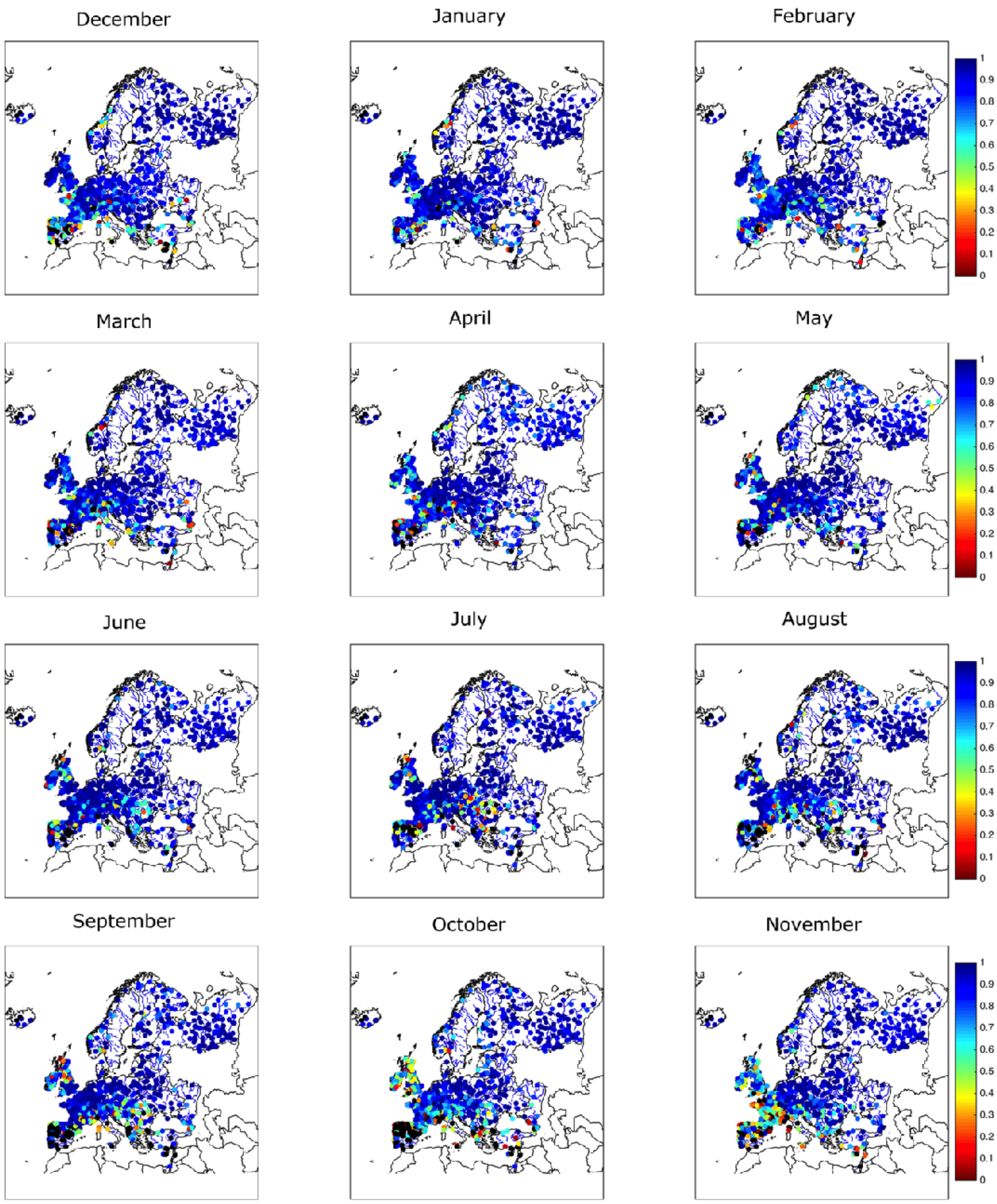

Figure 4 Spatial variability of the *beta* performance for all months and lead month 0.

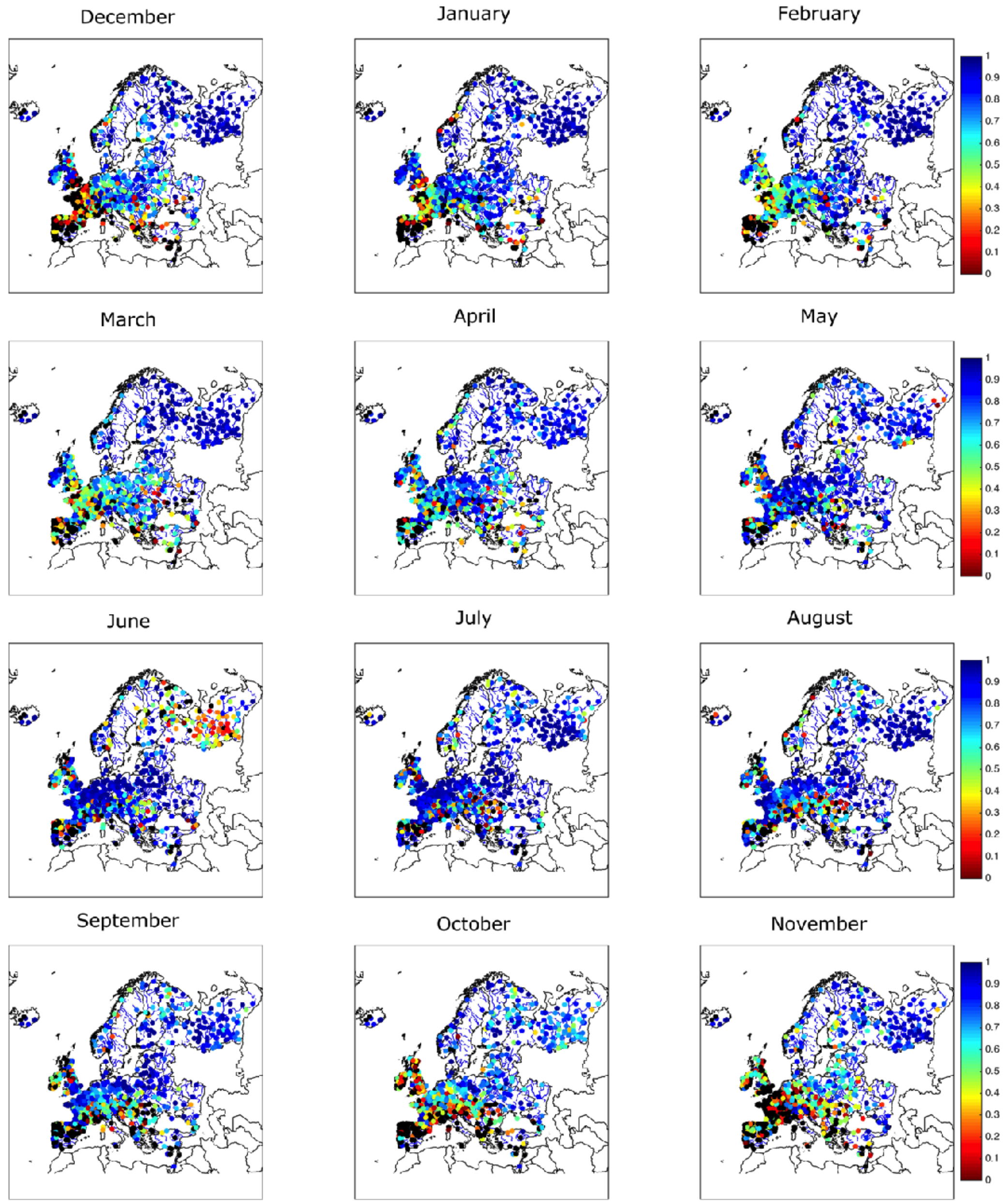

Figure 5 Spatial variability of the *beta* performance for all months and lead month 2.

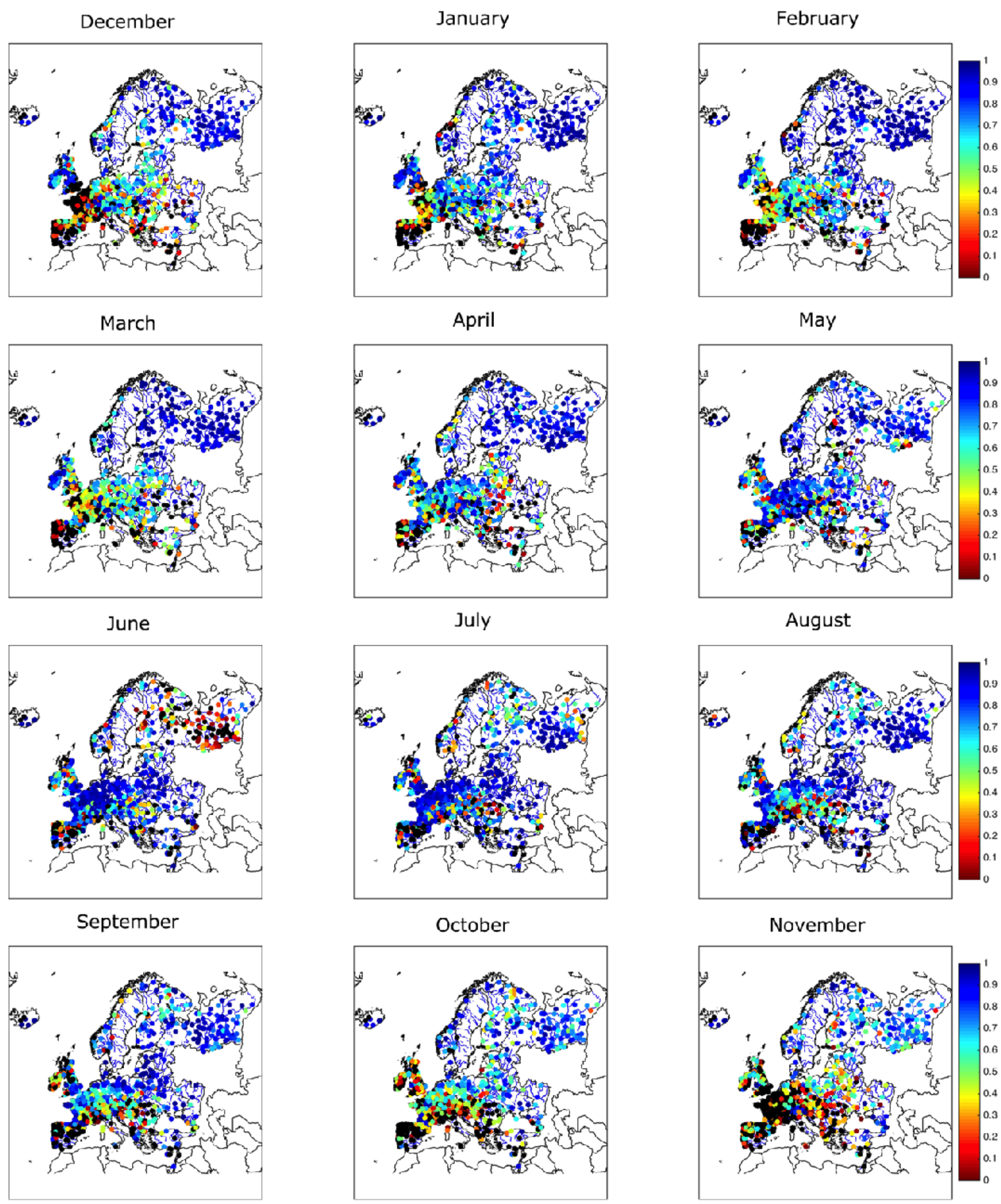

Figure 6 Spatial variability of the *beta* performance for all months and lead month 4.

Focussing the analysis on three large European river basins, i.e. Umeälven, Rhine and Po, we present the *beta* metric for all months and lead times (Figure 7). It is interesting to note that the skill remains high for all lead months and months of the year for the Umeälven. Snow accumulates over winter and melts over spring in this basin, which is a process that could also be reproduced by climatology. However, as the basin is heavily regulated, the skill of the seasonal climate forecasts may not have a direct impact on the hydrological forecasting skill. The skill in the Rhine seems to be controlled by seasonality. Flow response in the summer months is not well captured which could be due to the poor seasonal climate forecasting skill over this region and period. The pattern is mixed in the Po. Although the skill generally deteriorates (during some months significantly so) with increased lead time, this does not seem to be obvious in the summer period probably due to the low rainfall occurring in these months.

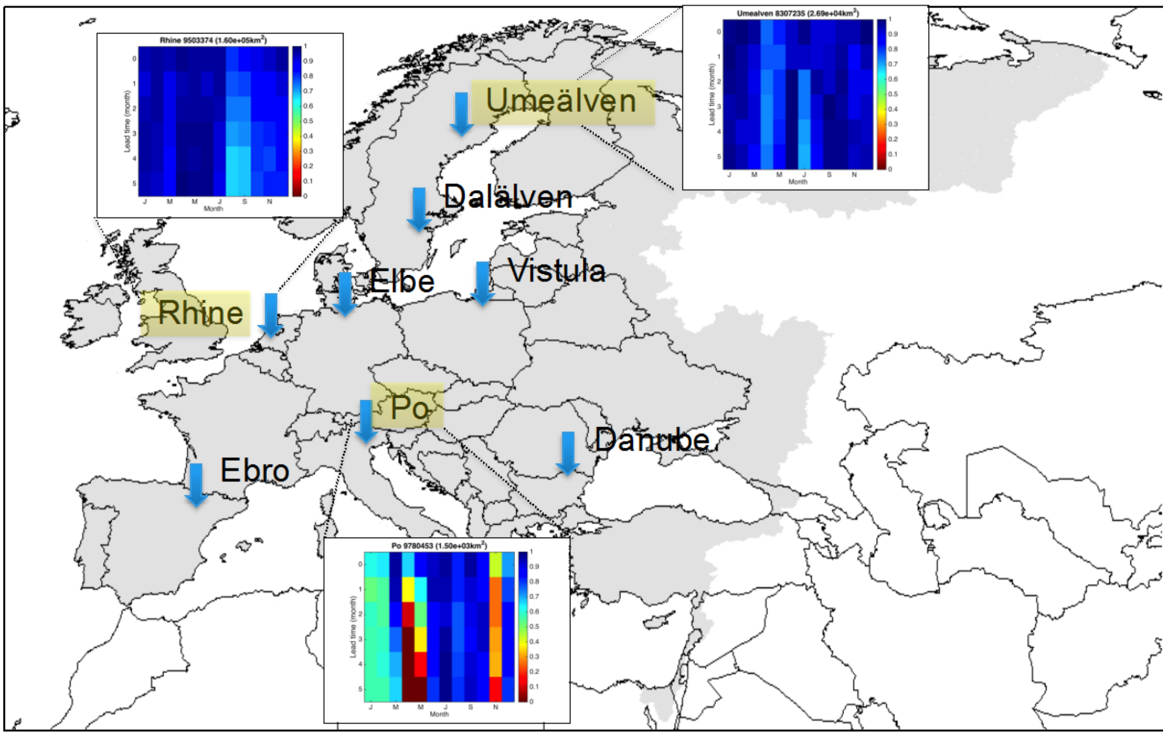

Figure 7 Forecast skill for all months and lead months in three EU rivers.

Conclusions

The evaluation spots the strengths and weaknesses of ensemble seasonal forecasts from ECMWF System 4 (15 members), including trends of performance in various months and lead times.

- Seasonal hydrological forecasts show skill with regard to discharge volume in the European domain at the beginning of the initialization of forecast.
- Forecasting skill is particularly clear in northern Europe; however skill deteriorates as a function of lead time. This is emphasized in the summer months.
- Central Europe and the Mediterranean region have the lesser skill. The skill is dependent on the lead time; however the skill seems to be better in the summer period compared to the rest seasons.
- Seasonal hydrological forecasting skill does not always have a direct dependency to the seasonal climatic forecasting skill. Hydrological processes have longer memory (i.e. snow accumulation/melting processes, processes in lakes and wetlands etc.), which further affect the skill in the system. In addition, hydrological forecasting skill is masked by the human influences to the natural system, i.e. regulation of reservoirs, particularly at regions downstream of the reservoir.

4.2 Low flow forecasts over France with the SAFRAN-ISBA-MODCOU hydrometeorological suite (Meteo-France)

Experiments have been conducted to assess the skill of the hydrological system, based on the SAFRAN-ISBA-MODCOU (SIM) hydrometeorological suite which computes soil moisture and river flow forecasts over a 8-km grid and more than 880 river gauging stations in France (Habets, Boone et al. 2008). The main season of interest is the low flow period in France, which spread generally from summer to autumn. This period is of high interest for one of our stakeholder, EPTB Seine-Grands Lacs, in charge of the management of the great lake-reservoir upstream the Seine basin.

To respond to our stakeholder's needs, we extended our verification to the whole period of forecast (7 months), even though we knew that skill is extremely low at this range. We used Meteo-France's previous operational model for seasonal forecasts, ARPEGE system 3, to benefit from its long hindcast (1979-2007). We present runoff predictability assessments, for forecasts initialised in May.

Runoff predictability assessment

First, we compared hydrological forecasts with reference values, obtained from SIM reanalysis, not from observations. This first step, in the model's world, prevents our scores from any influence due to anthropogenic effects not represented in the model (e.g. dams). Scores are calculated over the 29-years hindcast, on monthly means river flow, in a deterministic approach (ensemble mean) and in a probabilistic approach for the lower tercile (which corresponds to low river flows). Here some results are presented.

An evaluation of the predictive skill for all the forecasted months is given by the temporal correlation maps (figure 8). They show a correlation higher than 0.7 for many river stations over the Seine basin up to August and still higher than 0.5 in September. Elsewhere, after June, the temporal correlation is rarely higher than 0.3. In October and November, only few stations have a score higher than 0.5.

Brier scores (Figure 9) and ROC areas (Figure 10) for the lower tercile confirm this rapid decrease in scores in most of the basins right from the month of June. Using this criterion, the Seine basin is still the most predictable area with our system.

To complete this verification, the seasonal forecast experiment (called SF) has been compared to a "climatological" one (called RAF, for Random Atmospheric Forcing). It consists on using the same initial states (soil moisture, snow cover, river flows…) as the seasonal experiment, but the atmospheric forcing is replaced by a set of past scenarios taken from reanalysis. This set has exactly the same size as the ensemble set of seasonal forecast (11 members). And globally, over the hindcast period, it has a climatological distribution. By comparing SF and RAF, one can expect to measure the part of skill given by the atmospheric forcing from the part resulting from initial conditions.

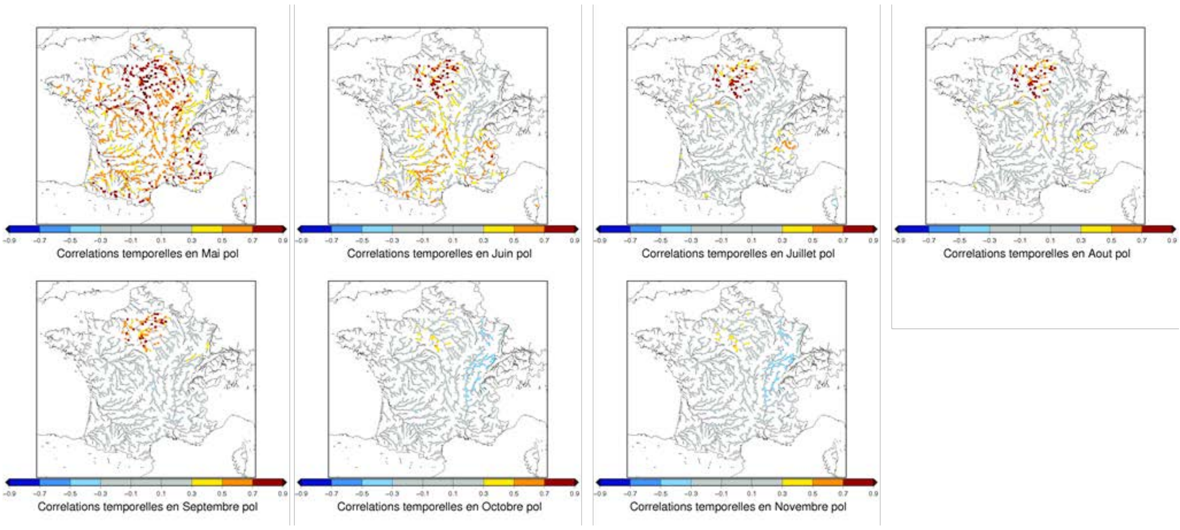

Figure 8 Monthly temporal correlation maps from the SIM model compared to its reanalysis, calculated over the 1979-2007 period, initial month is May, forecast from May to November. Points with black circles are stations of interest for EPTB.

Looking at the Brier Skill Scores maps for the lower tercile (figure 11) for months of May to August (further, the SF skill is very low, skill-scores are then not useful), SF appears to perform significantly better than RAF in May and June for the Seine River basin and surrounding areas, and for many stations in the Southern half part of France. For longer range, the added-value of SF seems weak and heterogeneously distributed.

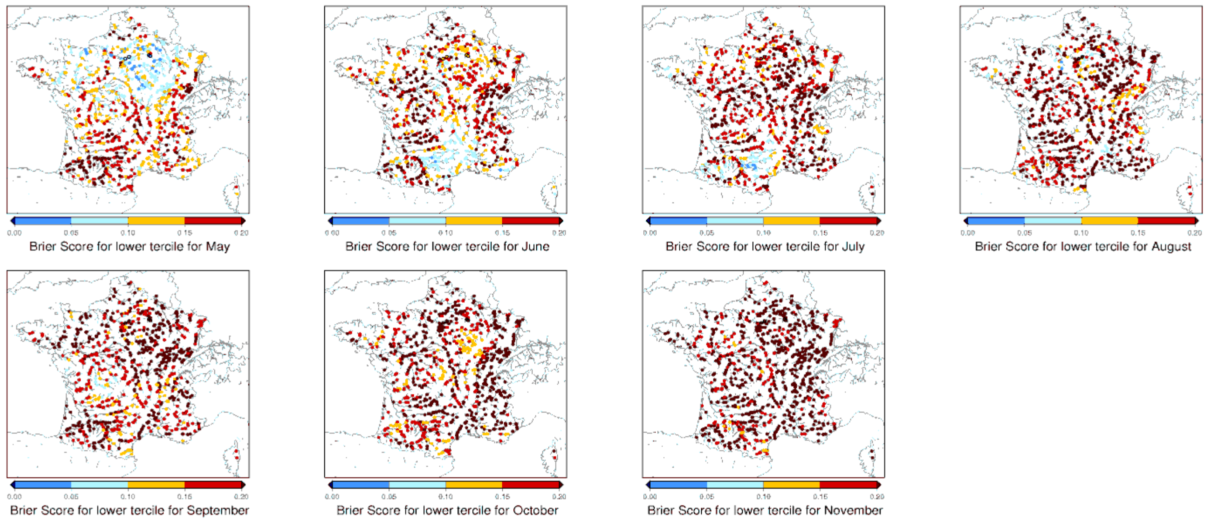

Figure 9 Maps of Brier score from the SIM model for the lower tercile, for each month of the forecasted period (May to November, initialised in May)

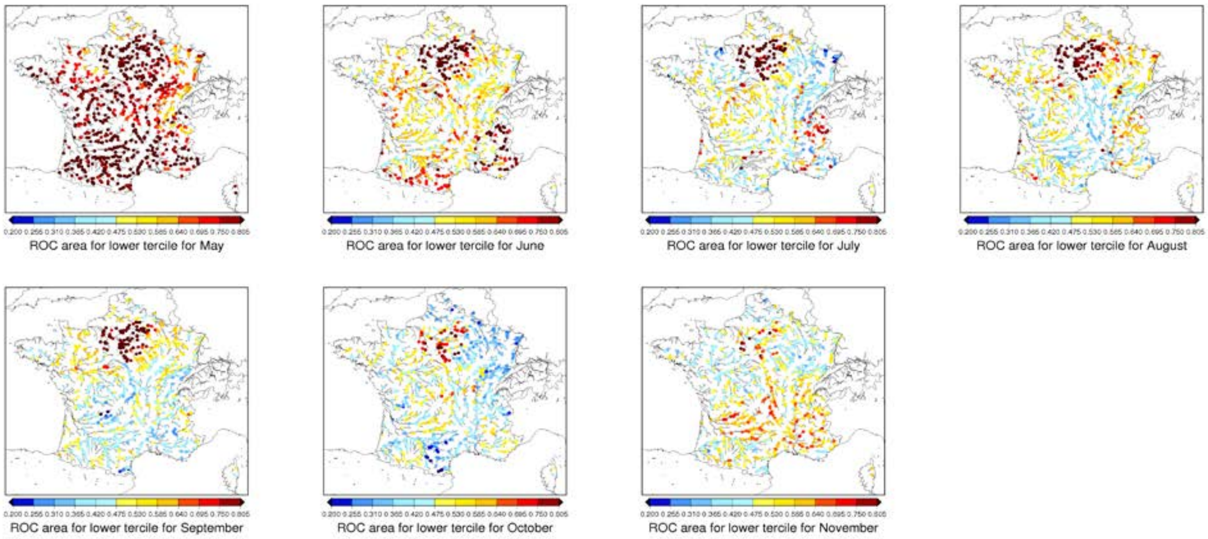

Figure 10 ROC areas for the lower tercile from the SIM model, for each month of the forecasted period (May to November, initialised in May).

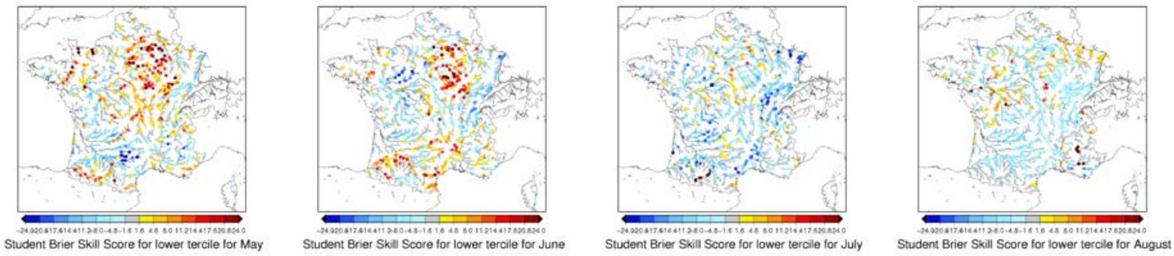

Figure 11 Monthly Student Brier Skill Scores maps from the SIM model SF experiment compared to the RAF experiment, calculated over the 1979-2007 period, initial month in May, forecast of the lower tercile from May to August. Grey means no significant difference between SF.

Predictability of impact parameters

The next step consists in comparing hydrological seasonal forecasts with observations. However our system is not taking into account human impact on runoff (there isn't any modelling of dam or reservoir). Therefore, because those impacts are concerning a huge majority of the French hydrological network, such an assessment is hard to achieve.

Thanks to our stakeholder for the Seine basin, we had access to their database of "naturalized" runoff to calibrate our forecasts. This calibration could thus be performed on their stations of interest. For the moment, we did it for only one station (Gournay, Marne basin, a tributary of the Seine river), in the framework of our prototype evaluation. We have compared different calibration method, to finally keep the most efficient, a simple quantile-quantile method.

After the runoff calibration, we were able to calculate the impact parameters that had been designed in collaboration with our stakeholder.

We focus here on two integrated indicators describing the drought severity. They were calculated with our SF and RAF experiments. They are both based on a comparison to a low level threshold (called "vigilance" threshold): when daily runoff drops below this threshold, it could lead to some interventions from the authorities. The first indicator is the number of days below the "vigilance" threshold, during a chosen period. The second one is the volume below the "vigilance" threshold.

Figure 12 presents the results of the SF experiment for the MJJA forecast period (May initial conditions). A simple evaluation consists in counting the years when the observation (number of days or volume) is in the interval [Q25, Q75], i.e. in the box of the boxplot. The results are in favour of the SF experiment, for the number of days below the threshold (11 years against 6 for the RAF experiment) and for the volume below the threshold (12 years against 9).

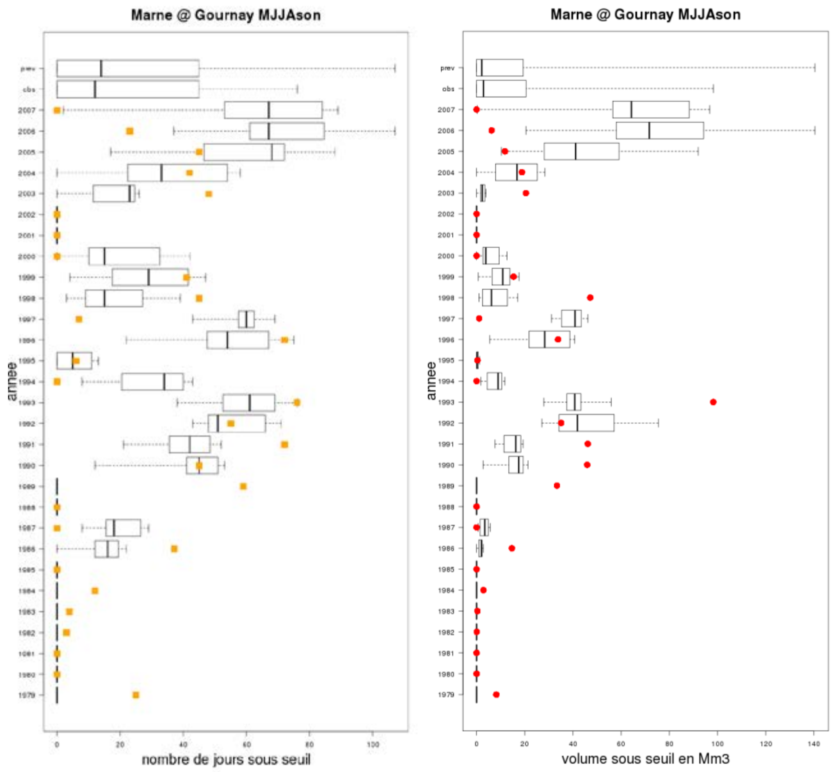

Figure 12 SIM model results for the Gournay station (Seine basin), number of days (left) and volume (right) under the "vigilance" threshold. The boxplot represents the SF experiment, the orange (red) square represents the observation. At the top, are presented the SF forecasts climatology (prev) and the observation climatology (obs), over the 1979-2007 period.

4.3 Multi model Europe-wide seasonal hydrological forecasting (WU)

WU has been working with two models that simulate water balance components including discharge: LPJml and VIC. The first is a generic global model ((Gerten, Schaphoff et al. 2004) (Biemans, Hutjes et al. 2009, Biemans, Haddeland et al. 2011)) which in the present context will be analysed for Europe only, with an online routing scheme that does include the effect of dams and their management too. VIC is a specifically for EUPORIAS implemented version for Europe only ((Liang, Lettenmaier et al. 1994, Haddeland, Clark et al. 2011)), using an offline routing scheme with no lakes and reservoirs. Neither of the models has been calibrated at basin level.

For both models three sets of runs have been / are being performed, following the procedure of figure 2, and all input and output is available in netcdf files:

- baseline/reference run forced by WFDEI
- hindcast with SYS4 forcing, **not** bias corrected (30yrs x 12mo x 15 members = 5400 runs of 7 months each)
- hindcast with SYS4 forcing, **bias** corrected (idem 5400 runs of 7 months each)

These are presently under evaluation. The base line run can be used for an evaluation of average model performance, preferably against observed discharge data, to establish e.g. model biases, etc. For the probabilistic skills we always consider the ability to predict above normal (AN) flows, i.e. flows of the upper tercile (p>.67), near normal flows (NN, 0.33<p<0.67) and below normal flows (BN, p<0.33).

VIC performance to date has been assessed deterministically only for a single hindcast ensemble member; probabilistic analysed awaiting completion of full SYS4 ensemble simulations.

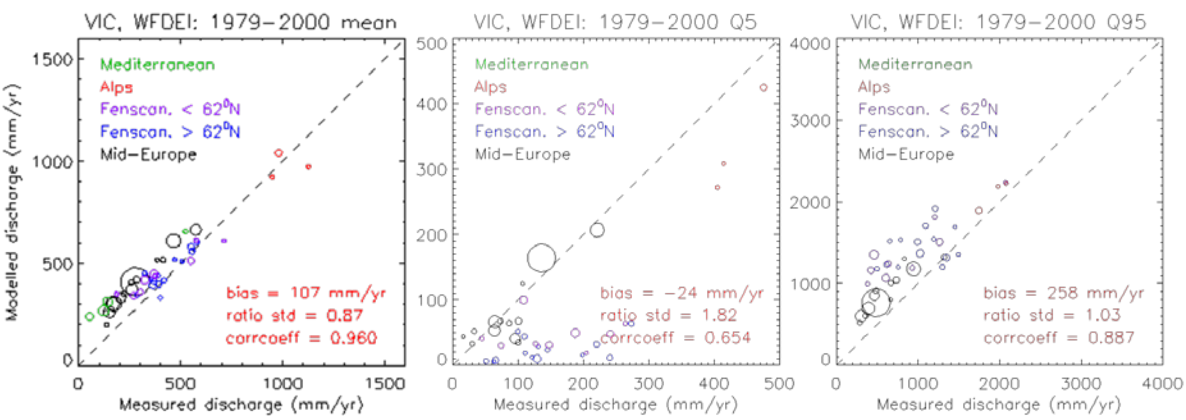

Figure 13 WFDEI forced VIC simulations validated against 46 stations across Europe for mean flow (left), low flow (<p5, middle) and high flow (>p95, right). Circles areas scale with basin area (the biggest is the Danube), colours refer to various sub-regions.

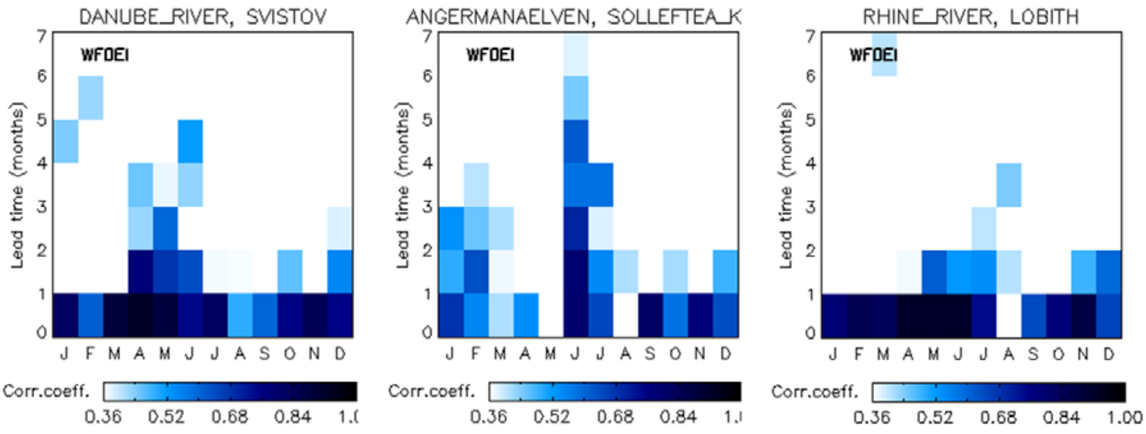

Figure 14 Anomaly correlations from SYS4 forced VIC simulations as a function of lead month (vertical) and time of year (hor.) for three stations in Europe and the Danube (right) Angerman Älven (Sweden, middle) and Rhine (right), respectively.

VIC has been validated against 39 stations from GRDC (more than half in Fennoscandia) plus 7additional stations on the Iberian Peninsula, in France and Poland from (Dai, Qian et al. 2009). Figure 13 shows its validation, exhibiting high correlations but positive biases for mean flows (especially in the Mediterranean), negative biases for low flows (especially in Fennoscandia) and considerable positive biases (>20%) for high flows everywhere.

Next an analysis of anomaly correlations was performed for a single member of the SYS4 forced simulation of VIC, a few examples for several stations are given in figure 14. Predicting anomalies for a month ahead performs generally quite well throughout the year, for longer lead times strong seasonal differences exist with skill occurring mostly in spring early summer with lead times up to 3-4 months.

Since the hindcast runs for VIC are still running we focus the remainder of our analysis on the LPJml results.

For LPJml a recoding now allows easier regional applications, still in parallel mode, where previously only global simulations were practically feasible. This greatly facilitates S2D applications that require relatively large ensembles to be run and analyzed. Previously LPJml was mainly used to study the effects of climate change on hydrology, generally requiring (after spin up) a few, century-long runs (for different CMIP models). The 5400 runs listed above are equivalent to more than 31 centuries, justifying the effort to increase computational efficiency.

Figure 15 on the following page shows such an evaluation of the LPJml reference run for 30 stations across Europe. The Taylor diagram shows correlations between observed and simulated monthly discharge are mostly between .70 and .90, standard deviations that are between 20% less to about 80% higher than observed and generally negative biases. The values for the Kuiper Skill Score (lower right) are around 0.8-0.9 for above and below normal which can be considered quite good (0.5 represents no skill).

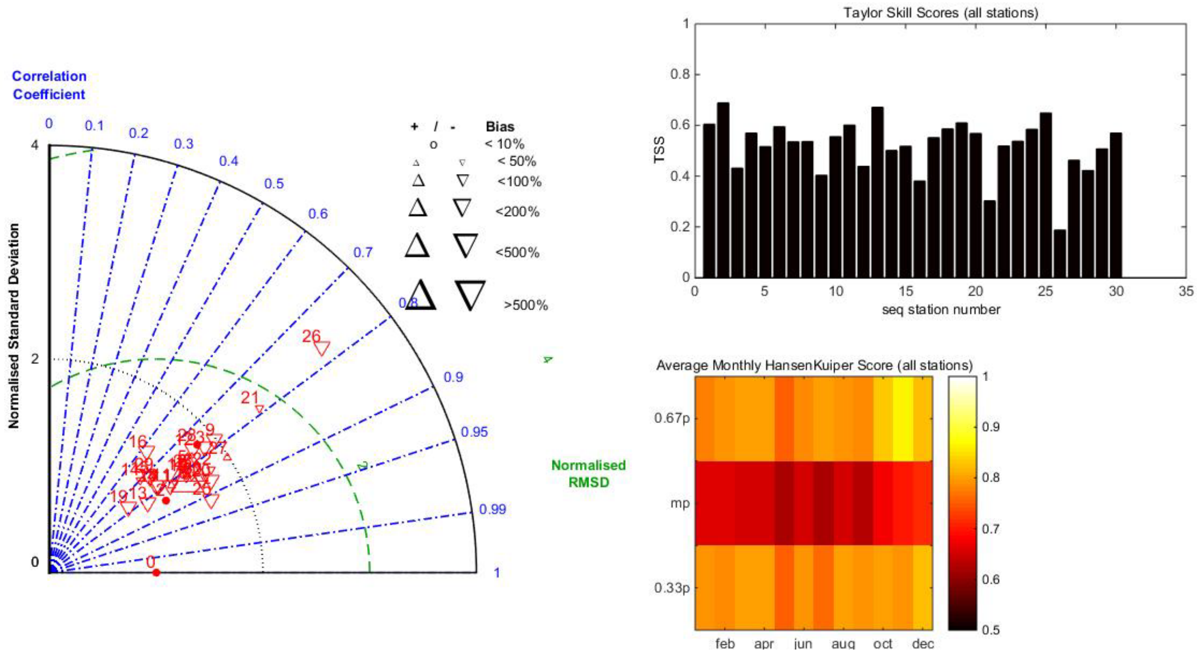

Figure 15 Validation of WFDEI forced LPJml discharge simulations against 30 stations GRDC data. At left a Taylor diagram is presented which shows normalised RMSD and Standard Deviation as well Correlation Coefficient of each station while the shape and size of the symbol reflects the average bias in discharge. The top right bar graph gives the Taylor Skill Score for each station in the diagram at left. The bottom right figure presents the ability of the model to simulate monthly anomalies for above normal (>.67 percentile), normal (0.33<p<.67) and below normal (<.33 p) discharge.

Next we highlight one station on the river Tisza, a tributary of the Danube, as a further example (figure 14). In this particular case the model overestimates the discharge and the variation in discharge both by about 30%. Monthly discharge anomalies are well simulated: floods best so in winter – spring (DJFMAM), droughts best from May till the end of the year (MJJA).

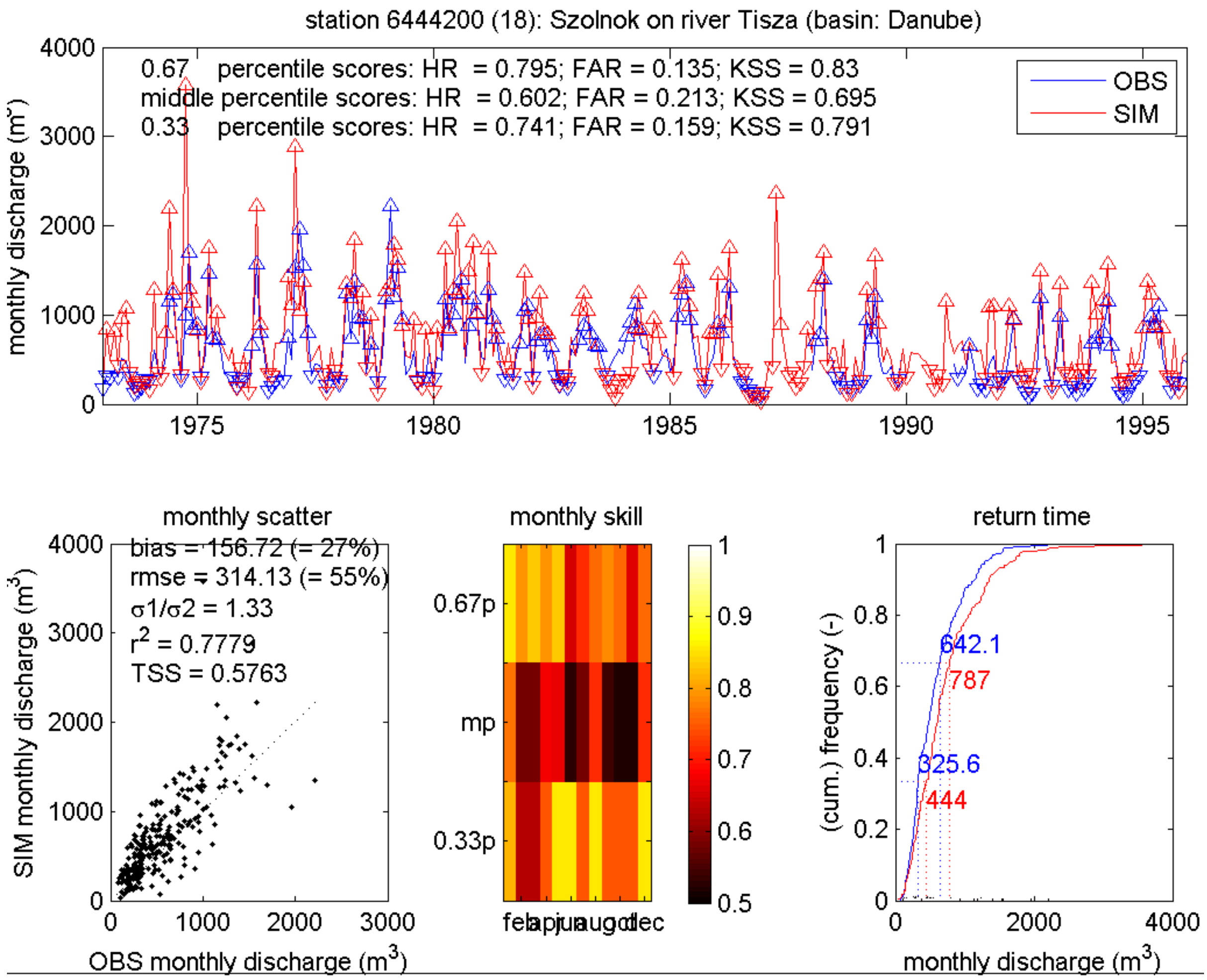

Figure 16 Example validation of WFDEI forcecd LPJml discharge simulations for one particular station (Szolnok on the Tisza, a tributary of the Danube; no 18 in the previous figure). It presents the time series of monthly discharge (top) a scatter diagram with some statistics (bottom left), the monthly Kuiper Skill Score and a flow-duration curve (bottom right, where the numbers indicate the .33 and .67 percentiles discharge).

For LPJml we compare the hindcast SYS4 simulated runoff and discharge against that of the base run WFDEI forced runoff and discharge, using some typical probabilistic skill score metrics. Scoring against real observations is presently still under evaluation. A further limitation of real data is that we can validate only one hydrological variable, i.e. discharge for relatively few stations only. Validation against the baseline run allows evaluation of more variables at pixel levels. Such an analysis may teach us more about the why of any (lack of) forecast skills. Performance scores against real data will probably be lower than those reported next.

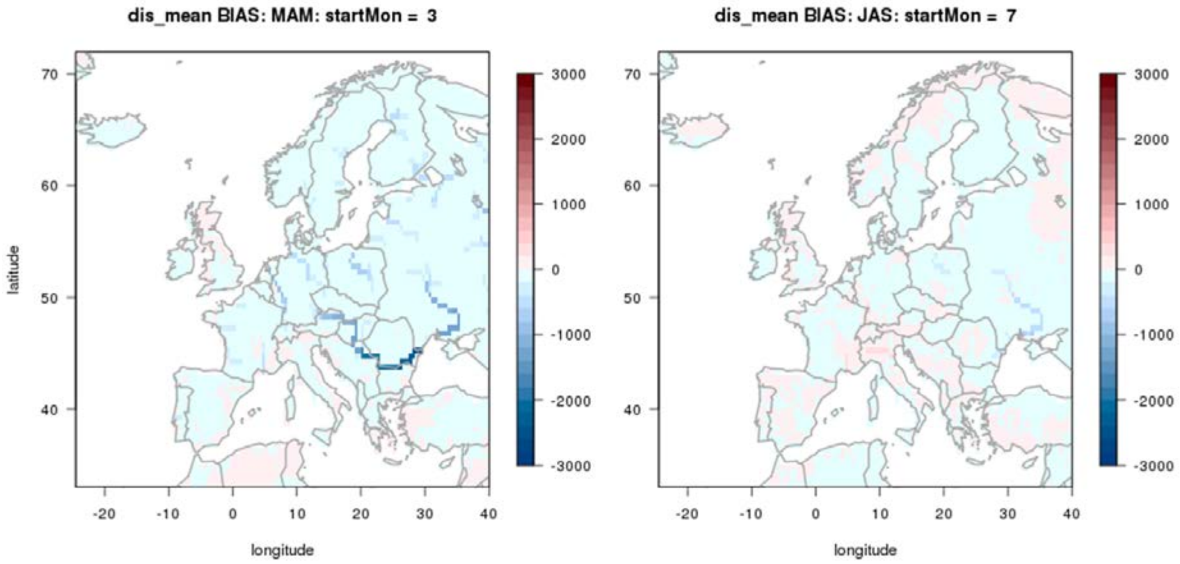

Figure 17 LPJml biases (SYS4 forced runs minus WFDEI forced run) in MAM and JAS discharge, lead month 1.

In figure 17 above, we start with a map of biases in MAM and JAS discharge, lead month 1 (the patterns change little with increasing lead times). SYS4 leads to slightly positive MAM discharge biases around the Mediterranean and in northern UK. The remainder of Europe has slightly negative MAM biases which accumulate in the main rivers stems. In JAS larger areas show slightly positive biases and apparently in many basins the positive and negative biases cancel out, leading to minimal biases (relative to those in MAM) in the main river stems.

Next we constructed ROC score diagrams for a few (yet) arbitrarily chosen basins. The figure 18 on the next page shows ROC diagrams for discharge at the mouth of the Göta Älv in SW Sweden. It shows considerable skill for positive and negative spring (MAM) anomalies forecasted as early as January (lead month 2). In summer there seems to be little skill in forecasting either positive or negative anomalies, although for longer lead times the scores are better than for shorter lead times. The next figure (figure 19) plots the surface under each of these lines in the ROC diagram, i.e. the AROC score against lead time for this basin again, as well as for three other basins across Europe (Danube, Rhône and Ebro). It shows considerable skill in forecasting MAM anomalies at the Danube delta up to 2 months in advance, and no skill for JAS anomalies. For the Rhône delta there seems to be no skill for either MAM or JAS anomalies, except for lead month 1. For the Ebro some minor skill seems to exist for JAS/summer droughts forecasted as early as April (lead month 4).

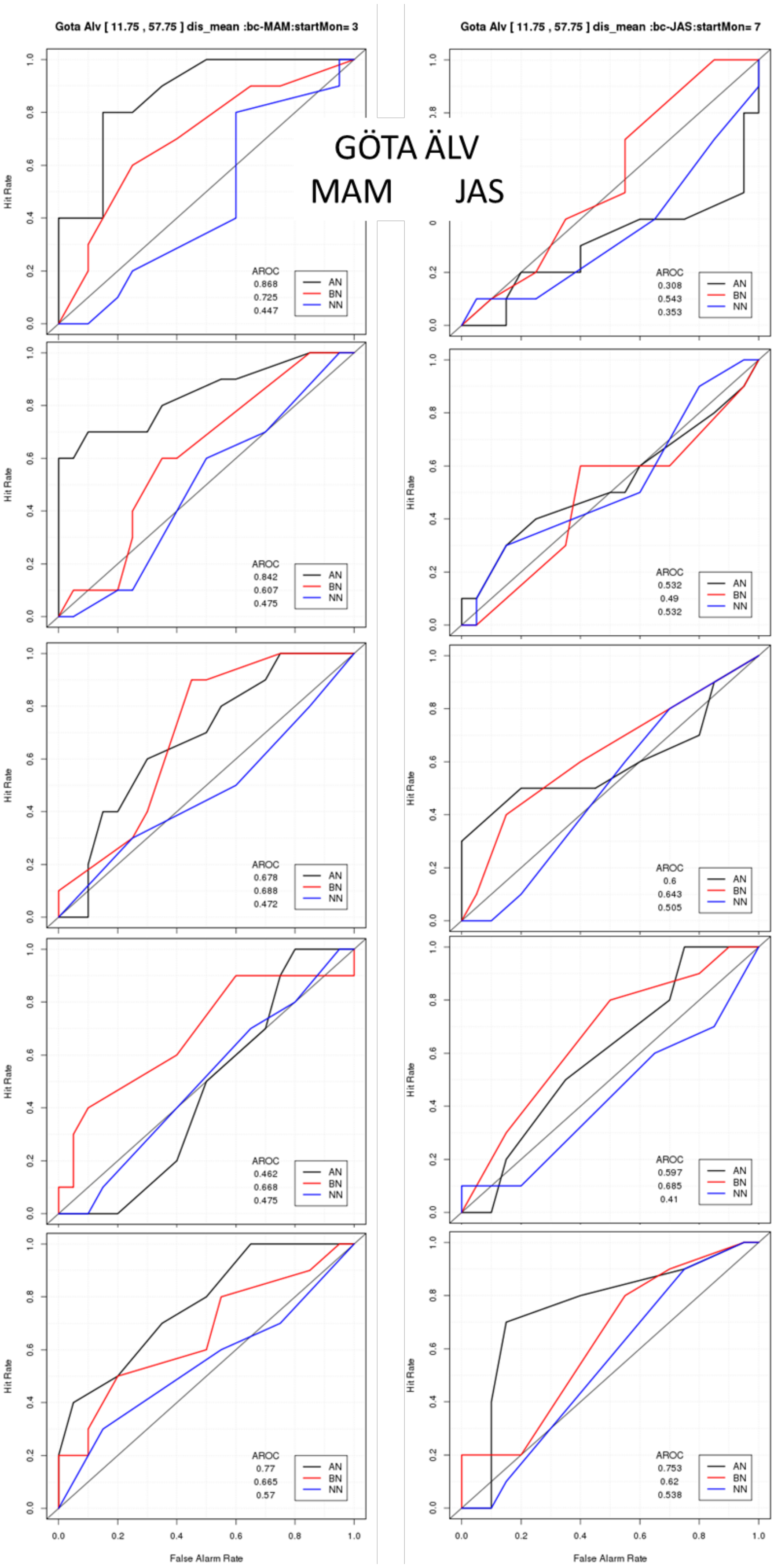

Figure 18 ROC diagrams for SYS4 forced LPJml simulated discharge at the mouth of the Göta Älv in SW Sweden. At left diagrams for MAM, i.e. spring anomalies, at right for JAS/summer anomalies. From top to bottom the lead time increases from 1 to 5 months. Black lines for Above Normal (AN), red lines for below normal (BN) and blue lines for near normal (NN) flows.

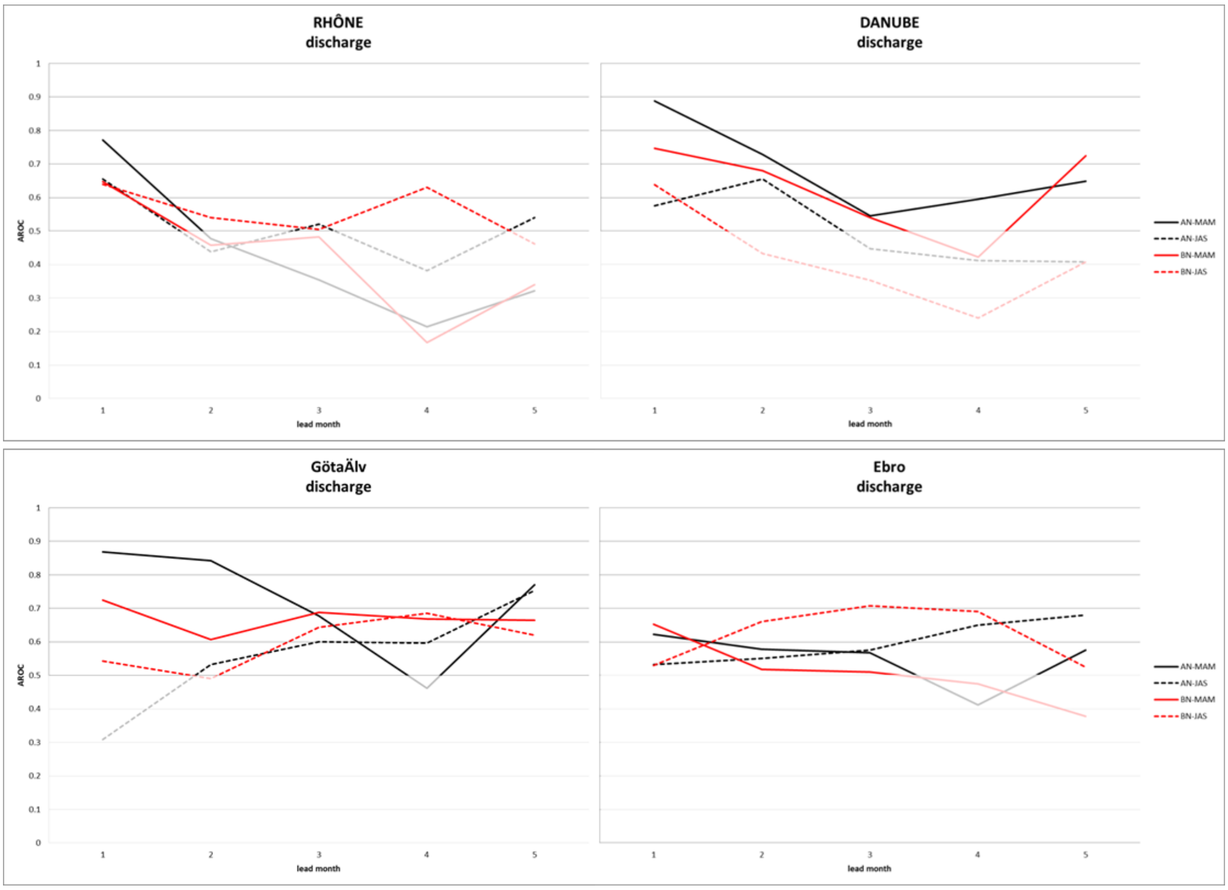

Figure 19 AROC scores diagrams for SYS4 forced LPJml simulations for 4 example basins for MAM and JAS discharge as a function of lead time. Broken lines are for JAS, continuous lines for MAM; black lines for AN, red lines for BN. AROC scores above 0.5 indicate some skill, so the lower half of each plot has been shaded out.

These AROC metrics can be combined with attribution and uncertainty scores, following the Murphy '73 decomposition, in the Brier Score (BS) which can then be mapped. Lower scores are better here. The figure 20 on the next page shows these for MAM discharge across Europe. For lead month 1 (top) it shows large areas with skills below 0.2 which can be considered good skill; the maps for BN events are remarkably similar to those for AN events. These gradually detoriate up to lead month 4, especially in NE Europe, though certain areas in SE Europe retain some skill. Surprisingly skills improve again for the longest lead time, a phenomenon that warrants further analysis. In the right column of the same figure MAM ranked probability skill scores (RPSS) are presented, with black dots indicating significant skill. These suggest considerable skill across most of Europe for short lead times, retracting to NE Europe for longer lead times. Again for the longest lead time the scores are more significant again and very comparable to those of lead time 2.

Finally figure 21 presents BS and RPSS for JAS discharge. Overall, BS are slightly worse in summer than in winter and vary surprisingly little with lead time. Also significant RPSS levels are much rare and seem to be confined to Northern Scandinavia, the Eastern Mediterranean and a few isolated but persistent 'hotspots' in the Swiss Alps and parts of the Iberian peninsula.

As noted before these is just a very brief tentative first probabilistic evaluation of forecast skills. The scatter in all the graphs and maps is still a bit high . Or phrased alternatively, the statistics are a bit poor for 10 bins for a single pixel of a 15 member ensemble. Pooling more pixels and/or reducing the number of bins will reduce the scatter and may thus produce more informative results. Also comparing these results to the skill of just using a climatological average as forecast, or to statistical forecasts, will better show the added value of the computationally very expensive modelling chain used here. The Brier Skill Score provides such a relative metric ($BSS = 1 - BS_{model}/BS_{climatology}$).

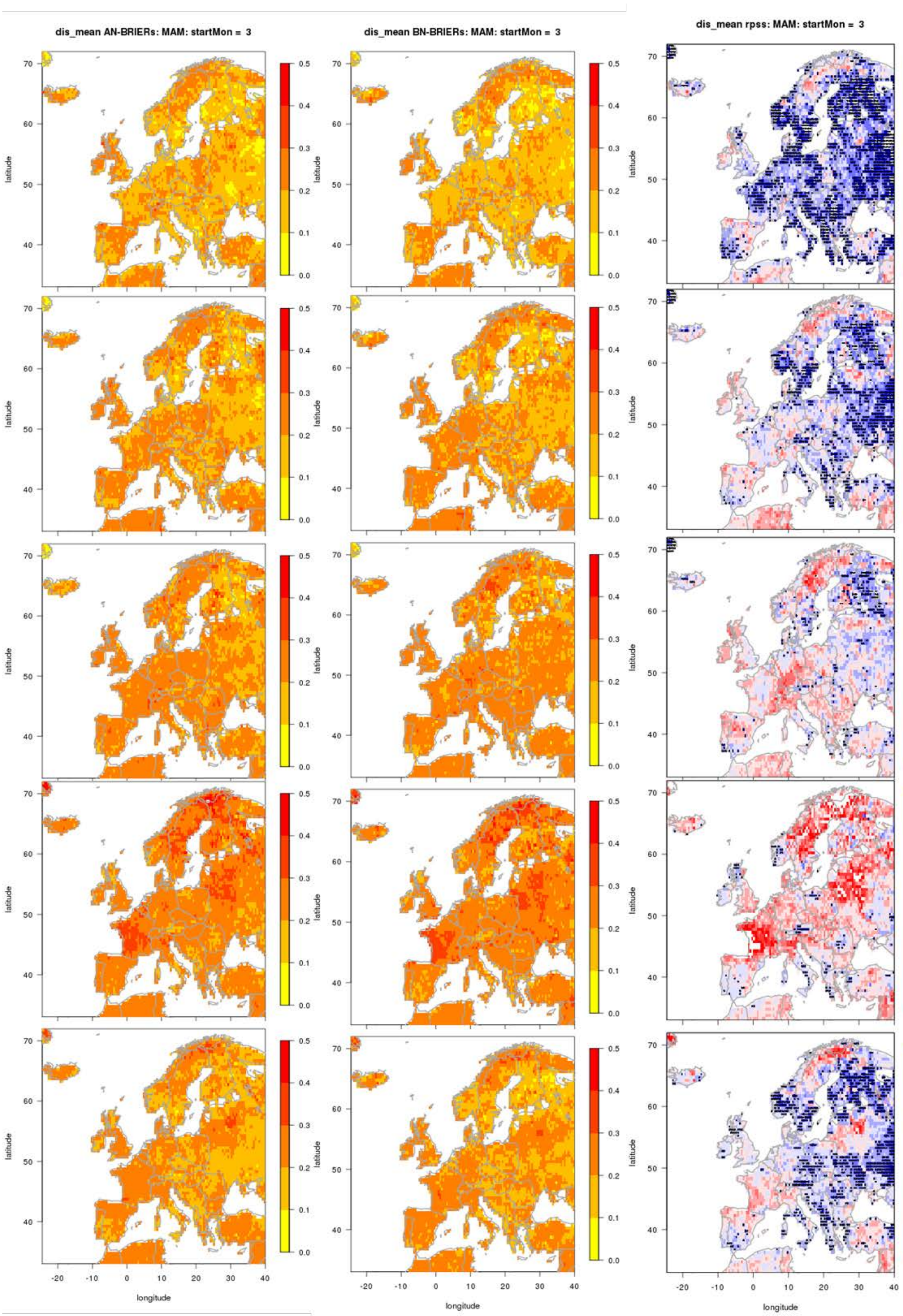

Figure 20 Brier Scores diagrams for SYS4 forced LPJml simulated discharge (left for An, middle for BN) and ranked probability scores (right) for MAM discharge across Europe. Lead months increase from top to bottom.

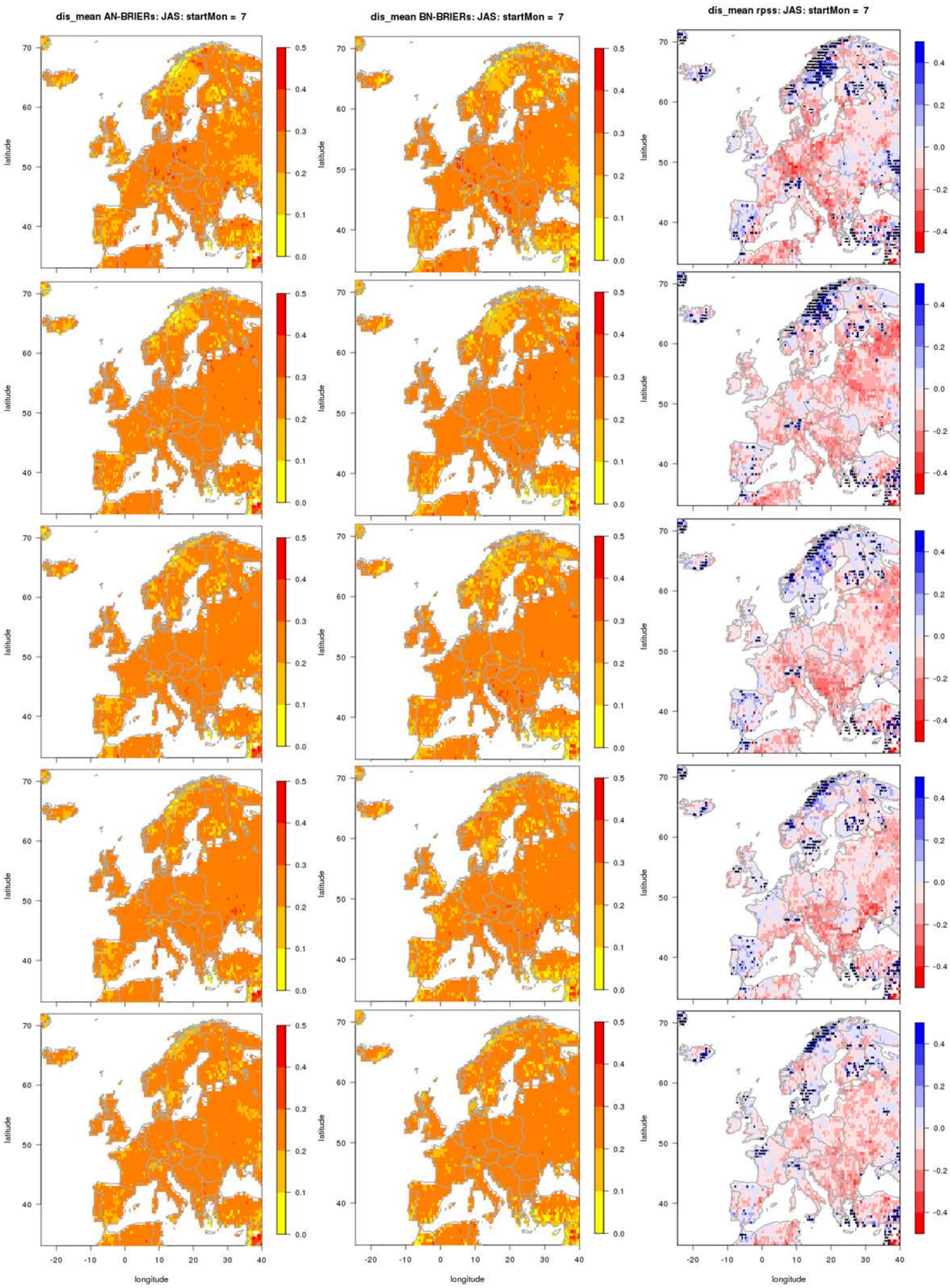

Figure 21 As previous figure, but for JAS discharge across Europe.

4.4 Seasonal prediction of reservoir inflow and water demands in Spain (CETaqua).

CETaqua assessed the predictive skill for different impacts in the water sector on seasonal timescales. Two applications have been studied in Spain, the first one concerns dam inflow predictions and the second one urban water demand predictions. These applications have been studied at a local scale (sub-basin and municipality) since this correspond to the management scale of the stakeholders.

For the first application, an existing water management tool called AQUATOOL has been used; SIMGES and SIMRISK are two modules of the AQUATOOL suite that have been used in the study. For the second application, a simple water demand prediction model has been developed. As defined in the objective of the WP23, for both applications a prototype operational workflow has been developed to use these models in S2D forecast mode, and hindcast have been analyse to assess and improve their predictive skill.

For dam inflow predictions, different seasonal climate predictions have been used (hindcast), including the flow predictions produced by the impact models VIC and E-Hype inside the WP23 of the EUPORIAS project. In addition, the prediction produced by the AEMET has been used in the development of the modelling framework. For urban water demand predictions, seasonal climate predictions from System4 have been used (hindcast), as well as the predictions from CFSv2 model (hindcast) for the development of the water demand prediction model.

The predictive skill has been estimated for both applications using only a few events. The tuning of the impacts models is continuing through WP41 and WP42. The results confirm the opportunities in using seasonal prediction but also identify the current limitations to use them in Spain.

The methodology for incorporating forecasts in the decision making has been developed through collaboration between a multi-disciplinary team including water managers, meteorologists, regulators and researchers. Cetaqua is particularly thankful to AEMET (Ernesto Rodriguez Camino, Beatriz Navascues , José Voces Aboy), UPV (Abel Solera) ,SMHI (Pechlivanidis Ilias), WUR (Wouter Greuell and Ronald Hutjes), Aqualogy (Pau Comas), Aigües de Barcelona (Meritxell Minoves Ruiz, Ramon Creus Rodriguez), DGA (Fernando Pastor, Mª Concepción García Gómez), and Spanish River Basin Agencies of Douro (Juan José Gil), Tagus (Delfina Gil) and Ebro (Rogelio Galván).

Dam inflow predictions: impacts on water uses at the river basin scale

Spain is characterized by a high irregularity in temporal and spatial distribution of water resources, and numerous areas are affected by water scarcity and frequent droughts (Ministerio de Medio Ambiente 2000). The development of new tools, such as the National Drought Indicator System, are allowing better prediction and management of the hydro-climatic risk in Spain (MAGRAMA 2014) and support the policies implementation, such as the drought management plan.

Climate forecast is the result of an attempt to produce an estimate of the actual evolution of the climate in the future, for example, at seasonal, interannual or decadal time scales. Accordingly they have the potential to help water managers and users make better-informed decisions on reservoir operations (release of water), environmental flow management, drought response strategies and development of water policies to ensure security of supply and demand management (Australian Bureau of Meteorology 2014).The vulnerability of the water sector and the needs of the water stakeholders have been assessed in details in WP11 and WP12, respectively.

Winter precipitations are critical for dam management in Spain since they represent most of the dam inflow (Figure 22). In this study the opportunities derived from the predictability of winter precipitations was analysed. Indeed, winter time precipitation in wide areas of western Iberia is mostly influenced by the North Atlantic Oscillation (NAO, Figure 23). AOGC models still show limited predictive power for the NAO on seasonal time scales but important progress has been recently achieved (Scaife et al. 2014).

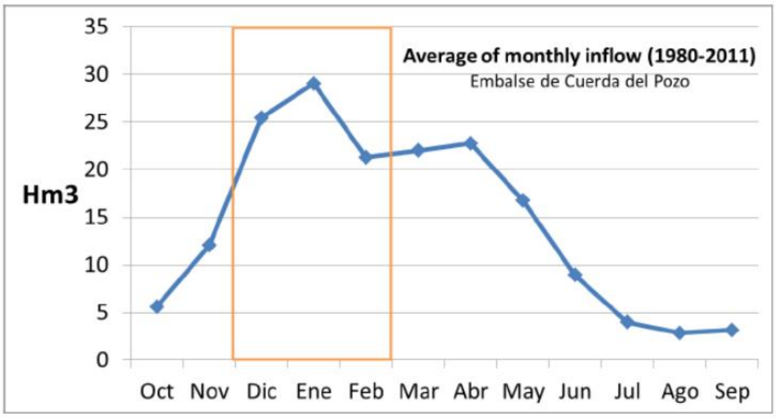

Figure 22 Average dam inflow for la Cuerda del Pozo (Duero basin).

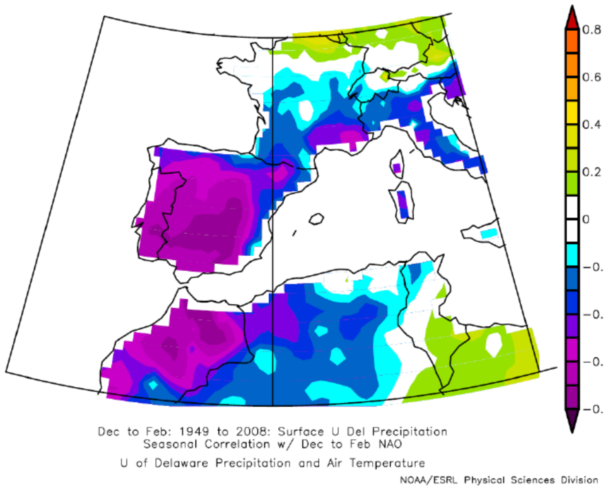

Figure 23 Correlation between NAO and Winter Precipitation (source NOAA).

Use of seasonal climate prediction in dam inflow prediction

By considering both current dam storage and anticipated dam inflow, the likelihood of meeting management goals can be improved (Gong et al. 2010). A number of regional water resource decision support system incorporating inflow forecasts have been attempted in recent years (Brown et al. 2010) such as the incorporation of seasonal inflow forecasts into existing water resource management practices in the upper Delaware River in the United States (Gong et al. 2010), the performance evaluation of different inflow forecasts for the Angat reservoir in the Philippines (Sankarasubramanian et al. 2009) or the Forecast and Reservoir Management system in California (Georgakakos et al. 2005).

The modelling framework (Figure 24 and 32) developed uses the seasonal prediction as input of water management model developed using the modelling tool SIMRISK from the AQUATOOL suite (Andreu Alvarez et al.). The model represents the dam considered, its rules of management and the different water demand associated to the dam. The model simulates the behaviour of the system, and predicts the state of the reservoir or the deficits for the water use for the coming months. According to the results, modified dam management rules could be tested in which the threshold to invoke decisions on the dam release consider the predicted reservoir state. Final performance in term of reduction in drought risk and impacts could be calculated.

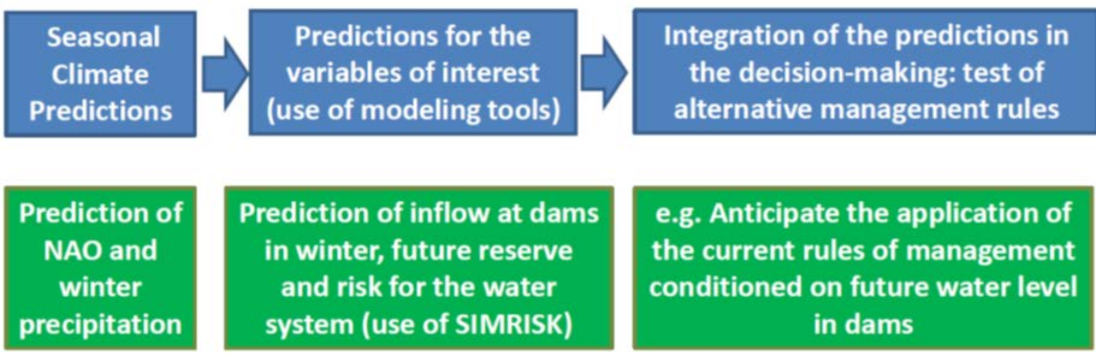

Figure 24 Modelling framework

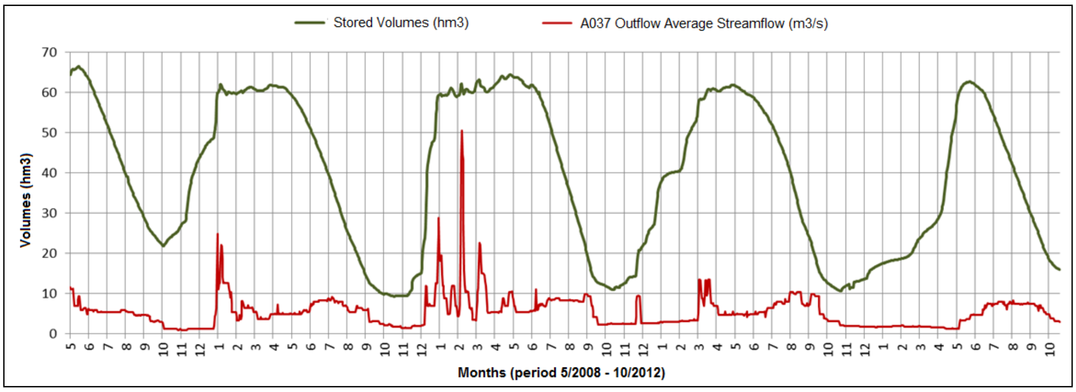

Figure 25 Volumes in the Mansilla dam and releases for the period 2008-2012

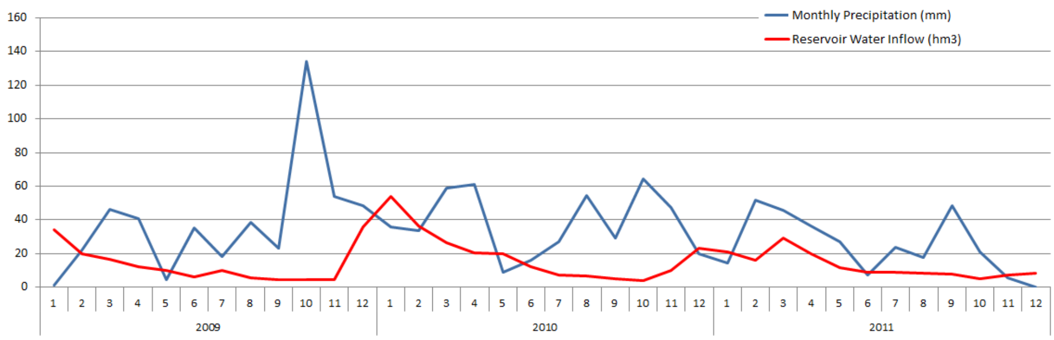

Figure 26 Monthly comparison between estimated inflow to the dam and local rainfall data.

The objective of this part of the study was to develop the inflow forecasts that will be integrated into a reservoir system model for scenario simulation and analysis.

Some first test were developed by CETaqua and described in Report 23.3. In these tests the response to the climate drivers was analyzed over a range of different time scales for a small river basin in Spain which was selected with Ebro River Basin Agency. The sub-basin studied, Najerilla basin, was part of the Ebro river basin and Mansilla dam.

According to the conclusions of these first tests, it was decided to change the basin of study to consider a dam more exposed to climate variability and with more confidence in the observed data. The selected catchment was the Ebro upstream basin (500km2) controlled by the Ebro dam (Figure 27).

Figure 27 Location of the Ebro dam.

Different possible methodologies for obtaining the dam inflows were compared:

- Use of hydrological models for simulating future dam inflows: one general drawback is the need to get some downscaled climate predictions, so this required some good data at a local scale
    - Ad-hoc hydrological model: tests were performed using HEC-HMS to build a simplified catchment model but the results were not correct. The possible reason could be the inaccuracy in the raw data (dam inflow and climate data) or the over-simplification of the hydrological processes. Due to these results and since this method is time-consuming, the approach was discarded.
    - Adaptation of local hydrological model: This was discussed with the Ebro River Basin Agency: hydrological models exist but they have been developed using different modelling tools and are mainly done for flood risk management (hourly time step). According to this situation and the previous experience of Cetaqua in calibrating "flood" hydrological model for low flow, the approach was put on-hold.
    - Adaptation of national hydrological model: Water management planning in Spain is based on simulation results provided by the CEDEX and using the SIMPA hydrological model (Álvarez, Sánchez et al. 2005, Milano, Ruelland et al. 2013). This model exists for all the Spanish basins and sub-basins (resolution of 1km square). Cetaqua analysed the parameters used in the SIMPA model and it seems that the model could be adapted for the purpose of the project. Collaboration with the CEDEX was intended (this was discussed in March 2014 during the EUPORIAS Water sector Workshop, and during 2014 via the Spanish General Water Direction) but currently put on-hold.
    - Use of Pan European hydrological model: this option was discussed with the WP23 project partners in the first half of 2014. The advantage is that the coupling of these models with climate model is already done, a potential issue was the accuracy of the model at local scale. Data from VIC and E-Hypes models were tested. It seems to be the more promising methodology for using hydrological models. The results are presented in the following paragraphs.
- Use of statistical models for estimating future dam inflows. In Spain, there are some

long records of dam inflow (40 or 50 years) updated regularly and easily available. In most cases upstream catchment have not change significantly since the dam construction. Accordingly time series of dam inflow are commonly used in water management for planning purpose. In those cases, each time series is considered as equiprobable. For the purpose of this project, different methodologies were considered to put some "weights" on each time-series in order to represent the likelihood of each time-series for the next months. The results are presented in the following paragraphs.

The data from VIC and E-HYPE model using the WATCH forcing dataset (WFDEI) were provided by the WP23 partners WUR and SMHI, respectively. The selected catchment was the Ebro dam upstream basin (500km2). While E-HYPE calculate hydrological variables (e.g.runoff, discharge, snow depth, groundwater level) for 35 000 subbasins (median resolution=215 km^2) across all of Europe, the VIC is a spatially distributed deterministic model providing information at grid cell (0.5 x 0.5 degree, equivalent to 250km^2 for the version used in WU).

The data were analysed for the purpose of the study:

- VIC data: extraction from NetCDF, analysis of the model grid cell representing the catchment of interest and weighting of the runoff from each grid cell according to the percentage of surface within the catchment of interest.
- E-HYPE: the catchment of interest is one of the subbasins represented by the model so the use of the data is quite straightforward.

The E-HYPE model was selected due to its good fit with observation for this basin considered (Figure 28, 29).

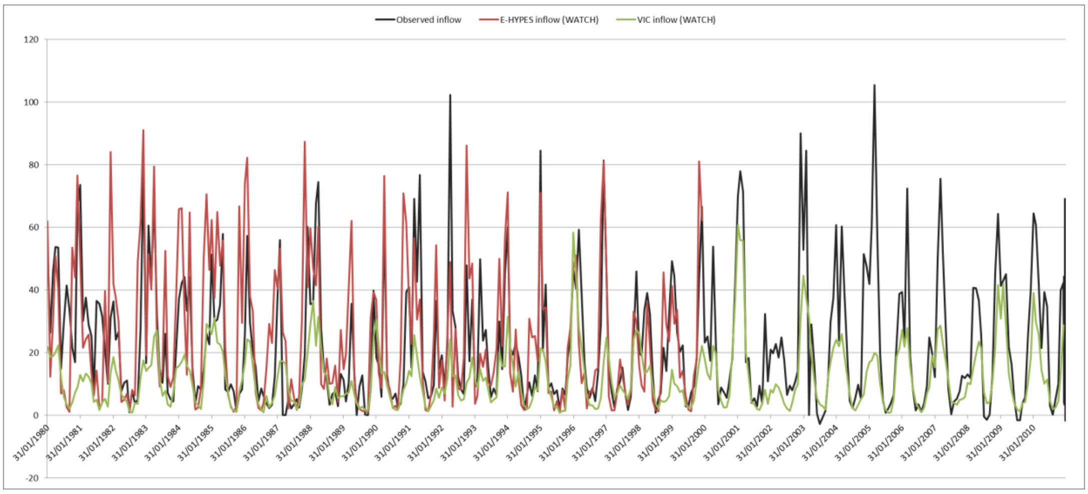

Figure 28 Monthly dam inflow (hm3 / month) at the Ebro dam. Comparison between VIC, E-HYPE and observed inflow. Period 1980 – 2010.

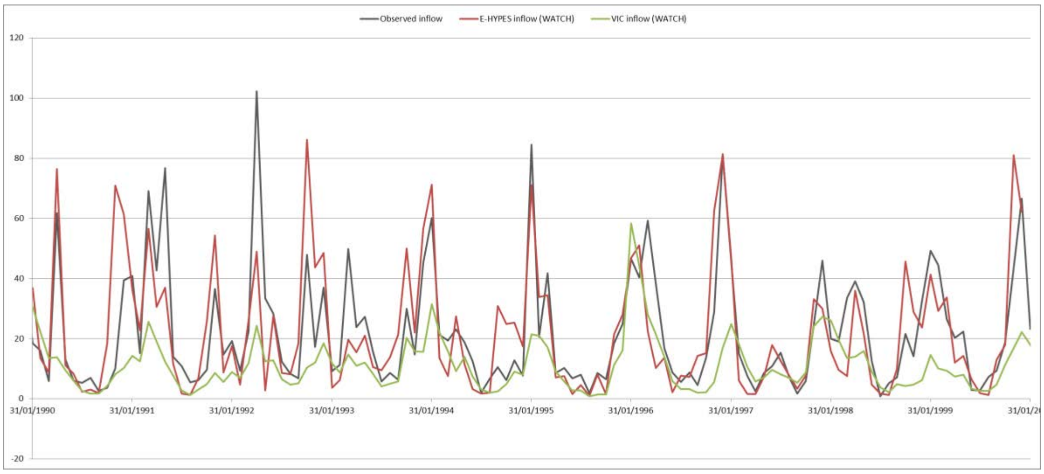

Figure 29 Monthly dam inflow (hm3 / month) at the Ebro dam. Comparison between VIC, E-HYPE and observed inflow. Period 1990 – 2000.

As explained in the introduction the critical period for dam inflow is winter (months December-January-February or DJF) so the results of the E-HYPE model have been analysed for this period.

Using WFDEI (WATCH-Forcing-Data-ERA-Interim) and compared with observation, the model show good results (Figure 30) but also some discrepancies such as an overestimation of dam inflow for most of the period considered.

Using S4 forcing, initialized in November and providing data for the period DJF (use of E-HYPE results with lead months 1, 2 and 3), the skill of predictions seems limited (Figure 31).

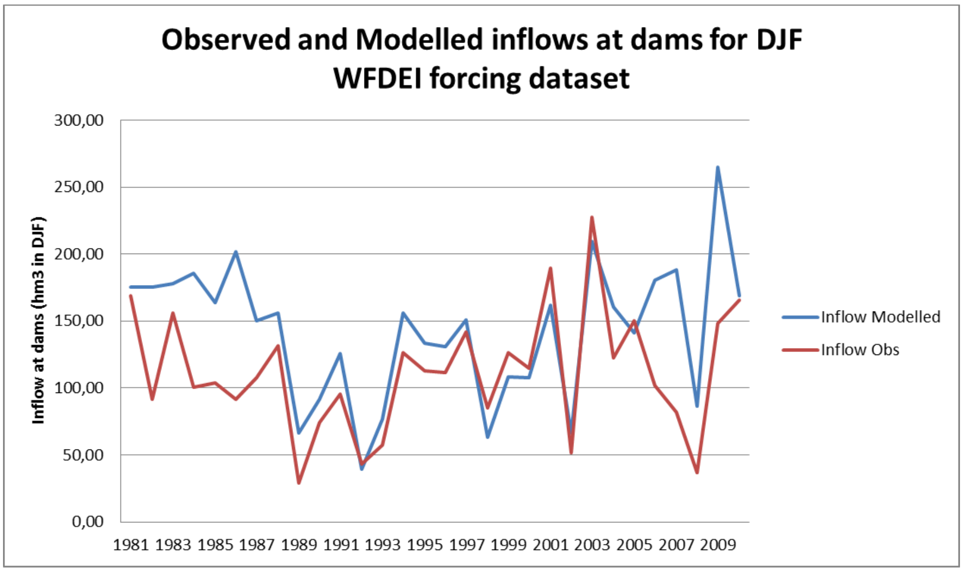

Figure 30 DJF dam inflow (hm3 / DJF months) at the Ebro dam. Comparison between E-HYPE and observed inflow. Period 1981 – 2009.

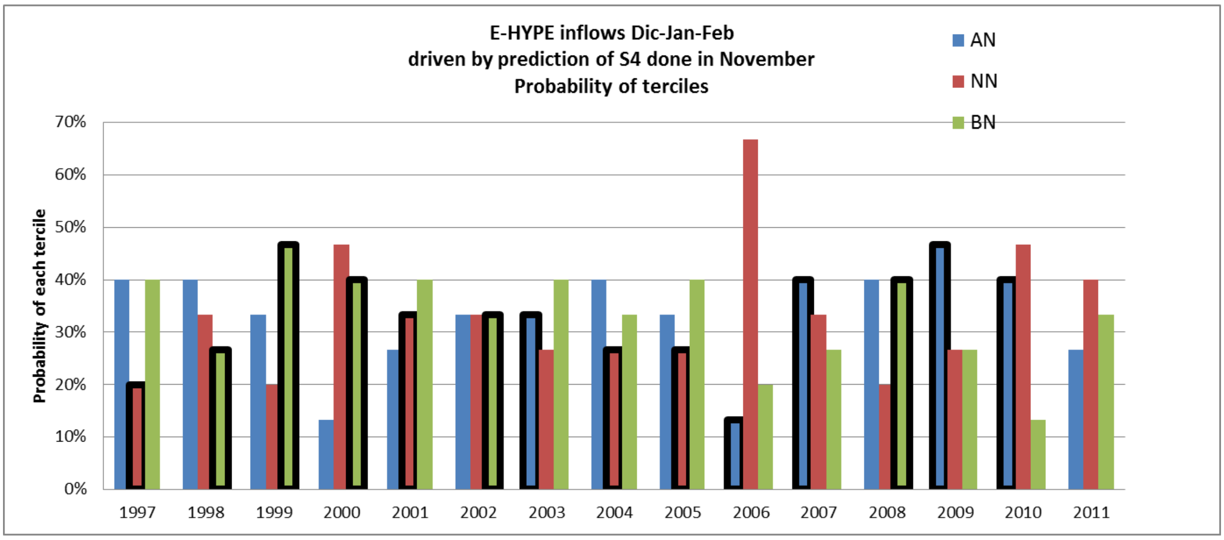

Figure 31 Results analysed by grouping results in terciles of the E-HYPE with S4 forcing for period 1997-2011, DJF months. The bars in bold indicate the tercile containing the observed value.

Use of statistical models for estimating future dam inflows

This option was analysed by AEMET and with the stakeholders. A statistical model was developed by the AEMET to predict NAO indices. Since winter precipitation is linked to NAO indices, another model was developed to take into account this relationship. As a results the statistical model provides the probability of occurrence of lower/middle/upper third of the historic inflow distribution and the probability of occurrence of each historical time series. Still, the skill of the model depends greatly on the strength of the correlation between NAO indices and dam inflows. This correlation is not significant for the Ebro sub-basin considered in this report (Figure 23) but other sub-basins are being studied (in Douro and Tagus river basins).

Link with water management model

The objective of this part of the study is to incorporate inflow forecasts into an existing reservoir system model for scenario simulation and analysis. The general framework of this methodology and the use of the SIMRISK modelling tool are presented below. The SIMRISK module was designed for its use in river basin management in the medium-term to evaluate the management risks (Haro, Solera et al. 2014). It runs a simulation of the management of the system for an initial condition of levels in reservoirs and aquifers, and uses as data multiple future hydrological inflows scenarios of one or more years. Probability calculations are done for each month of the simulated period from the results of all the scenarios. These can be used as probable estimation of the final situation of the system at the end of the present campaign, or after two or more hydrological years (Andreu Alvarez et al.).

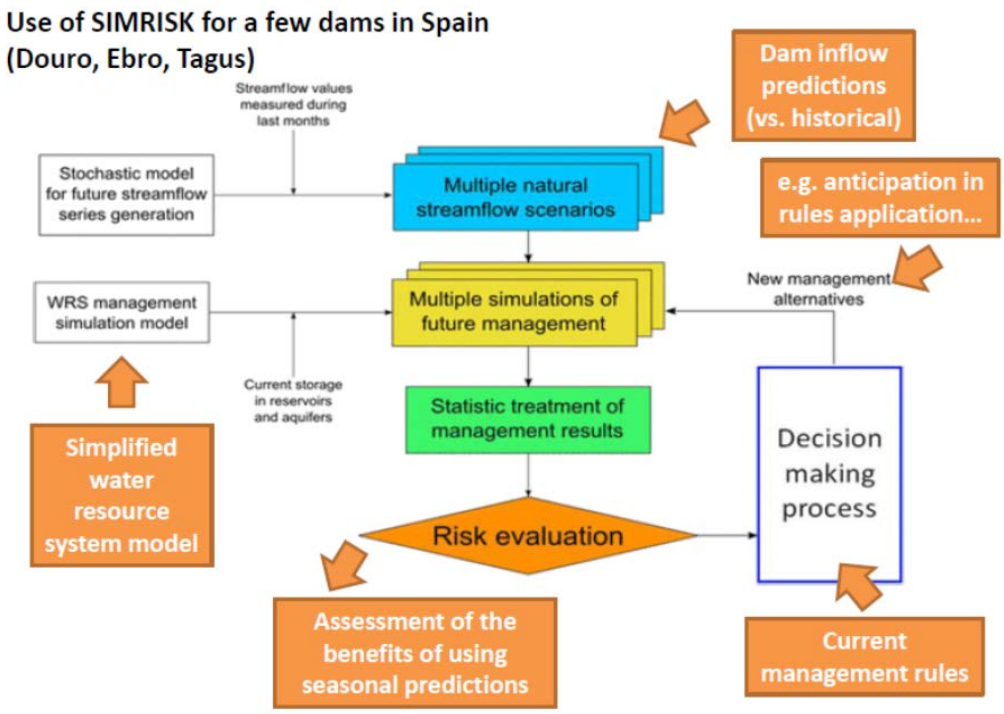

Figure 32 Framework for the use of SIMRISK.

As a first step, historical data of dam inflow, dam reserve and dam release are gathered (publicly available at http://sig.magrama.es/aforos/). The systems characteristics are recompiled from the Water Management Plan of the river basin.

The second step is the development of the SIMRISK model. For the purpose of this study, a simplified model has been done with the following elements:

- dam inflow: use of monthly time series
- dam characteristics and management rules: from the Water Management Plan (maximum, minimum and objective volume)
- demand: in this case the demand from the downstream consumption point is approximated to the dam release for a year without any restriction.
- initial reserve: from historical time series

The selected period of simulation is December to September, so it encompass the period of inflow to the dam (principally winter) and the period of consumption (summer, mainly for irrigation).

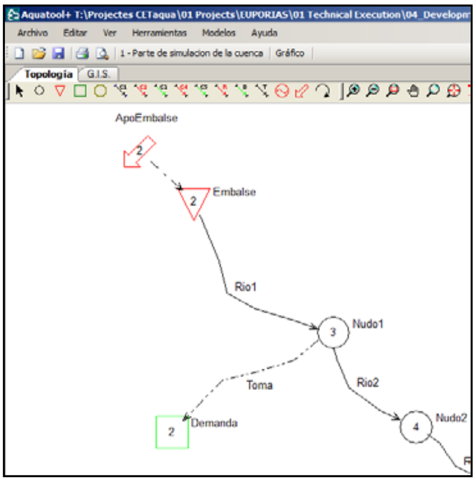

Figure 33 Scheme of the model done in SIMRISK

Different options exist to integrate the dam inflow predictions into the SIMRISK model:

- Use of the time series of dam inflow produce by E-Hype and driven by the System 4 input. Some adjustment in the E-Hype model results (bias correction) or in the E-Hype model parameters might be necessary.
- Indirect use of the seasonal prediction, by “weighting” the historical time series of dam inflow. This methodology has the advantage of being simpler to use and adapted to predictions coming from either hydrological model or statistical model.

The second methodology was tested in the case study. The historical data from the period 1947 -2011 were used. The SIMRISK model results do not show significant benefit in using the predictions for the catchment considered. Indeed, almost no differences in the system state (volume in reservoir, deficit in water demand) can be observed between the simulations done with the predictions and the one done using the historical data (climatology). The main reason is the limited skills of the predictions in the area and period considered, which do not provide additional information than climatology.

Some examples of the tests done are described below. A large number of simulations are performed with SIMRISK (around 100 simulations) with different dam inflows for the period December-November. As a result, the modelling tool shows the probability of getting some conditions. Figure 34 shows the evolution of the probability of being in different dam reserve state using historical data, while Figure 35 shows the same results but using predictions of lower flow. A key indicator is the reserve in the dam at the end of the irrigation period (in September). In the example below, there is a 20% probability of being below 50hm^3 using historical data, while using prediction there is a 20% probability of being below 40hm^3.

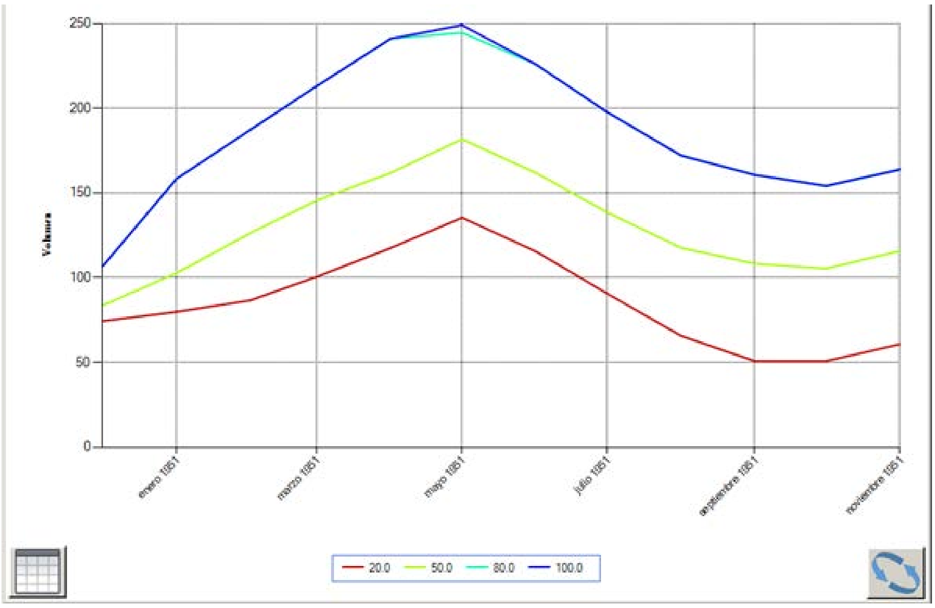

Figure 34 Reserve in Dam using historical data.

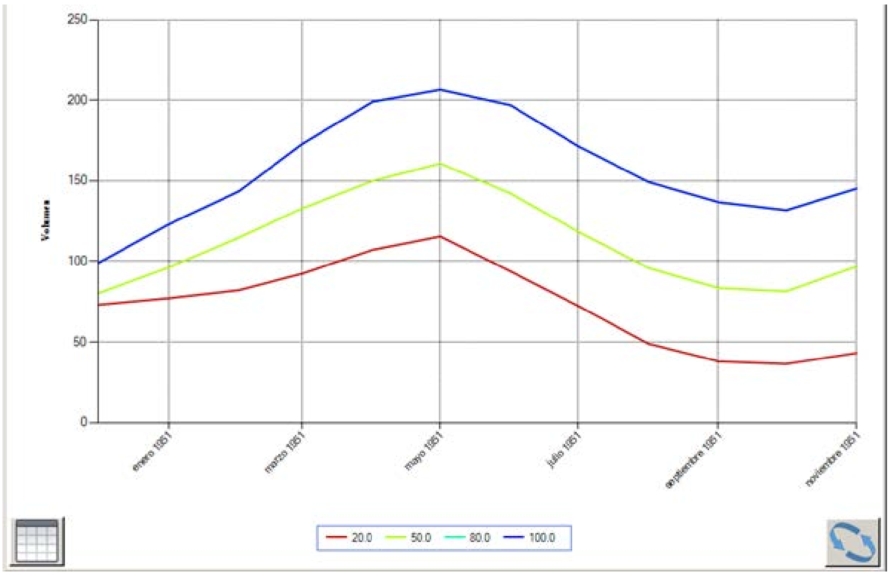

Figure 35 Reserve in Dam using prediction indicating lower flow than average.

Water demand predictions

Urban water demand tends to increase during a hot, dry period (Zhou et al. 2000), and rainfall occurence tends to reduce water demand (Martinez-Espiñeira 2002). The meteorological variables commonly used for residential water demand forecast are precipitation and air temperature, and less often evapotranspiration, minutes of sunshine or wind speed (Arbués, Garcıa-Valiñas, and Martınez-Espiñeira 2003). The values used for these variables are generally based on short-term weather forecasts (for the next days) or past observations when predictions have to be made for the next months.

The use of seasonal climate forecast could help in improving such predictions and anticipate management actions. In the EUPORIAS project, several tests are realized to check the relevance of using seasonal climate forecast of air temperature as an explanatory variable. A first approach was to develop a simple model based on regression equations linking air temperature and water demand, results of the case study , for the district of Bellamar are commented in the next section.

In the district of Bellamar, situated in the Mediterranean coast, the water demand time series show a marked seasonality (summer consumption is almost twice the one of winter) and a strong inter-annual differences for the period considered (2004-2013). The correlation between anomaly in water demand and anomaly in air temperature (station of Barcelona-El Prat Airport) is calculated. To calculate the anomaly, seasonal mean and trend component are excluded. As a result, the period June-July-August (JJA) shows the highest correlation coefficient (value of 0.56 considering all the years, value of 0.68 excluding the year 2008 affected by water restriction). As a general remark, water demand equals water consumption if there is no restriction.

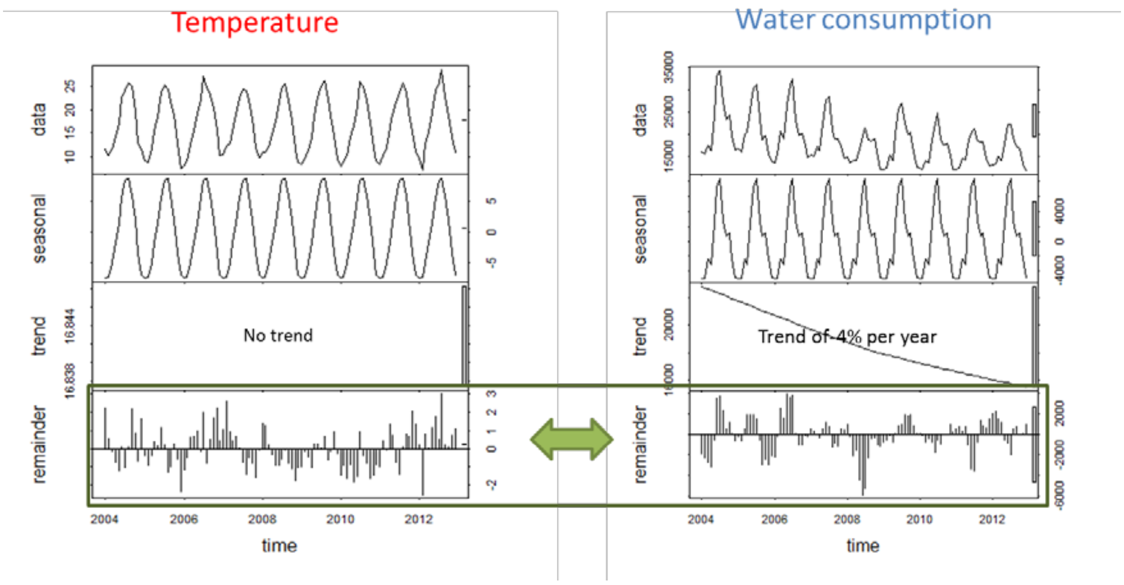

Figure 36 Temperature and Water consumption time series analysis

Table 4 Correlation coefficient between anomalies (or remainder) in temperature and water consumption.

	All months	MAM	JJA	SON	DJF
Consumption	0.27	0.27	0.11	0.33	0.30
Consumption without trend	0.45	0.45	0.57	0.27	0.52
Consumption without trend without 2008	0.43	0.45	**0.68**	0.20	0.53

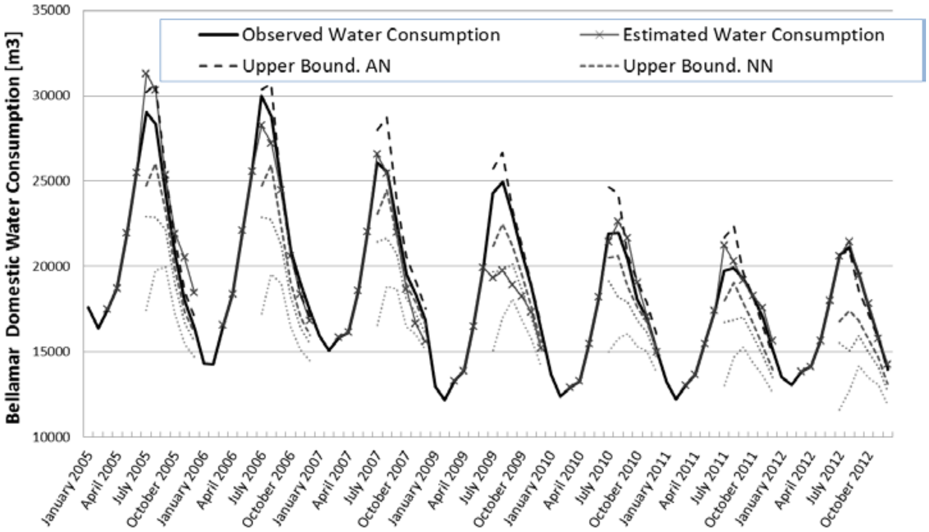

Figure 37: Estimated water demand using regression equations based on air temperature.

For each trimester of the year, simple regression equations linking air temperature and water demand have been developed. The equations have been applied with the temperature observed during the trimester. As shown in Figure 37, using the simple regression equations, water demand is well estimated (line with crosses, “estimated water consumption”), except for the year 2009 influenced by previous year deficit.

In order to use the seasonal climate prediction to predict the water consumption two options have been studied:

- Applied the regression model for the upper and lower limits of each temperature terciles (use of historical records); and use the predictions for giving the probability of occurrence of each tercile. This could be quite straightforward for the user since this type of predictions is commonly freely available.
- Applied the regression model for all the ensemble members of the predictions of temperature. In this case the user would need to access to the ensemble members values and make a bias-correction of these data.

The application of the first method has been tested using hindcast data from the NCEP coupled forecast system model version 2 (CFSv2) available at the ECOMS User Data Gateway (J. Bedia et al. 2013). The results of this model for the area considered are shown in Table 5. Comparison were done between the consumption estimated using CFSv2 and the one observed. For example for predictions issued in May and covering the period June-November, in 23 cases the predictions indicate a higher probability for one terciles, and for 18 of this 23 cases observation match the predictions. Still, the methodology presents some drawbacks such as 1) the use of historical data for determining the terciles boundary without considering trends (but summer temperatures in the last years were almost always hotter than average), 2) the use of regression equations for temperature values outside the range observed in the period 2004-2013 and 3) the very reduced number of years (9 years) used for developing the regression equations.

Table 5. Results of the CFSv2 model for the area considered (prediction issued in April)

	2005			2006			2007			2009			2010			2011			2012		
	AMJ	JAS	OND	AMJ	JAS	OND	AMJ	JAS	OND	AMJ	JAS	OND	AMJ	JAS	OND	AMJ	JAS	OND	AMJ	JAS	OND
AN	40	33	40	33	33	40	40	40	40	40	33	45	40	60	33	40	45	15	55	40	33
NN	35	33	35	33	33	35	35	35	35	35	33	35	35	30	33	35	35	35	30	35	33
BN	25	33	25	33	33	25	25	25	25	25	33	20	25	10	33	25	20	50	15	25	33

The application of the second method has been tested using System4 dataset (from ECMWF downloaded using the ECOMS User Data Gateway (J. Bedia et al. 2013) and bias-corrected using the R toolbox developed in the EUPORIAS project and the WFDEI database (from ECOMS User Data Gateway). The bias-correction techniques (figure 38) have applied to the cells encompassing the area of study (*lonLim = 1.5,2.5 ; latLim = 40.5, 42.5).*

The results for the tests performed are presented for the year 2010 in Figure 39 (following page) and compared with the results obtained with the previous methodology. Figure 40 shows the results for all the year considered. As a conclusion, while the accuracy of the predictions seems to be improved by using System4 hindcast, the same drawback as mentioned in points 2 and 3 applied.

The feasibility of using the seasonal climate prediction in water consumption prediction has been demonstrated. Still the simplified model developed in the study show some limitations. Accordingly, other options are currently studied, such as the use of existing water consumption model and the improvement of the model developed in the study.

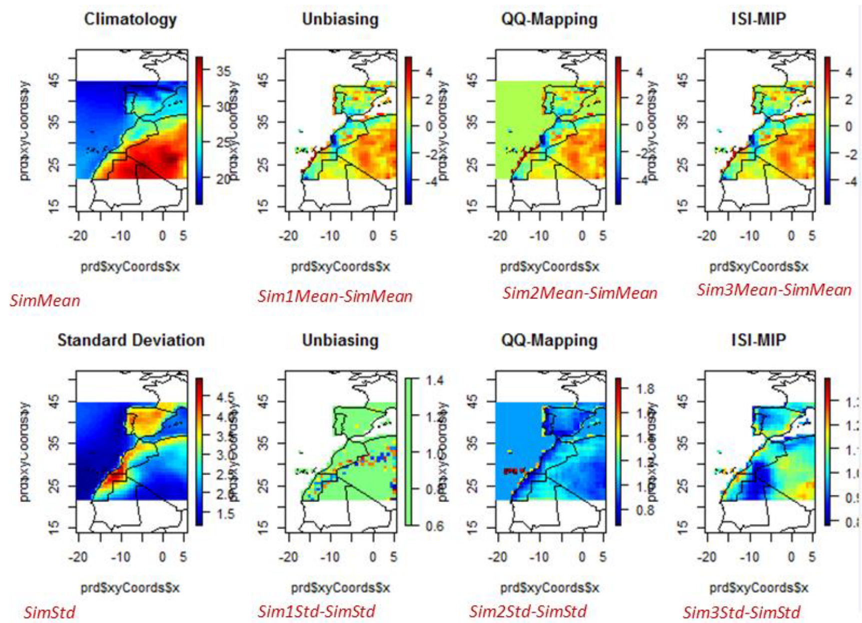

Figure 38: Applying to SYS4 forcing data 3 different bias correction techniques against WFDEI data.

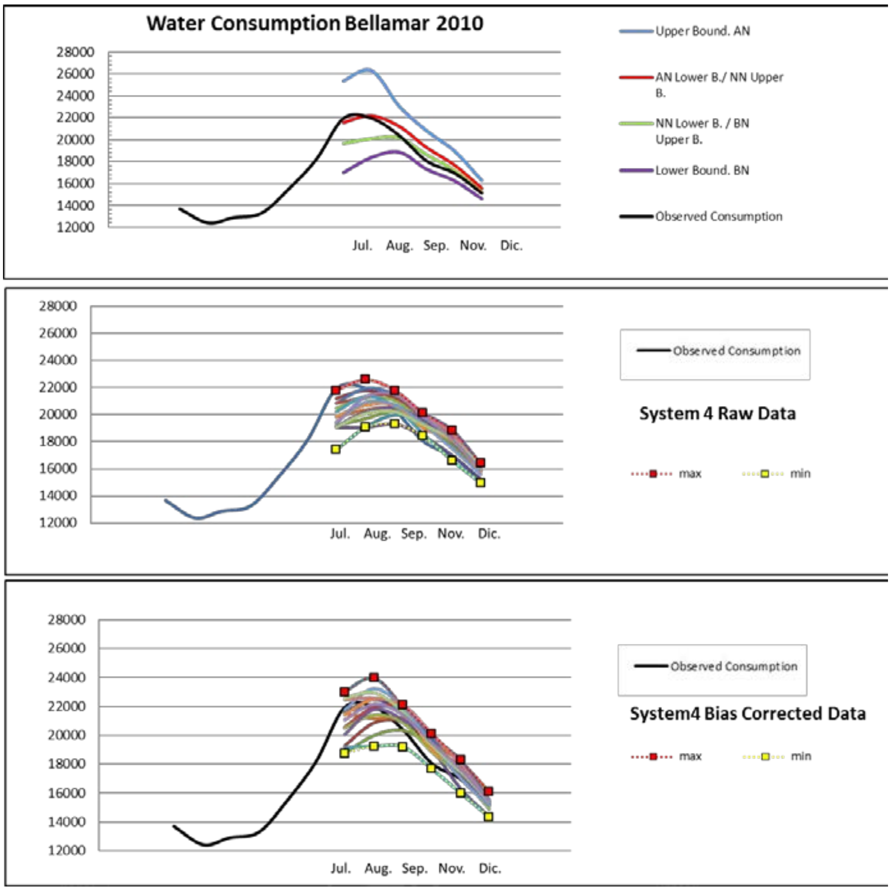

Figure 39 Statistical water demand prediction for the year 2010.

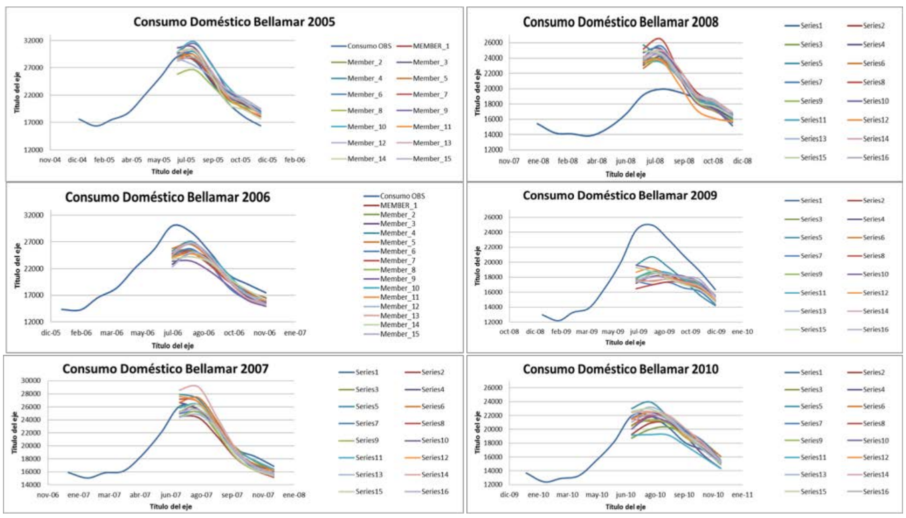

Figure 40 Statistical water demand prediction for the period studied (2005-2010).

5. Lessons Learnt

The model performance with WFDEI datasets of uncalibrated hydrological models has revealed varying skill across Europe, on average somewhat lower (in terms of biases and correlations) than the calibrated models. However, as seasonal forecast deals with predicting relatively broad anomalies (typically defined as terciles) predicting variability is more important than exact mean flows. The results highlighted in more detail in the report, tentatively seem to confirm this. Though the different hydrological models analysed in WP23 vary in their performance to represent interannual variability in discharge across models, regions, basins and lead-times, there are also similarities in broad spatial and temporal skill patterns. In the models assessed so far skill is generally better in NE Europe, better in winter than in summer, better for high flows than for low flows.

An important strategy to assess (potential) skill is to do such an assessment not only against observed discharges for relevant stations, but also against synthetic observations, i.e. simulated discharge forced by the best known meteorology (i.e. WFDEI here). This prevents skill scores to be influenced by non-represented anthropogenic flow artefacts, e.g. from reservoir management and flow regulations.

Most hydrological modellers in this WP23 are new to seasonal forecasts. While they use established verification tools, the interpretation of the various probabilistic skill metrics and their relative importance in the context of hydrological forecasts is not trivial to them. More interactions with the meteorological seasonal forecast community may help them to improve their ability communicate the skill of their models.

6. Links Built

The work presented here will be continued in WP31 where we will analyse the causes for (lack of) skill for a number of common case studies / events, and where also the relative benefit of multi model ensemble forecasts as opposed to that of any single model will be analysed, using already agreed protocols.

Case studies for hydrology-Europe have been selected from the SPECS/EUPORIAS prioritized case study inventory (see https://euporias.wikidot.com/wp23-minutes-hydro-casestudy): we may focus on Central Europe, i.e. the Elbe and Danube (sub) basins for both a wet/flooding anomaly in 2002 and for the dry/drought anomaly in 2003, possibly extended to a French (Seine) and Spanish basin (Ebro). Fort these cases skill/error propagation will be analysed from climate forecasts, initial conditions and various water balance parameters until discharge.

To asses multi model ensemble skill data from EHYP, VIC and LPJml will combined via agreed (netcdf) file formats.

Finally, the work presented here should also feed into the climate service prototypes that will be developed in WP42 for a) the river flow forecasts for water resource management over two river catchments (lead Meteo-France, stakeholders, EPTB Seine Grands Lacs, SMEAG), and b) the sector specific prototype that will be developed for the use of seasonal climate forecasts for water management in Spain (lead, CETaqua, AEMET, DHI).

The work presented here also has obvious links with the objectives of the global Hydrologic Ensemble Prediction Experiment (HEPEX, http://hepex.irstea.fr/) programme. Contributions to its upcoming conference in sept 2015 by several EUPORIAS partners is foreseen.

7. Publications from this WP23

Completed:

Pete Falloon, David Fereday, Nicky Stringer, Karina Williams, Jemma Gornall, Emily Wallace, Rosie Eade, Anca Brookshaw, Joanne Camp, Richard Betts, Rutger Dankers, Kathryn Nicklin, Michael Vellinga, Richard Graham, Alberto Arribas and Craig Maclachlan (2013) Assessing skill for impacts in seasonal to decadal climate forecasts (editorial), J GEOL GEOSCI 2: e111, doi: 10.4172/2329-6755.1000e111.

Ilias Pechlivanidis, Henrik Spångmyr, Thomas Bosshard, David Gustafsson, and Jonas Olsson (2015). Ensemble seasonal hydrological forecasting at the pan-European scale. EGU General Assembly, session HS4.3/AS1.3/NH1.3, 15 April 2015 Vienna.

Foreseen:

Greuell, J.W., W.H.P. Franssen, H. Biemans and R.W.A. Hutjes. Verification of ensemble seasonal forecasting of pan European river discharge with VIC and LPJml. (in prep)

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Appendix A Bias correction SYS4 forcing

WU downloaded all required daily variables for the hydrological and agricultural impact models from ECOMS-UDG for two domains Europe and East Africa for all 15 available members. These were bias corrected against WFDEI, using QQ mapping based on the scripts developed in collaboration with UniCAN, using one common set of correction parameters for all 15 members. Then these were interpolated from the native grid (0.75^{o}) to the WFDEI grid (0.5^{o}) land masked and rearranged into one NETCDF file containing all variables for each hindcast run of 7 months. In total 2regions x 2resolutions x 30yrs x 12mo x 15 members = 21600 files. An NCDUMP is given in the appendix. These are shared with all EUPORIAS wp23/31 partners.

The effect of the bias corrections is shown in the following example figure. This shows maps of differences between WFDEI and SYS4-BC and SYS4-noBC for temperature (top 2 rows) and precipitation (bottom two rows) for the seven forecast months (left to right) starting in January. It clearly shows that temperature biases are strongly related to topography effects (2nd row) and that these are perfectly corrected for (1st row). Precipitation biases are due to a combination of topography and regional effects and the residual bias after correction is less than 0.1mm.

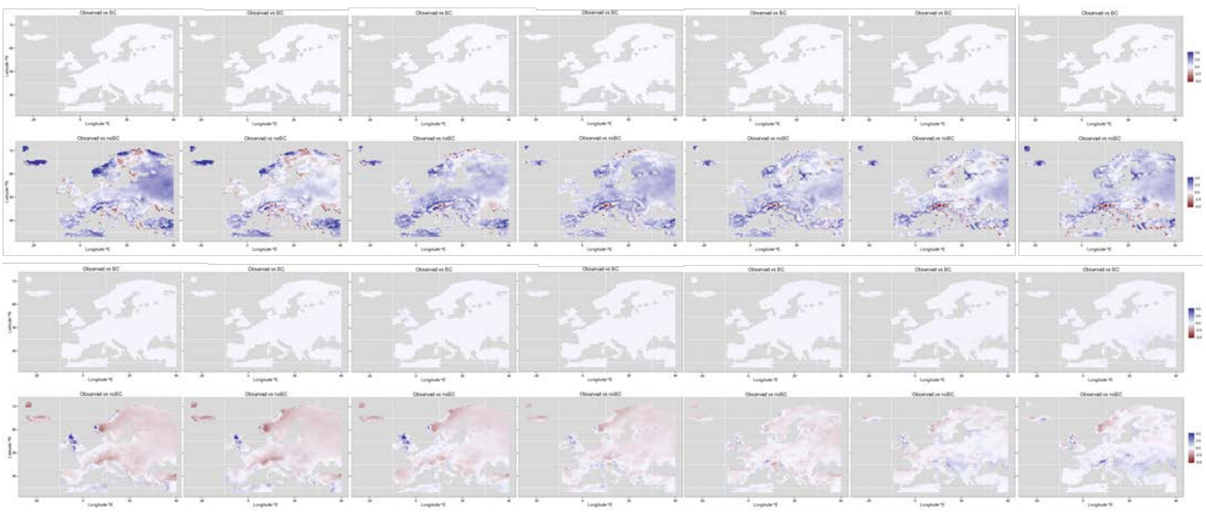

Figure 41 Bias correction effects on SYSTEM4 temperature (top 2 rows) and precipitation (bottom 2 rows) for start month January.

The figure below shows histograms for January/lead month 1, for one particular grid box of temperature (top) and rainfall (bottom) for the observed (red bars), bias-corrected (green) and non-bias corrected (blue) data respectively. It again shows perfect correction for temperature and precipitation; the red and green bars coincide.

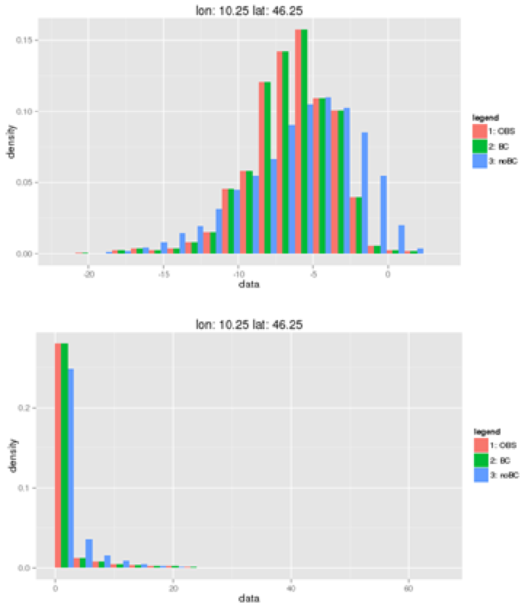

Figure 42 Histograms of bias correction effects on temperature (top) and precipitation (bottom). Red bars are observations (i.e. WFDEI), green bars bias corrected data, blue bars non- corrected data.

NCDUMP of one of the forcing files created by WU for the European domain for each of the 5400 hindcasts

File naming convention: **"forcing_seas15_EU_BC_E01_1981_01.nc4"**

forcing_seas15 refers to the ECMWF System 4, 15 member, 7 months (~212 days) seasonal forecasts

EU	refers to Europe; **GHA** for Greater Horn of Africa, i.e. Eastern Africa
BC	refers to Bias Corrected data; **noBC** for non corrected data
E01	refers to ensemble member 1 (out of 15)
1981_01	refers to start month of forecast
.nc4	refers to NETCDF v4 compressed format

```
netcdf file:/D:/bigdata_werk/EUPORIAS/S4_GHA/forcing_seas15_EU_BC_E01_1981_01.nc4 {
 dimensions:
 lon = 129;
 lat = 78;
 time = UNLIMITED; // (212 currently
 variables:
 double lon(lon=129);
 :standard_name = "longitude";
 :long_name = "Longitude";
 :units = "degrees_east";
 :axis = "X";

 double lat(lat=78);
 :standard_name = "latitude";
 :long_name = "Latitude";
 :units = "degrees_north";
 :axis = "Y";

 double time(time=212);
 :standard_name = "time";
 :long_name = "time";
 :units = "days since 1981-01-01 00:00:00";
 :calendar = "standard";
 :_ChunkSize = 1; // int

 float tas(time=212, lat=78, lon=129);
 :standard_name = "air_temperature";
 :long_name = "Near-Surface Air Temperature";
 :units = "K";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 float tasmax(time=212, lat=78, lon=129);
 :standard_name = "air_temperature";
 :long_name = "Daily Maximum Near-Surface Air Temperature";
 :units = "K";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 float tasmin(time=212, lat=78, lon=129);
 :standard_name = "air_temperature";
 :long_name = "Daily Minimum Near-Surface Air Temperature";
 :units = "K";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 float pr(time=212, lat=78, lon=129);
 :standard_name = "precipitation_flux";
 :long_name = "Precipitation";
 :units = "kg m-2 s-1";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 float rsds(time=212, lat=78, lon=129);
```

```
 :standard_name = "surface_downwelling_shortwave_flux_in_air";
 :long_name = "Surface Downwelling Shortwave Radiation";
 :units = "W m-2";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 float rlds(time=212, lat=78, lon=129);
 :standard_name = "surface_downwelling_longwave_flux_in_air";
 :long_name = "Surface Downwelling Longwave Radiation";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :units = "W m-2";
 :_ChunkSize = 1, 78, 129; // int

 float huss(time=212, lat=78, lon=129);
 :standard_name = "specific_humidity";
 :long_name = "Near-Surface Specific Humidity";
 :units = "1";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 float sfcWind(time=212, lat=78, lon=129);
 :standard_name = "wind_speed";
 :long_name = "Near-Surface Wind Speed";
 :units = "m s-1";
 :_FillValue = 1.0E20f; // float
 :missing_value = 1.0E20f; // float
 :_ChunkSize = 1, 78, 129; // int

 // global attributes:
 :institution = "Wageningen University and Research centre (WUR)";
 :source1 = "distributed by ECOMS User Data Gateway (ECOMS-UDG), partially funded by the European Union
FP under Grant Agreement no 308291 (EUPORIAS), http://meteo.unican.es/ecoms-udg";
 :source2 = "IPR remains with European Centre For Medium-Range Weather Forecasts (ECMWF)";
 :source3 = "ECMWF System4 hindcast, seasonal-15: 12 Runtimes per year (the 1st of J,F,etc) running for 7
months. Ensemble of 15 members for 1981-2010";
 :source4 = "variables renamed, domain subset, masking, reorganised, interpolated to 0.5 degree by
Wageningen University, Earth System Sciences";
 :source5 = "variables naming convention: CMIP5 (http://cmip-pcmdi.llnl.gov/cmip5/docs/standard_output.pdf)";
 :domain = "Europe";
 :member = 1; // int
 :comment1 = "Processed and regridded by W.Franssen";
}
```