Development of a monthly to seasonal forecast framework tailored to inland waterway transport in Central Europe

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Abstract. Traditionally, navigation-related forecasts in Central Europe cover short- to medium-range lead-times linked to
10 the travel times of vessels to pass the main waterway bottlenecks leaving the loading ports. Without doubt, this aspect is still essential for navigational users, but in light of the growing political intention to use the free capacity of the inland waterway transport in Europe, additional lead-time supporting strategic decisions is more and more in demand. However, no such predictions offering extended lead-times of several weeks up to several months ahead currently exist for considerable parts of the European waterway network.

15 This paper describes the set-up of a monthly to seasonal forecasting system for the German stretches of the international waterways of Rhine, Danube and Elbe rivers. Two competitive forecast approaches have been implemented: the dynamical set-up forces a hydrological model with post-processed outputs from ECMWF general circulation model System 4, whereas the statistical approach is based on the empirical relationship ("teleconnection") of global oceanic, climate and regional hydro-meteorological data with river flows. The performance of both forecast methods is evaluated in relation to the

20 climatological forecast (ensemble of historical streamflow) and the well-known Ensemble Streamflow Prediction approach (ESP, ensemble based on historical meteorology) using common performance indicators (correlation coefficient, mean absolute error (skill score), mean squared error (skill score), continuous ranked probability (skill) score) as well as an impact-based evaluation quantifying the potential economic gain.

The following four key findings result from this study: 1) As former studies for other regions of Central Europe indicate, the

25 accuracy / skill of the meteorological forcing used has larger effect than the quality of initial hydrological conditions for relevant stations along the German waterways. 2) Despite the predictive limitations on longer lead-times over Central Europe, this study reveals the existence of a valuable predictability of streamflow at monthly up to seasonal time-scales along Rhine, Upper Danube and Elbe, while the Elbe achieves the highest skill and value. 3) The more physically-based as well as the statistical approach are able to improve the predictive skills and economic value compared to climatology and the

30 ESP-approach. The specific forecast skill highly depends on the forecast location, the lead-time and the season. 4) Currently, the statistical approach seems to be most skilful for the three waterways investigated. The lagged relationship between the

monthly / seasonal streamflow and the climatic / oceanic variables vary between one month (e. g. local precipitation and temperature, soil moisture) up to six months (e.g. sea surface temperature).

Besides improving the forecast methodology, especially by combining the individual approaches, the focus is on developing useful forecast products on monthly to seasonal time-scale for waterway transport and to operationalize the related forecasting service.

1   Introduction

Competitive transport systems are vital for Europe's prosperity as well as its economic growth and the demand, especially for freight transport, will significantly increase within the coming years. Besides safeguarding a high degree of efficiency, accessibility and safety, today's European and national transport policy is clearly oriented towards sustainable and energy-efficient transport systems. In this regards, the importance of inland waterway transport (IWT) will further increase, because it's an environmentally friendly and safe mode of transport, which still has plenty of spare capacity (European Commission 2001). But IWT also faces a few drawbacks. Besides the low transport velocity and the comparatively low network density, the natural variability of the fairway conditions and the availability along substantial parts of the European waterway network pose the main weakness. In this respect, low stream flows, floods and river ice are the significant hydrological hazards concerning IWT in Central Europe. The relevance of these impacts depends on the geographical position, the season and the characteristic of the waterway (Nilson et al. 2012; Meißner and Klein 2016). IWT's main vulnerability with regard to hydrological impacts results from (long-lasting) droughts leading to low stream flow and respectively low water-levels along the free-flowing waterways, which represent a substantial share of Europe's inland waterway network. Although there is no low-water threshold beyond which navigation is prohibited, low water-levels and the corresponding reduced water-depths are a limiting factor. During low flow situations additional (small) ships are needed to handle the same amount of cargo as during periods with mean water-level conditions. This cause increasing transport costs (see Fig. 1). But especially in the case of extreme or long lasting low flow periods the available small ship volume is limited compared to the transport demand and goods have to be shifted to other modes of transport, if this is technically possible and if transport volume is available there. Besides determining the maximum cargo-carrying capacity the water-level affects energy consumption and time of travel, altogether being reflected in the transport costs. Figure 1 schematically depicts the close correlation of water-level, fairway and vessel parameter and transportation costs. Furthermore, low flow situations increase the danger of ship-grounding and ship-to-ship collisions due to a reduced depth and width of the affected fairways.

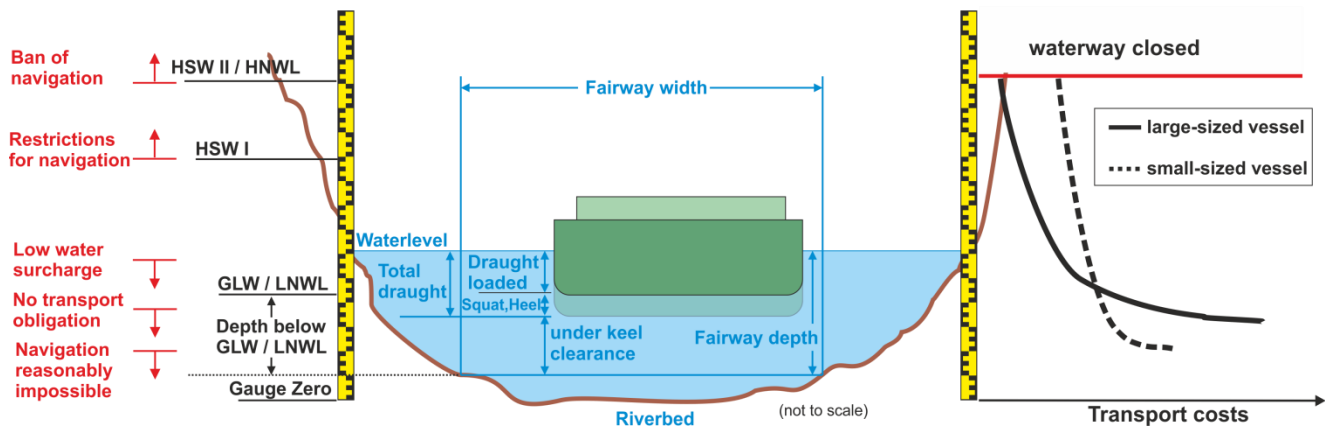



Figure 1. Schematic representation of the interaction between hydrologic conditions (water-level), waterway parameter (fairway depths), specific navigation thresholds and transport costs.

Originally, navigation-related forecasts have been developed in order to primarily support the individual skipper, who aims at maximizing the load of an upcoming trip. Therefore current lead-times of water level forecasts for the Central European waterways range from one to several days complying with the travel time of the vessels to pass the main bottlenecks of a waterway leaving the loading port. Such forecasts allowing short-term operational decision making remain vital to the waterway transport sector, but there is an increasing demand for additional forecast information going beyond this short- to medium-range (Klein and Meißner 2016, Meißner and Klein 2017). Extended forecast lead-times offer the possibility to sustainably increase IWT's efficiency as well as to support medium- to long-term waterway management. In the context of the EU-founded project EUPORIAS (European Provision Of Regional Impacts Assessments on Seasonal and Decadal Timescales; www.euporias.eu) the specific vulnerability of the waterway transportation sector on the Rhine was analyzed and a prototypical service, called SOS RHINE, was designed with the collaboration of the German and the Dutch meteorological service and the German Federal Institute of Hydrology (Funk et al. 2015). But so far, no such forecasts exist for the main parts of the trans-European waterway network – primarily due to the limited skill of long-term hydro-meteorological forecasts in northern extratropical regions when compared to other parts of the world (Ionita et al. 2008; Domeisen et al. 2015). Associated with this there's still a widespread scepticism whether seasonal predictions can be trustworthy for decision making in practice.

Despite the predictive limitations, several studies prove skill for seasonal river flow forecasts in different parts of Europe (Wilby et al. 2004; Gámiz-Fortis et al. 2008; Ionita et al. 2012; Ionita et al. 2014). In recent years, multiple region-specific forecast methods and systems have been developed to predict hydrological variables several weeks and months in advance to anticipate water availability in Europe (Olsson et al. 2016; Svensson 2016; Demirel et al. 2015; Gelfan et al. 2015; Fundel et al. 2013, Jörg-Hess et al. 2015). The most common objectives behind these systems are water supply, reservoir operations and hydropower. The European Flood Awareness System (EFAS, Bartholmes et al. 2009) also publishes a seasonal hydrological outlook with a lead-time up to two months since 2016. This outlook offers Europe-wide homogenous

information on surplus or deficit of water resources as weekly averages aggregated for major hydrological units. Nevertheless the generation of flood early warning information up to two weeks ahead for regional, national or European authorities remains EFAS focal point, but the seasonal products supplements this continental hydrological information service. Regarding the underlying methodologies applied in seasonal hydrological forecasting two categories, aside from using observed climatology, are usually distinguished: dynamical and statistical approaches (e.g. Crochemore et al. 2016, and references therein). While the models of the second category rely on the statistical relationship between various observed predictors and the hydrological predictand (Demirel et al. 2013), the methods of the first category use seasonal meteorological forecasts and hydro-meteorological observations to drive hydrological models. Ensemble Streamflow Prediction (ESP) is probably the most famous dynamical approach applied already for many years in research contexts as well as in operational applications (Day, 1985; Wood et al. 2002; see also Sect. 3.3). The choice between the different approaches is usually based on the purpose and the region of the forecast as well as the availability of models and data, but sometimes also the principles and philosophy within the executing institutions influence such a decision. In addition, to use the two aforementioned methods alongside some studies show that within so-called hybrid or mixed approaches statistical and dynamical methods could complement each other leading to an increased forecast performance (Robertson et al. 2013).

This paper describes the set-up and performance of a monthly to seasonal forecasting framework for the major waterways crossing Germany, namely Rhine, Danube and Elbe. The work was initiated by the Federal Institute of Hydrology, which is in charge of developing, maintaining and operating the navigation-related forecasting systems for the German waterways, realizing the high demand of long-term hydrological forecasts by the transport sector. The paper is structured as follows: first we describe the study area focusing on the hydrological characteristics relevant for IWT, followed by the specification of the forecasting methods and the underlying data implemented in the framework. After defining the methods and metrics to evaluate forecast skill and value Sect. 4 shows the intercomparison of the different approaches. In Sect. 5 the main conclusion are discussed and an outlook on the coming steps to an operational monthly to seasonal forecasting service tailored to inland waterway transport is given.

2   Study domain: the German waterways

The European inland waterways offer more than 40,000 km network of canals, rivers and lakes connecting cities and industrial regions across the continent. The German inland waterway network – an integral part of the trans-European waterway system – comprises about 7,350 kilometres, of which approximately 75 percent are rivers and 25 percent canals. The major inland waterways with regard to freight transport are the Rhine (with its tributaries Neckar, Main, Moselle and Saar) and the Danube, as well as parts of Elbe and some canals interconnecting the natural waterways. About two third of the German waterways are of international relevance, whereupon the importance of River Rhine is outstanding: with almost 200 million tons transported along the Rhine per year (approximately 2/3 of the European IWT volume) the Rhine isn't solely Germany's, but also Europe's most important inland waterway (CCNR 2016). Approximately one third of the rivers in

Germany used as waterways are free-flowing, so they are particularly affected by low flows as the dominating hydro-meteorological impact on IWT. Therefore this study focusses on the free flowing stretches of the international waterways Rhine, Danube and Elbe (see Fig. 2).

The River Rhine, with a total length of 1,230 km, drains an area of approx. 200,000 km^2 with a mean flow rate of approx. 2,500 m³/s at its mouth in the North Sea. It is shippable for large vessels between Rotterdam and Basel on a length of about 800 km. While the main shippable tributaries of the River Rhine are impounded offering a guaranteed fairway depth, the Rhine itself is a free flowing waterway between Iffezheim / Karlsruhe and the beginning of the delta near Pannerdensche Kop in the Netherlands (approximately 500 km). The flow regime of the River Rhine (see right panel of Fig. 2) shifts in downstream direction from a snow-dominated regime (nival, e.g. gauge Maxau) induced by the Alps to a complex flow regime in the Middle (gauge Kaub) and Lower Rhine stretch (gauge Ruhrort) due to the increasing influence of the rainfall dominated (pluvial) flow regimes of the major tributaries (Neckar, Main, Moselle). Low flows, leading to restrictions for waterway transport, typically occur in the River Rhine in late summer and autumn due to high evaporation and low melt water input from the Alpine region (Funk et al. 2015). The River Danube, with a total length of 2,826 km, drains an area of 817,000 km² with a mean flow rate of approximately 6,500 m³/s. It is shippable on a length of 2,415 km between Kelheim and the Black Sea.The German part of the waterway (ca. 220 km) is impounded offering a minimum fairway depth of 2.70 m up to 2.90 m, except for a 70 km section between Straubing and Vilshofen. The flow regime in this critical stretch for waterway transport is pluvio-nival with a complex broad-peaked runoff shape resulting from an overlapping of rainfall and snowmelt influences. Autumn is the typical low flow season, often extended to the winter months. More downstream after the Alpine river Inn entered the Danube the flow regime changes to a nival regime (see gauges Kienstock and Nagymaros).

The River Elbe, with a total length 1,090 km, drains an area of approx. 150,000 km² with a mean flow rate of approximately 860 m³/s. About 930 km are shippable between Pardubice in the Czech Republic and the mouth in the North Sea at Cuxhaven / Germany. The stretch upstream of Geesthacht up to the German - Czech border (nearly 600 km) is free-flowing. The Elbe between Dresden and Neu-Darchau shows pronounced pluvial runoff regimes with maximum flows in late winter / spring and lowest flow values in summer and autumn. Compared to Rhine and Danube, the low flow season relevant for waterway transport already starts in early summer and lasts until autumn. Figure 2 (right panels) visualizes the flow regime of the three waterways represented by the long-term monthly mean flow rate at selected gauges (period 1981 – 2010).

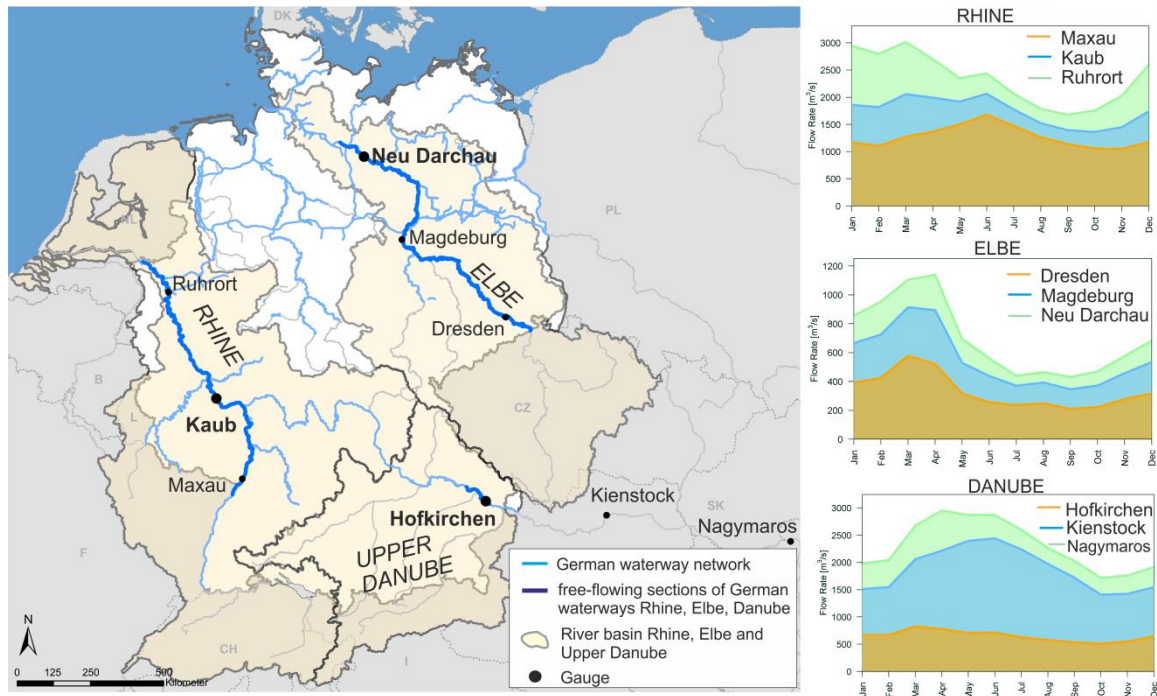



Figure 2. Map showing the German stretches of the international waterways Rhine, Danube and Elbe (left part), for relevant gauges (black dots) the long-term monthly mean flow rates (1981-2000) are visualized (right part).

In order to analyse the performance of the different forecast approaches implemented in the forecast framework, as described in the following sections, one gauge at Rhine, Danube and Elbe has been selected, which is of special relevance for navigation along the particular waterway (black dots, bold labels in Fig 2). Especially gauge Kaub is a very prominent station; up to 4.500 requests per day on the current short-term forecasts, which are published via the River Information System ELWIS (www.elwis.de), are recorded during low flows. Table 1 gives an overview about characterising statistics of the three selected gauges. The mean flow has been calculated as the arithmetic mean of the daily flows within the reference period (listed in Table 1), while the mean low flow is calculated as the arithmetic mean of the lowest daily flows of each year within the particular reference period.

Table 1. Catchment size, annual mean and mean low flow at selected gauges at Rhine, Danube and Elbe

Gauge	River	Area (km^2)	Mean Flow (m^3/s)	Mean Low Flow (m^3/s)
Kaub	Rhine	103,488	1659 (1911-2011)	799 (1911-2011)
Hofkirchen	Danube	47,518	638 (1901-2008)	301 (1901-2008)
Neu Darchau	Elbe	131,950	710 (1890-2006)	290 (1890-2006)

3 Forecast framework

3.1 Input data and hydrological model

Various sorts of input data from different providers have been integrated into the monthly to seasonal forecasting framework presented in this study. The basic requirement is that all data sources are operationally available, that means the data is continuously updated near real-time. The input data selected could be grouped as hydrological measurements, climate and reanalysis data as well as seasonal meteorological forecasts.

Measured streamflow and water-level data (daily mean values) at the gauges relevant for navigation were provided by the Federal Waterway and Shipping Administration (WSV) for the period 1951 to 2015. The data was used to validate model and forecasts performance as well as to calculate climatological forecasts. The latter are generated by averaging the measured values for the same month(s) of the year as the one(s) forecasted.

The precipitation and temperature data, used to force the hydrological model in simulation mode up to the initialization of the particular forecast, is taken from the E-OBS dataset, version 13.1 (Haylock et al. 2008). The downward surface solar radiation is extracted from the ERA-Interim reanalysis (Dee et al. 2011) for the period 1979-2015. In order to preserve the statistical properties of the 5 km by 5 km HYRAS data set (Rauthe et al. 2013), which was used for calibrating the hydrological model LASIM-ME, the data from E-OBS and ERA-Interim had to be downscaled and bias-corrected. A large number of different bias correction methods are available ranging from simple methods as linear scaling (see e.g. Lenderink et al. 2007), linear scaling with additional correction of the standard deviation (Leander and Buishand 2007), to more complex methods such as the distribution based correction method Quantile Mapping (see e.g. Piani et al 2010). We applied these different methods to bias correct E-OBS and ERA-Interim and compared the goodness-of-fit of the flow simulation using the downscaled and bias-corrected meteorological input. As the goodness-of-fit measures such as the Nash-Sutcliffe Efficiency and correlation were very similar we decided to use the most simple bias correction method linear scaling. Monthly linear scaling with reference to the HYRAS dataset was applied on a coarse grid (25 km x 25 km). The monthly scaling factors and monthly additive terms for precipitation and temperature, respectively, have been derived for the period 1951-2000. Subsequently the processed E-OBS data was downscaled to the required 5 km by 5 km model grid by taking into account the long-term monthly ratio between HYRAS on the two different resolutions (5 km, 25 km) for precipitation and respectively by assuming a constant lapse rate of 0.48°/100 m between the grid cell heights for temperature. The ERA-Interim downward surface solar radiation was processed in a similar way as the E-OBS precipitation. As high resolution global radiation reference data for bias correction and downscaling the surface solar irradiance (SIS) of EURO4M (DWD 2013), over the period 1991-2010 was used. In addition, to initialize the hydrological model before starting a forecast, the aforementioned input data was used to run the continuous model simulation and the ESP-forecasts (see Sect. 3.2).

For the statistical approach different meteorological, climatological and oceanic data products have been selected as predictors. These data sets / re-analysis products are listed in Table 2.

Table 2. Climate and oceanic data sources used in the statistical forecast approach

Dataset (Provider)	Variable(s)	Spatial coverage	Spatial resolution	Reference
E-OBSv13.1 (ECA&D Project, KNMI)	precipitation temperature	Europe	0.25º x 0.25º	Haylock et al. 2008
CDC (DWD)	precipitation temperature	Germany	areal mean values (2.500 km² - 48.000 km²)	-
ERSST v4 (NOAA)	sea surface temperature	global	2° x 2°	Huang et al. 2010
NCEP/NCAR Reanalysis 1 (NOAA NCEP-NCAR)	volumetric soil moisture	global	2.5° x 2.5°	Kistler et al. 2001
CDAS-1 MONTHLY (NOAA NCEP-NCAR)	soil moisture geopotential height (700-mb) relative humidity specific humidity zonal and meridional wind (700-mb) mean sea level pressure	global	2.5° x 2.5°	Kalnay et al. 1996

As seasonal meteorological forecast used in the dynamical forecast approach, we used the reforecast dataset from ECMWF's Seasonal Forecast System 4 (S4 hereafter) for the period 1981 – 2014. For the period 1981 – 2011 the ensemble size varies between 15 members (initialization months January, March, April, June, July, September, October, December) and 51 members (for the remaining months). Since 2012, the ensemble size is 51 members all over the year. Before feeding the hydrological model, the output from S4 (daily total precipitation and air temperature), interpolated to a 50 kmx50 km grid (multiple of the 5 km x 5 km model grid), was bias-corrected with the meteorological observation dataset used for the baseline simulation. Again several bias correction and post-processing methods of different complexities for ensemble forecasts are available (see e.g. Crochemore et al. 2016; Zhao et al. 2017). After the experiences of the bias correction of EOBS and ERA-Interim we decided to stick to the most simple bias correction method linear scaling, successful applied for bias correction of seasonal forecasts (Crochemore et al. 2016). We corrected daily values of the different parameter on a monthly basis, which means each daily value of the same month is corrected by the same scaling. In future applications different bias-correction and post-processing methods will be applied and analyzed. As meteorological seasonal forecasts tend to drift towards the climate model from which they are issued with increasing lead-time, giving rise to model bias, separate bias correction factors have been estimated for each forecast initialization date (calendar month) and monthly lead

time (month 1 to month 6). In the final step the corrected precipitation and temperature are downscaled to the 5 km by 5 km model grid.

The hydrological model used in this forecasting environment is based on the model software LARSIM (Large Area Runoff SImulation Model). LARSIM is a deterministic distributed conceptual hydrological model for the simulation and forecasting

5   of the terrestrial water cycle and flow in rivers. It has been originally developed by Ludwig and Bremicker (2006) and is currently maintained and further developed by a transnational developer community of several forecasting centers from Germany and Switzerland. The spatial discretization of the model can be grid-based subareas or subareas according to hydrologic sub catchments. Hydrological processes are modelled for each single land use category or alternatively for each land use and soil type combination in a subarea (hydrological response unit HRU). Due to the strong altitude dependence of

10   temperature HRU could be further subdivided in elevation zones for the simulation of the snow processes. To avoid unnaturally high snow accumulation and to consider snow mass transport mechanism the new LARSIM snow mass transport option could be activated. Using this option snow only can accumulate up to a gradient-dependent threshold and exceeding snow is simply passed to the next model element downhill. These options (subdivision in elevation zones and snow mass transport) in LARSIM are currently used for Rhine basin. For Elbe and Danube they will be implemented in the near future.

15   The LARSIM model used in this context is called LARSIM-ME (ME – MittelEuropa = Central Europe). LARSIM-ME covers the catchments of the rivers Rhine, Elbe, Weser/Ems, Odra and Danube up to gauge Nagymaros in Hungary. The total catchment size, simulated by the model, is approximately 800 000 km². The spatial resolution is a 5 km x 5 km and the computational time-step is daily. To estimate the model parameters of such a large model domain a regionalization approach based on clustering was applied. In total 9 clusters with similar flow characteristics have been identified for the model

20   domain based on the following steps:

1)   Definition of statistical flow values for 132 headwater catchments, relatively free of anthropogenic influences. As statistical values we chose
    – Mean flow / basin area
    – High flow with a 2-year recurrence frequency / mean flow
25   – Monthly mean low flow / mean flow
    – Mean flow in winter / mean flow in summer
2)   Identification of 9 clusters using the k-means clustering algorithm
3)   Selection auf 7 geographical factors (e.g. height, slope, areal share of forest, areal share of field, areal share of unconsolidated rock, mean permeability of upper and lower soil) in order to characterize the clusters
30   4)   rule-based mapping of all subbasins to the clusters

Subsequently a subset of 72 catchments, that are relatively free from anthropogenic effects (catchment sizes ranging from 200 km² to 2100 km²) and evenly distributed over the model domain, were calibrated manually together with the 9 clusters using the HYRAS dataset as forcings. The manual calibration for the period 1998 to 2006 (validation 1976 – 2006) followed the guideline to calibrate LARSIM water balance models (Haag et al. 2016), which recommends the relevant parameters to

35   be calibrated, the parameter range and a calibration procedure. The manual calibration strategy applied involved the

following steps: 1) adjustment of the parameters of the snow modules with focus on the water balance and floods caused by snow melting, 2) adjustment of base flow storage relevant parameters to reproduce discharges at low flow conditions, 3) adjustment of the parameters relevant for interflow to reproduce mean flow conditions, 4) adjustment of relevant parameters to reproduce flood hydrographs 5) final validation and fine adjustment of all parameters. By using this well-proven process-

5 based calibration strategy for LARSIM models conducted by experienced hydrologists instead of a non-process based automatic calibration procedure we expected to reduce the degree of parameter uncertainty in the clusters due to the problem of parameter equifinality (Beven 1996). But the fact that different sets of model parameters reproduce equally good output signals stays an issue in any hydrological model calibration and it is a significant aspect in particular when applying those models for predictions. Afterwards the parameter means and parameter spans have been derived for the clusters and

10 transferred to the respective clusters in the whole model domain. As a next step a fine calibration of the model parameters within the parameter spans of the clusters have been conducted for selected parts / gauges of the Upper Danube, the Elbe and the River Rhine. The fine calibration for Elbe, Danube and Rhine was based on the same period as the input dataset (HYRAS). Special attention was given to anthropogenic effects dominating the flow behavior in several catchments (dams, regulated lakes, water transfers) and the most relevant structures have been implemented explicitly. In order to retain the

15 consistent spatial parameter distribution, the parameters have been optimized within the identified parameter spread of the specific cluster of the initial calibration. The standard deviation of the parameter values has been used as indicator to identify potential room for parameter optimization.

In the forecast framework different meteorological input (EOBS, ERA-Interim instead of the non-operational HYRAS-dataset) has to be used. Therefore we show in Fig. 3 the output from the LARSIM-model set-up for monthly to seasonal

20 forecasting for the hindcast period from 1981 to 2015. Figure 3 illustrates the simulated and observed long-term monthly mean streamflow of the period 1981-2015, the distribution of the simulated and observed monthly mean flows within the individual months of the year as box-and-whisker plots, as well as the correlation r and Nash-Sutcliffe Efficiency (NSE). The box of the box-and-whisker plots represents the 25%–75% inter-quantile range with the median as band inside the box. The whiskers represent one and a half times the inter-quantile range and values beyond are plotted as single data points. All

25 gauges show NSE > 0.8 and r > 0.9 for monthly mean values. On the original daily time-step, the gauges show NSE > 0.7 and r > 0.85. Especially for the Elbe the model performance on daily basis is somewhat lower, mainly due to shortcomings in the river routing. The climatological seasonality of streamflow is well reproduced at the gauges Hofkirchen – Danube and Neu Darchau – Elbe. At gauge Kaub – Rhine, especially in the spring months effected by snow melt, LARSIM-ME underestimates the flow. This underestimation is an indicator for problems in modelling snow processes, which will be a

30 focus in the future model developments of LARSIM-ME.

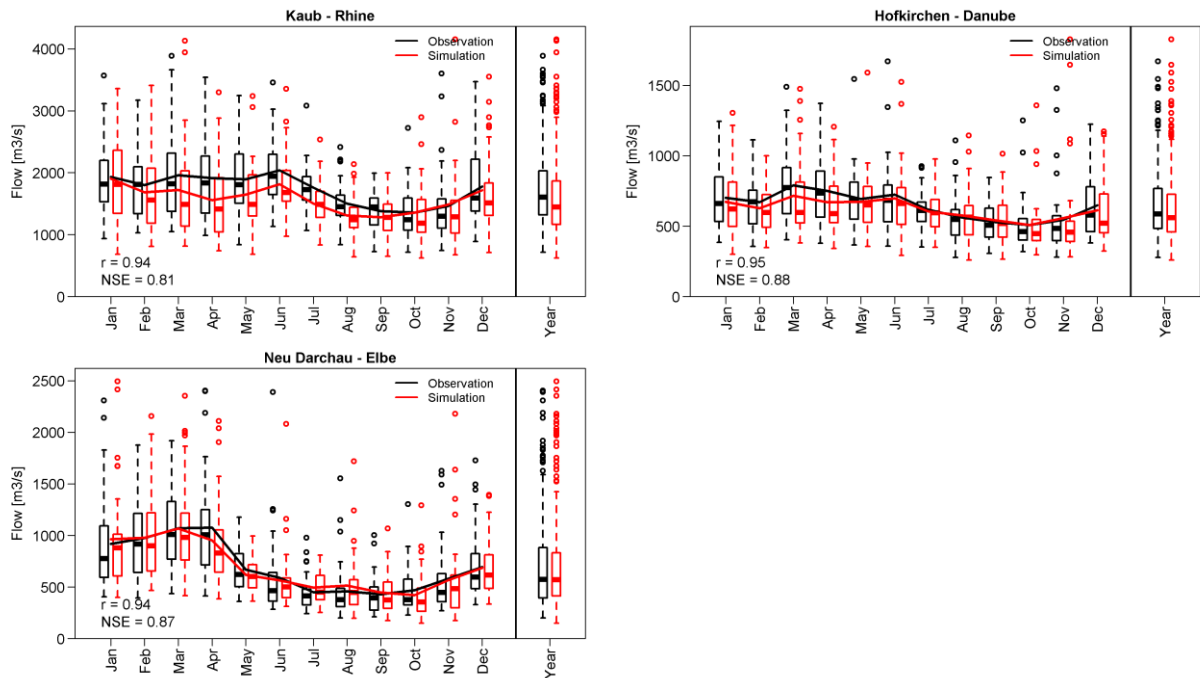



Figure 3. Comparison of the simulated (red) and observed (black) long-term (1981-2015) monthly mean streamflow and the distribution of the simulated and observed monthly mean streamflow within the different months and for the whole year illustrated as box-and-whisker plots of the gauges Kaub - Rhine (top left), Hofkirchen – Danube (top right) and Neu Darchau – Elbe (bottom).

5   Another effect is anthropogenic influences, especially regulated dams, lakes and water transfers. As it is quite challenging to account for such impacts in a large scale hydrological model like LARSIM_ME, just the major barrages and water transfers together with their regulation rules have been implemented so far. This is not due limitations in the model functionality, but due to the difficulties in getting the required information. Therefore some of the problems the LARSIM models show to reproduce the flow behaviour result from missing or incomplete reproduction of anthropogenic effects.

3.2 Forecast parameter and forecast benchmark

In preparation of the development of the forecast framework three forecast parameters have been selected in agreement with the users. For the monthly forecast the monthly mean flow (MoMQ) and the lowest arithmetic mean of flow on seven consecutive days within a month (MoNM$_7$Q) were chosen. For the seasonal forecast the 3-monthly mean flow (3MoMQ) is predicted. MoMQ and 3MoMQ are quite common forecast parameters on longer lead-times (e.g. Yossef et al. 2013;

15   Svensson 2016; Tucci et al. 2003), NM$_7$Q is a variable primarily used as low flow indicator in the context of hydrological monitoring or ecological purposes (Richter et al. 1998; Marke 2008). Low NM$_7$Q values imply the existence of a long-lasting drought period (Klein and Meißner 2016). Furthermore, the NM$_7$Q is a robust indicator, because it is insensitive to distorting singularities like short-term fluctuations due to natural or anthropogenic errors. For decision making in the IWT sector on monthly or seasonal time-scales a monthly / three-monthly resolution is sufficient. Users don't estimate the load of

a specific ship on a specific trip, as it is the case on short- to medium-ranges time-sales, but typical decisions (e.g. how to compose an optimal fleet for the coming month) require information on "average" or the "worst" conditions characterized e.g. by the monthly mean flow or the lowest arithmetic mean of 7 consecutive daily values within a month.

Traditionally, for short- to medium-range forecasts the water-level is the parameter of main interest for navigation purposes as it determines via the shape of the river bed the available water-depths and therefore the possible vessel draught. As in many river stretches the shape of the riverbed changes over time due to morphological dynamics, it is problematic to compare water-levels over long periods of time. To overcome this issue, we decided at this stage of development to analyse discharges, rather than water-levels.

As reference data, in order to evaluate the forecast quality of each forecast approach, we used two datasets: 1) observed discharges at the forecasting gauges representing the real-world situation and 2) simulated discharges at the forecasting gauges generated by the hydrological model LARSIM-ME forced with observed meteorology (see Sect. 3.1). This reference, also called pseudo-observations, was used in some of the analysis on the predictability in order to mask the error coming out of the hydrological model itself (Shukla and Lettenmaier 2011; van Dijk et al. 2013; Wood et al. 2016).

Forecast benchmarks are used to demonstrate and quantify the added skill and value of the analysed forecast approaches. On the one hand the benchmarks have been selected on current practice (climatological forecast) and on the other hand a standard method requiring extensive input data was chosen. As Fig. 2 shows, the discharges along the waterways are subject to seasonal variability dependent on the flow regime. Therefore, only flows of the same month in each year have been included into the respective climatological forecast, e.g. the climatological forecast for January is based on the measured flows of the first 31 days within each year. As standard seasonal forecasting method, we applied the already mentioned ESP approach. The set-up of ESP is relatively simple although a hydrological model of the basin of interest is required. Each forecast run is initialized with the best estimated initial hydrological conditions, which is based on forcing the hydrological model with measured meteorological inputs. Potential improvements might be achieved by data assimilation techniques (see e.g. Yossef et al 2013). Based on this initialization, from which the predictive skill of ESP originates, the hydrological model is forced with an ensemble of historical time-series of observed meteorology from previous years (Wood et al. 2002). ESP doesn't require seasonal meteorological forecasts, but it solely relies on the resampled meteorology, which is a limitation at the same time, because meteorology doesn't contribute to an improved forecast skill in relation to the climatological forecast. Nevertheless, ESP proved to be a robust forecast approach used in several operational applications for years.

In addition to ESP, Wood and Lettenmaier (2008) suggested a complementary approach for sensitivity analysis, called reverse-ESP. In contrast to an ESP-forecast, the hydrological model in a reverse-ESP run is initialized with an ensemble of initial conditions based on climatology. Along the forecast period the model is driven with the measured meteorology. As reverse-ESP requires the 'perfect' meteorology along the forecast lead-time, it is not suitable as forecast approach in operational practice. While the skill of ESP results from the initial hydrological conditions, reverse-ESP obtains skill from the (perfect) meteorological forecast. That's why Wood and Lettenmaier (2008) suggested comparing the skill of ESP and reverse-ESP as a function of lead-time, season, basin etc. in order to determine, which of the two main components of a

seasonal hydrological forecast (hydrological memory or meteorological forcing) is dominating the particular forecast skill. Recently, this method was extended by Wood et al. (2016) to a method called VESPA (Variational Ensemble Streamflow Prediction Assessment), which is able to blend the two sources of seasonal forecast skill systematically.

3.3 Forecast approaches

5   In order to find an optimized (related to forecast quality, data and model requirements, computing time etc.) seasonal forecast procedure for navigation-related forecasting multiple approaches representing the different philosophies (dynamical versus statistical) in seasonal hydrological forecasting have been implemented and tested under operational conditions. The above mentioned dynamical method ESP is primarily applied to analyse the different sources of predictability on seasonal time-scales as well as to act as benchmark for the other methods. Furthermore, a dynamical approach similar to the one used

10   for short- to medium-range forecasting was implemented, linking a hydrological model with seasonal meteorological predictions. The hydrological model LARSIM-ME was forced with measured data (up to the forecast starting date) and subsequently with the forecasts from ECMWF's System 4. The hydrological model, as well as the processing of the meteorological inputs, is described in Sect. 3.1.

For the statistical approach a methodology has been adopted, which was already successfully applied to predict seasonal

15   streamflow anomalies at the Romanian Danube (Rimbu et al. 2005) as well as monthly to three-monthly streamflow at the lower Elbe in Germany for specific events and seasons (Ionita et al. 2009; Ionita et al. 2015). The basic idea is to use climate and hydro-meteorological variables (e.g. sea surface temperature, precipitation etc.) as predictors instead of climate indices (e.g. North Atlantic Oscillation, Southern Oscillation Index). Since the early days of seasonal hydrological forecasting, large-scale climatic patterns have been used as predictors for seasonal streamflow anomalies (Maurer and Lettenmaier 2003, Wang

20   et al. 2011). For Europe, the North Atlantic Oscillation (NAO) and the El Niño Southern-Oscillation (ENSO) indices are most commonly used as predictors of hydrological variables like streamflow (Rimbu et al. 2004, Trigo et al. 2004). Although these teleconnections are detectable, they are significantly less pronounced for Central Europe than for other continents like Africa or Australia. Furthermore, they are characterised by non-stationarity issues which means that the strength of the correlation between the indices of these two phenomena and streamflow anomalies varies over time (Ionita et al. 2008). The

25   climate and hydro-meteorological variables used in the approach presented here have to fulfil a stability criterion for the correlation between predictor and predictand. The concept of predictor stability, wherein the so-called stability maps are a crucial tool, was introduced by Lohmann et al. (2005). In order to detect stable predictors the variability of the correlation between the streamflow at a specific location and the potential predictors are investigated within a 31-year moving window within the period 1948 to 2012. The correlation is considered to be stable for those spatial units where the current streamflow

30   and previous months' climate variables are significantly correlated at 90% level or 80% level for more than 80 % of the moving window. Based on the following three steps stability correlation maps are generated:

1) Each predictand (e.g. 3MoMQ for March-April-May at station Kaub / Rhine) is correlated with numerous potential predictors. Different lags (e.g. mean sea level pressure in February, mean sea level pressure in January) and regions of the same variable are regarded as independent predictor.

2) The correlation is computed in a moving window of 31 years within the period from 1948 to 2012 (window 1: 1948-1979, window 2: 1949-1980, …, window 34: 1981-2012).

3) The correlation is considered to be stable for those grid points / regions where predictor and predictand are significantly correlated at the 90% level and respectively 80 % level for more than 80% of the 31-year windows within the period 1948–2012. According to the level of significance grid points / regions are colorized in red to yellow shades (stable positive correlation), shades of blue to green (stable negative correlation) or white (non-stable correlation) in order to create a stability correlation map for each potential predictor. Figure 4 illustrates this procedure: 3-monthly mean flow in spring (March – April – May) at Kaub / Rhine and mean sea level pressure (SLP) of previous winter (December – January – February) from region (a) are positively correlated for all 31-year windows of the period 1948-2012 and above the 90 % significance level for more than 80% of the windows (left part of Fig. 4). Therefore, these grid points are stable correlated with streamflow and are represented on the stability map in red (right part of Fig. 4). The 3MoMQ and SLP from the grid-points in region (b) are negative and above 90% significance level correlated for more than 80% of the moving windows. These grid points are represented on the stability correlation map as blue. Grid points significantly correlated for less than 80% windows, like those in region (c)are regarded as "unstable" (white colour on the stability correlation map). In the left part of Fig. 4, the correlation is plotted in the middle of each 31-year window. So, the first point represents the correlation between 3MoMQ and previous winter SLP from 1948 to 1979, while the last point represents the correlation from 1981 to 2012.

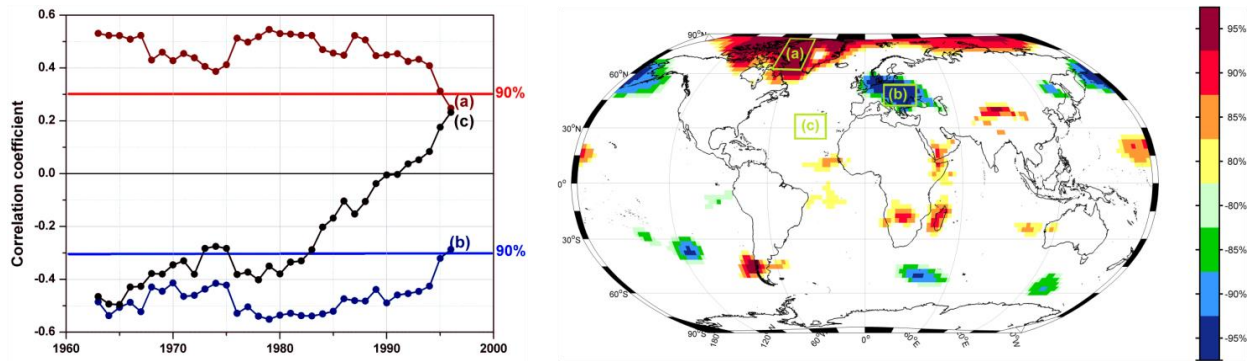



Figure 4. Example of a stability correlation map. Left: correlation between three-monthly streamflow at Kaub / Rhine and SLP of previous winter in a 31-year moving window for selected grid areas; right: map showing the areas with the corresponding correlations.

The final composition of the predictors for the forecasting model is established by stepwise regression of the stable predictors using the Akaike information criterion and the explained variance of forecast errors. Originally, this method was solely applied for European and global climate datasets like E-OBS or ERSST (see Table 2). In the context of this

navigation-related forecast framework also regional to local precipitation and temperature datasets from the German Meteorological Service DWD have been included as well as the historical discharges at the gauges of interest. Especially, the consideration of the measured discharges, which are an aggregated proxy of the hydrological history as well as of the current conditions, led to an additional increase of forecast skill. To quantify the importance of measured discharges it has been excluded from the regression model in an experimental set-up. The last column of Fig. 11 shows the forecast results without using measured discharges as predictor for June's (month with the highest $MoNM_7Q$), September's and November's (a low flow month, typically affecting inland navigation) $MoMN_7Q$ at the station Kaub / Rhine. The selected scores clearly indicate an improved forecast skill when using measured discharge of previous months as predictor.

3.4 Forecast evaluation – skill and value

The skill of the forecasts was assessed in terms of the correlation coefficient (CC), the mean absolute error (MAE) and the mean squared error (MSE) as deterministic measures. In order to evaluate the skill improvement with respect to the reference forecast (climatology, ESP) as well as to be able to compare the skill amongst the different waterways the corresponding skill scores have been additionally used for evaluation (MAE-SS, MSE-SS). While the perfect score is zero for MAE and MSE, an optimal forecast produces a CC, MAE-SS and MSE-SS of one. The skill scores are a function of the forecast as well as the reference forecast and the observations. The skill scores are positive (negative) if the forecast skill is higher (lower) then the one of the reference forecast. A skill score might be interpreted as the percentage improvement with regard to the reference forecast by multiplying the skill score by 100. As probabilistic measure of forecast skill we applied the continuous ranked probability score (CRPS) and respectively the CRPSS as its corresponding skill score (Hersbach 2000). CRPS / CRPSS are appropriate indicators of the overall performance of probabilistic forecast systems comparable to the MAE / MAE-SS in case of a deterministic forecast.

For the ensemble-based forecasts (ESP, dynamic approach based ECMWF S-4) the deterministic metrics MAE and MSE have been determined relative to the observation for each ensemble member separately and afterwards the average of the single values was calculated. The correlation coefficient CC is calculated from the ensemble mean. The forecasts of interest as well as the climatology are thereby treated as real ensembles instead of single realizations (e.g. the ensemble mean or median).

For the climatological forecast, as well as for the ESP approach, we considered a subsample of observations covering the study period from 1981 to 2014. In each case, we used the historical values of the same days in each year along the forecast length. Additionally, we followed the leave-one-out cross validation procedure by excluding the values of the validation year from the measurements when generating the respective climatological forecast as well as the meteorological input to the hydrological model in case of ESP.

Besides the verification of forecast skill we aim at evaluating the value of the forecast, too. The value of a forecast and respectively a forecasting service arises by improving decisions of the user conditioned by the forecast (Murphy 1993). Forecast value and skill aren't necessarily the same and their relationship in real world applications could be quite complex

as the analysis of forecast value always has to consider the specific user context. A feasible approach successfully applied in several applications before, most often in meteorological (Richardson 2000; Wilks 2001; Richardson 2011) seldom in hydrological contexts (Roulin 2007, Fundel and Zappa 2011), is the concept of the relative economic value. In order to evaluate the potential economic gain of a forecast dependent on the user specific cost-loss ratio, the original continuous

5 hydrological forecasts are converted to categorical forecasts and subsequently combined with a relatively simple static cost-loss model. According to this model, costs (C) will incur whenever the forecast indicates an event, because the user will take preventive actions. It is assumed that these preventive actions offer a total protection, so that the investment prevents any losses (L). Losses will only incur, if the forecast misses an event. If no event is forecasted and it actually did not happen, neither costs nor losses incur. The decision strategy behind the relative economic value assumes that the user aims at a long-

10 term economic optimum, the user's decisions solely depend on economic reasons and that the user acts risk-neutral. In order to compare different forecasting systems based on their economic value Richardson (2000) suggested to calculate a relative score, showing the added value of a forecast compared to the climatological forecast. The relative economic value score V is defined as the difference of the long-term average expected expenses (EE) of the climatological forecast and the forecast of interest in relation to the difference of the climatological and a perfect forecast:

15 $$V = \frac{EE_{clim} - EE_{forecast}}{EE_{clim} - EE_{perfect}}$$ (1)

A perfect forecast prevents losses (all events are predicted correctly) and costs only incur in case of an event, which occurs with climatological recurrence interval P_i. Therefore $EE_{perfect} = P_i \cdot C$. The best strategy to act, based on a climatological forecast, is to find the optimum of the two options "always protect" or "never protect" by minimizing the related expenses $EE_{clim} = min (C, P_i \cdot L)$. In the long-term average a user with a specific cost-loss ratio below the climatological recurrence

20 interval P_i of the event will always protect, otherwise it is economically advantageous to accept the losses of the event. All of the aforementioned assumptions lead to the relative economic value score definition by Richardson (2000):

$$V = \frac{min\left(\frac{C}{L}, P_i\right) - POFD \cdot \frac{C}{L} \cdot (1 - P_i) + POD \cdot P_i \cdot \left(1 - \frac{C}{L}\right) - P_i}{min\left(\frac{C}{L}, P_i\right) - P_i \cdot \frac{C}{L}},$$ (2)

with   POD = Probability of detection / hit rate (fraction of observed events that is forecast correctly)

        POFD = Probability of false detection / false alarm rate (fraction of false alarms conditioned on observations)

25   C/L = cost-loss ratio

       P_i = recurrence interval of the disastrous event.

The maximum value score is 1 for perfect forecasts, while V = 0 indicates no added value of the forecast under investigation compared to the optimal use of a climatological forecast. In case of relative economic values below zero the user should refuse the forecast and better use climatology. The maximum relative value score V_{max} is reached for $P_i = C / L$. V_{max}

30 corresponds to the difference of hit and false alarm rate, which is also known as the Pierce Skill Score or Kuipers skill score (Manzato 2007). The economic value depends on the quality of the forecast (expressed via the hit rate and the false alarm

rate), the definition of the event, expressed through the climatological frequency, and on the individual user represented by the cost-loss ratio. As different forecast users with different decision problems will gain different levels of economic value from an optimal use of the same forecasts, the relative value score is often expressed graphically as a function of the cost-loss ratio. A suitable numerical score, aside from V_{max}, is the area below the economic value function (Fig. 9 and Fig. 10), with an optimum value of one.

4 Results

4.1 Sources of predictability

In the course of designing the forecasting framework we conducted the typical ESP / reverse ESP experiments, as various predictability studies did before (Wood and Lettenmaier 2008). Being aware that this experiment is just able to represent the two (in most cases unrealistic) endpoints of forecast uncertainty (zero and perfect information about future forcings and initial conditions, see chapter 3.2), it is a feasible and pragmatic way to gain more insight into the relative role of the two main sources of predictability as a function of forecast location, lead-time and initialization month. Figure 5 visualizes the MSE-SS for ESP and reverse-ESP in relation to the simulated climatology at the gauges Kaub / Rhine, Hofkirchen / Danube and Neu Darchau / Elbe for forecast months 1 to 6. Eight initialization months (Jan, Mar, May, Jul, Aug, Sep, Oct, Dec) have been selected in order to clearly arrange the graphs, while focussing on the typical low flow period (July to October).

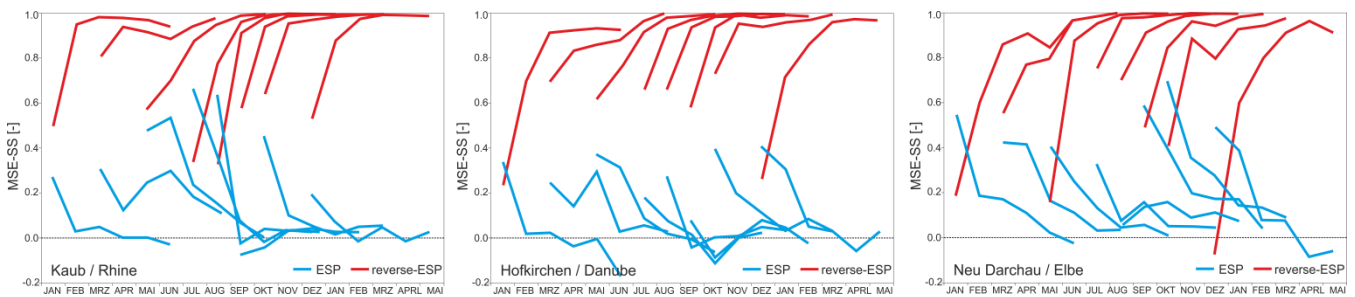



Figure 5. MSE-SS of the ESP (blue) and reverse ESP (red) forecast (reference: simulated to the MSE from using a climatology) for the gauges Kaub / Rhine, Hofkirchen / Danube and Neu Darchau / Elbe over a lead-time of 6 months (verification period 1981 – 2014).

Figure 5 clearly indicates that the differences in flow regime, climate region and catchment characteristics at the waterways (see Sect. 2) sustainably affect the relative importance of the predictability sources within the seasonal cycle. But despite all differences amongst the gauges / waterways, the overall conclusion of the ESP / reverse-ESP experiment is that for the majority of initialization months and lead-times, the mean squared forecast error is dominated by the meteorological forcing. In many cases, already in the first forecast month, future weather is the leading source of forecast skill as the MSE-SS of the ESP drops below the corresponding reverse-ESP values. Nevertheless, in some months (e.g. July and August at gauge Kaub) the initial hydrological conditions noticeable influence forecast skill, at least for the first forecast month; in rare cases also

for the subsequent months (e.g. forecast at gauge Neu Darchau initialized in December). Although a sound estimation of initial hydrological conditions are essential (see also Demirel et al. 2013; Fundel et al. 2013), it could be concluded that solely relying on the "hydrological memory" as source of predictability won't be sufficient to produce skilful streamflow forecasts with lead-times beyond one month for the German waterways.

4.2 Long-term evaluation

Following the history of the stepwise set-up of the forecast framework for the German waterways, we first compare the dynamical forecast approach based on ECMWF S4 forecasts with the ESP-approach for the period 1981 to 2014. Although it is well known that Central Europe is a region offering limited skill of seasonal meteorological forecasts, in particular for precipitation as the most-important input to hydrological models, the question was if the information of these forecasts could provide some additional information to the seasonal hydrological forecasts. Figure 6 displays the MSE-SS between the ESP-based as well as the S4-based forecasts and observed climatology for the gauges Kaub, Neu Darchau and Hofkirchen as a function of forecast month (1-6) and initialization month (January to December). Dark coloured pixels indicate high forecast skill compared to climatology. It is obvious that for both approaches and all stations, the skill significantly diminishes with increasing lead-time, but that the use of the S4 forecasts leads to additional skill for the majority of lead-times and initialization months at all gauges. Overall, the forecast skill for the Elbe (gauge Neu Darchau) is higher than for Rhine (gauge Kaub) and Danube (gauge Hofkirchen). The skill scores at all stations show a noticeable pattern indicating higher scores in spring and late autumn, which might be induced snow melt (spring) and snow accumulation (autumn). This characteristic remains visible, in some cases becomes even more obvious, for the S4 based forecasts (e.g. for the October / November forecast at Rhine and Danube).

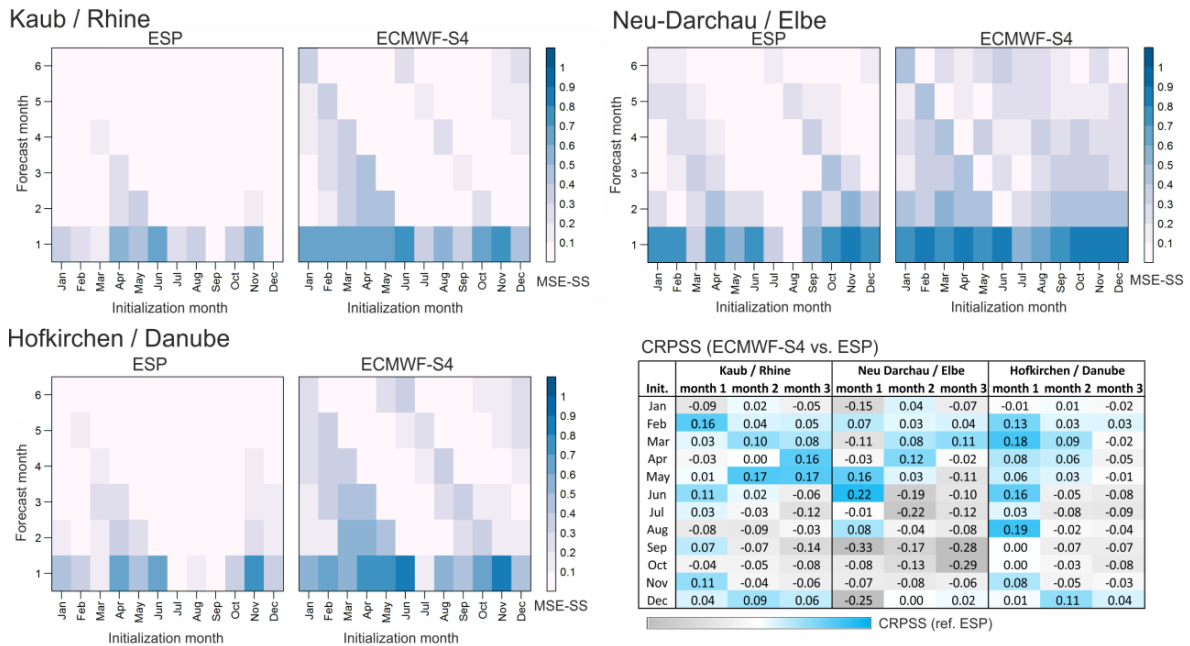



Figure 6. MSE-SS for ESP and S4-driven forecast for each initialisation and forecast month at the stations Kaub, Neu Darchau, Hofkirchen and CRPSS values of S4-driven forecast related to ESP for forecast month 1 to 3 (verification period 1981 – 2014).

5   The increase of forecast skill is proved by the CRPSS shown for the first three month of lead-time at Kaub, Neu Darchau and Hofkirchen in the table at the bottom, right of Fig. 6. As reference forecast we selected ESP so that a positive CRPSS directly implies an improved forecast skill by using S4 inputs. Especially the first forecast months show an improved skill. Unfortunately, the improvements are less pronounced in the typical low flow season (July to October) particularly relevant for IWT.

10   As second forecast approach the multiple linear regression model (MLR) based on the stability analysis (Sect. 3.3) was implemented. In Fig. 7 all three forecast approaches currently implemented in the forecast framework are compared by different skill metrics (see section 3.4) for the period 1981 to 2014 for the first forecast month and initializations. The monthly $MoNM_7Q$ was chosen as forecast variable, because it shows slightly more robust forecast results as the monthly MQ. From Fig. 7 it is evident that the statistical approach is able to further improve forecast quality of the dynamical

15   approach. While forecast skill is rather fluctuating for ESP and S4, it is significantly more stable for the statistical approach. There is still a decrease in forecast skill within the typical low flow period in late summer / autumn, but still on a proper level.

Initialization Month	Score	Kaub / Rhine			Neu Darchau / Elbe			Hofkirchen / Danube		
		ESP	S-4	MLR	ESP	S-4	MLR	ESP	S-4	MLR
January	CC	0.673	0.682	0.939	0.860	0.783	0.939	0.679	0.703	0.939
	MSE-SS	0.41	0.54	0.89	0.70	0.73	0.89	0.49	0.63	0.89
	MAE-SS	0.23	0.34	0.65	0.47	0.54	0.65	0.29	0.44	0.65
	CRPSS	0.25	0.17		0.48	0.400		0.29	0.28	
February	CC	0.640	0.789	0.856	0.728	0.790	0.856	0.622	0.766	0.856
	MSE-SS	0.36	0.63	0.74	0.57	0.71	0.74	0.46	0.71	0.74
	MAE-SS	0.24	0.41	0.43	0.39	0.51	0.43	0.36	0.51	0.43
	CRPSS	0.19	0.32		0.37	0.41		0.29	0.39	
March	CC	0.654	0.832	0.912	0.861	0.842	0.912	0.620	0.793	0.912
	MSE-SS	0.10	0.46	0.84	0.55	0.72	0.84	0.38	0.70	0.84
	MAE-SS	0.08	0.27	0.64	0.39	0.51	0.64	0.26	0.51	0.64
	CRPSS	-0.02	0.00		0.47	0.41		0.23	0.37	
April	CC	0.726	0.796	0.903	0.734	0.767	0.903	0.768	0.828	0.903
	MSE-SS	0.36	0.52	0.82	0.58	0.67	0.82	0.59	0.74	0.82
	MAE-SS	0.23	0.34	0.60	0.39	0.46	0.60	0.40	0.53	0.60
	CRPSS	-0.05	-0.08		0.24	0.22		0.26	0.32	
May	CC	0.839	0.890	0.966	0.519	0.712	0.966	0.766	0.786	0.966
	MSE-SS	0.50	0.67	0.93	0.35	0.63	0.93	0.63	0.72	0.93
	MAE-SS	0.29	0.40	0.76	0.22	0.42	0.76	0.42	0.51	0.76
	CRPSS	0.02	0.03		0.16	0.29		0.37	0.41	
June	CC	0.857	0.875	0.872	0.721	0.881	0.872	0.787	0.823	0.872
	MSE-SS	0.52	0.67	0.77	0.61	0.79	0.77	0.60	0.66	0.77
	MAE-SS	0.32	0.45	0.54	0.36	0.52	0.54	0.38	0.46	0.54
	CRPSS	0.28	0.36		0.29	0.45		0.39	0.48	
July	CC	0.677	0.672	0.955	0.609	0.604	0.955	0.378	0.412	0.955
	MSE-SS	0.15	0.27	0.91	0.18	0.50	0.91	0.01	0.18	0.91
	MAE-SS	-0.06	0.05	0.60	0.10	0.29	0.60	-0.03	0.08	0.60
	CRPSS	-0.28	-0.241		0.18	0.172		-0.02	0.02	
August	CC	0.618	0.695	0.831	0.770	0.816	0.831	0.446	0.631	0.831
	MSE-SS	0.14	0.25	0.71	0.49	0.69	0.71	0.18	0.44	0.71
	MAE-SS	0.03	0.15	0.43	0.33	0.44	0.43	0.11	0.30	0.43
	CRPSS	-0.26	-0.36		0.36	0.41		0.13	0.30	
September	CC	0.625	0.735	0.890	0.868	0.777	0.890	0.585	0.669	0.890
	MSE-SS	0.20	0.46	0.79	0.63	0.63	0.79	0.03	0.38	0.79
	MAE-SS	0.10	0.27	0.57	0.40	0.37	0.57	0.10	0.24	0.57
	CRPSS	0.06	0.12		0.39	0.19		0.18	0.18	
October	CC	0.678	0.713	0.864	0.842	0.860	0.864	0.651	0.634	0.864
	MSE-SS	0.49	0.60	0.76	0.47	0.53	0.76	0.53	0.59	0.76
	MAE-SS	0.31	0.39	0.52	0.26	0.28	0.52	0.28	0.37	0.52
	CRPSS	0.30	0.27		0.00	-0.08		0.19	0.19	
November	CC	0.653	0.802	0.908	0.866	0.866	0.908	0.763	0.870	0.908
	MSE-SS	0.47	0.70	0.82	0.72	0.76	0.82	0.64	0.80	0.82
	MAE-SS	0.33	0.48	0.52	0.43	0.47	0.52	0.43	0.54	0.52
	CRPSS	0.30	0.27		0.25	0.19		0.38	0.43	
December	CC	0.721	0.677	0.879	0.925	0.928	0.879	0.725	0.681	0.879
	MSE-SS	0.46	0.54	0.77	0.78	0.84	0.77	0.48	0.52	0.77
	MAE-SS	0.31	0.43	0.46	0.54	0.56	0.46	0.34	0.46	0.46
	CRPSS	0.27	0.30		0.51	0.39		0.30	0.30	

Figure 7. Comparison of monthly forecast skill of ESP, S4-driven and statistical forecasts at the stations Kaub, Neu Darchau, Hofkirchen predicting lowest seven day mean flow MoNM7Q of the current month (verification period 1981 – 2014).

The results for the seasonal forecasts (3-monthly mean discharge of the upcoming meteorological season) shown in Fig. 8 confirm the findings described above. While forecast skill (see section 3.4) based on ESP and S4 at Rhine und especially Danube is comparatively low when compared to climatology, the skill for the Elbe turn out to be significantly higher. The statistical approach leads to a sustainable increase in forecast skill at all waterways, even the skill for the Elbe could be further increased. Based on the skill metrics applied, the statistical approach shows the best results overall.

Initialization Month	Category	Kaub / Rhine			Neu Darchau / Elbe			Hofkirchen / Danube		
		ESP	S-4	MLR	ESP	S-4	MLR	ESP	S-4	MLR
March	CC	0.404	0.632	0.945	0.651	0.737	0.945	0.476	0.657	0.945
	MSE-SS	0.12	0.48	0.90	0.40	0.65	0.90	0.29	0.61	0.90
	MAE-SS	0.08	0.33	0.68	0.24	0.41	0.68	0.18	0.40	0.68
	CRPSS	0.00	0.04		0.24	0.245		0.13	0.20	
June	CC	0.647	0.643	0.921	0.772	0.778	0.921	0.625	0.648	0.921
	MSE-SS	0.26	0.29	0.86	0.58	0.64	0.86	0.42	0.34	0.86
	MAE-SS	0.13	0.12	0.63	0.33	0.39	0.63	0.25	0.21	0.63
	CRPSS	0.03	-0.10		0.27	0.34		0.26	0.23	
September	CC	0.175	0.286	0.846	0.752	0.717	0.846	0.127	0.230	0.846
	MSE-SS	-0.37	0.10	0.72	0.37	0.56	0.72	-0.33	0.31	0.72
	MAE-SS	-0.10	0.08	0.40	0.24	0.37	0.40	-0.11	0.18	0.40
	CRPSS	0.02	-0.14		0.29	0.14		-0.01	-0.03	
December	CC	0.451	0.528	0.861	0.724	0.751	0.861	0.525	0.543	0.861
	MSE-SS	0.04	0.19	0.76	0.52	0.63	0.76	0.28	0.29	0.76
	MAE-SS	0.01	0.08	0.52	0.25	0.36	0.52	0.14	0.17	0.52
	CRPSS	0.07	-0.04		0.27	0.27		0.12	0.02	

Figure 8. Comparison of forecast skill of ESP, ECMWF-driven and statistical forecasts at the stations Kaub, Neu Darchau, Hofkirchen predicting mean flow of the next 3 months 3MoMQ initialized in March, June, September and December (verification period 1981 – 2014).

The inter-comparison of the forecast approaches, based on the relative economic value, was conducted for MoNM$_7$Q. In order to calculate the relative economic value, three discharge thresholds have been selected to generate the categorical forecast: the median of the observed NM$_7$Q of the particular month the forecast is issued for (period 1951 – 2014), the NM$_7$Q with a recurrence interval (RI) of 2 years and 5 years, respectively. The recurrence intervals have been calculated based on the time-series 1961 – 2015 using Weibull-3 distribution fitted by method of moments. The relative economic value was examined for the non-exceedance of the aforementioned thresholds. In Fig. 9 the relative economic value is shown for the station Kaub (Rhine) and the different forecast approaches as a function of the cost-loss ratio.

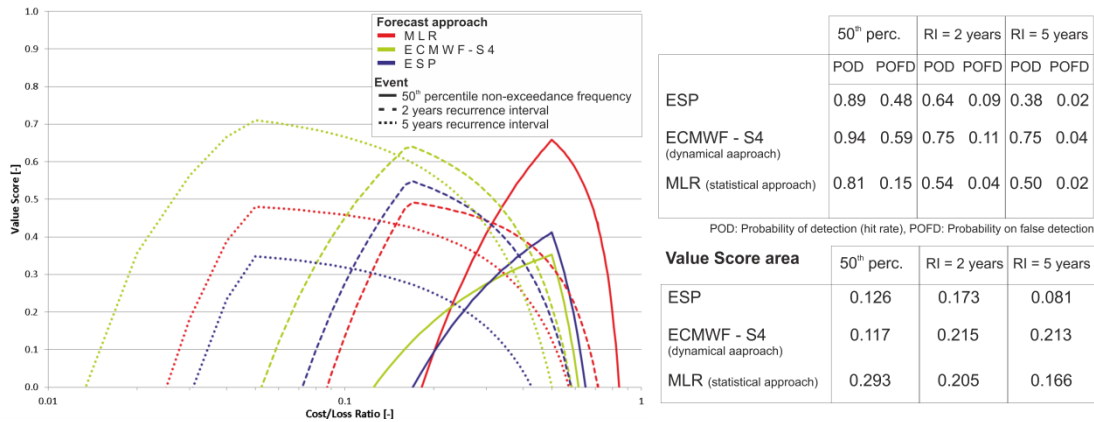



Figure 9. Economic value score plotted against cost-loss ratio for three forecast approaches predicting the lowest seven day mean MoNM$_7$Q of the current month at the gauge Kaub / Rhine for three different event thresholds within the typical low flow season July to November (verification period 1981 – 2014).

The value was calculated for the relevant low flow season between July and November usually affecting inland waterway transport along the river Rhine within the period 1981 – 2014. Overall the three approaches provide positive economic values for a wide range of cost-loss-situations, but the economic value considerably varies amongst the forecast methods as well as the selected events. For the statistical approach the economic values decrease with decreasing return period, while the S4-driven dynamical approach achieves stable or even higher economic values for more extreme low flow events. The S4-driven forecasts show the highest probability of detection (POD) for all events, but especially for the highest threshold (50th perc.), the probability of false detection (POFD) is quite high (0.59), too. In this case the median don't seem to be the optimal representative for the ensemble and choosing another quantile might lead to better economic vales. Also the ESP-forecast suffer from a comparatively high POFD. For the more rare low flow events, the POFD of the S4-driven forecast significantly drops and is relatively close to the one from ESP- and MLR-forecast, while the POD stays best. For all events and cost-loss-situations the benchmark approach (ESP) could be improved at least by one of the two alternative approaches.

An inter-comparison of the economic value between the three waterways Rhine, Elbe and Danube based on the statistical forecast approach is shown in Fig. 10. Three different thresholds based on the 50th, 25th and 10th percentile haven been

selected. For the event occurring most often (50th percentile threshold), the forecasts for the Elbe river produces the highest economic value, which corresponds to the best forecast skill achieved for Neu Darchau when compared to Kaub and Hofkirchen (see Fig. 7). Overall, the forecasts for the Danube provide the lowest relative economic values for all selected thresholds. Nevertheless, the values are still positive (that means added value compared to the currently used climatological forecast) for a wide range of cost-loss situations. For more extreme low flow events, the economic values for Rhine and Elbe get closer and for the 10%-percentile threshold, the forecast at the Rhine reaches slightly higher relative economic values that the ones at the Elbe (see also the value score area).

		50th perc.		25th perc.		10th perc.	
		POD	POFD	POD	POFD	POD	POFD
Kaub / Rhine		0.83	0.09	0.73	0.07	0.65	0.05
Hofkirchen / Danube		0.78	0.15	0.65	0.10	0.49	0.04
Neu Darchau / Elbe		0.87	0.09	0.72	0.05	0.68	0.07

POD: Probability of detection (hit rate), POFD: Probability on false detection

Value Score area (based on MLR approach)	50th perc.	25th perc.	10th perc.
Kaub / Rhine	0.405	0.316	0.222
Hofkirchen / Danube	0.259	0.201	0.161
Neu Darchau / Elbe	0.453	0.339	0.202

Figure 10. Economic value score plotted against cost-loss ratio for the forecast of the lowest seven day mean flow MoN_7Q of the current month at the gauges Kaub / Rhine, Hofkirchen / Danube and Neu Darchau / Elbe based on the statistical approach (verification period 1951 – 2014).

As the most recent step in setting up the monthly to seasonal forecast framework, we tested the combination of the statistical approach with the ESP-method. This combined method doesn't require seasonal meteorological forecasts (and its respective post-processing to force the hydrological model), but it might benefit from the ability of the hydrological model to emulate the initial hydrological conditions prior to the forecast. Therefore, we added the ESP-benchmark forecasts for NM_7Q at the gauge Kaub / Rhine into the corresponding final statistical forecast model. Figure 11 contains the selected skill measures comparing the basic statistical model (MLR) with the one extended by ESP-results as additional predictor (MLR+ESP) for three initialization months: June as the month with the highest ESP-skill, September as one of the months showing the lowest skill of the ESP-forecasts and November, which shows an intermediate ESP-skill (see Fig. 7). The forecasts of NM_7Q in June and November significantly benefit from the ESP-forecasts as all measures indicate. For the September forecasts, where ESP shows a relative low skill, the combined approach gives comparable results as the basic statistical approach. So, adding (low skill) ESP-results as predictor doesn't improve forecast skill, as expected, but it neither deteriorate the skill.

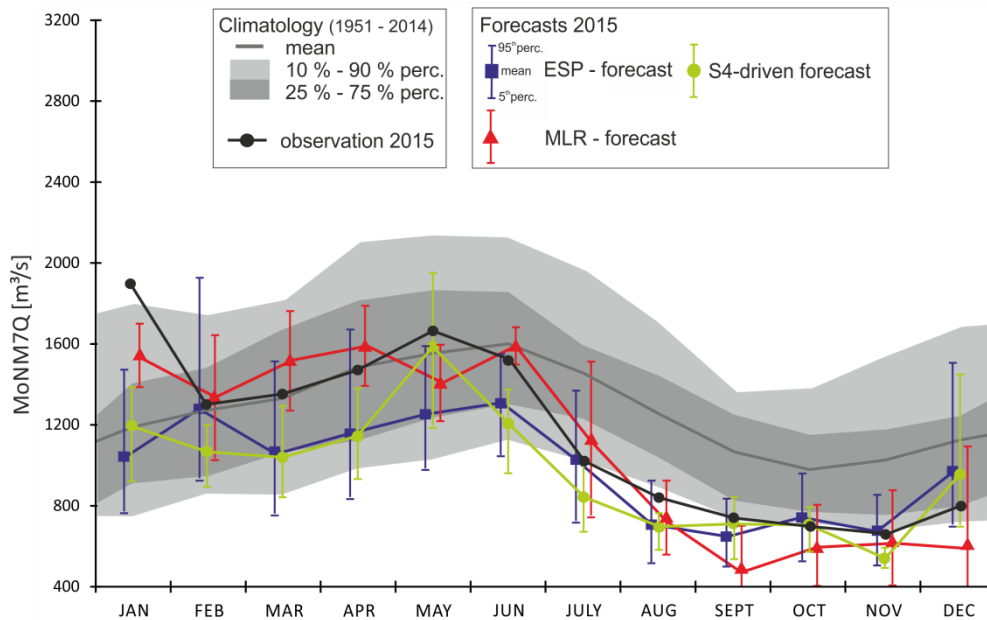
| Initialization | | Kaub / Rhine | | | | |
Month	Score	ESP	S-4	MLR	MLR + ESP	MLR excl. Q
June	CC	0.857	0.875	0.872	0.913	0.751
	MSE-SS	0.52	0.67	0.77	0.84	0.58
	MAE-SS	0.32	0.45	0.54	0.62	0.33
	CRPSS	0.28	0.36			
September	CC	0.625	0.735	0.890	0.889	0.830
	MSE-SS	0.20	0.46	0.79	0.79	0.69
	MAE-SS	0.10	0.27	0.57	0.57	0.45
	CRPSS	0.06	0.12			
November	CC	0.653	0.802	0.908	0.917	0.865
	MSE-SS	0.47	0.70	0.82	0.84	0.75
	MAE-SS	0.33	0.48	0.52	0.54	0.49
	CRPSS	0.30	0.37			

Figure 11: Comparison of forecast skill of the statistical forecast approach using ESP-results as additional predictor for June and September forecasts at station Kaub / Rhine (predictand lowest seven day mean flow MoNM7Q of the current month, verification period 1981 – 2014).

4.3 Evaluation for a significant low flow event

In 2015 a long-lasting drought hit Europe, especially affecting its central and eastern part, where it was one of the worst drought events since the major droughts 1976 and 2003 (van Lanen et al. 2016, Ionita et al. 2017, Laaha et al. 2017). Large-scale deficits in precipitation in combination with high evapotranspiration losses led to deficit in soil moisture and subsequently manifest itself as a long-lasting hydrological drought, with low water-levels and deficits in streamflow along several major European rivers. The 2015 drought showed numerous socio-economic impacts, like constraints in drinking water supply, energy production and agriculture. Also IWT was significantly impacted especially in the second half of 2015, notably in France, the Netherlands, Germany and European Russia. In Germany, load losses on the Rhine, Danube, Elbe, Odra and Weser Rivers and in Russia on the Don River were up to 50% (van Lanen et al. 2016).

At the beginning of 2015, the aforementioned forecast framework was in place, at least for off-line use to support advisory activities. The forecasts could be issued within the first days of the particular month / the particular seasons as soon as all input data / predictands became available. The monthly NM_7Q for the year 2015 at the station Kaub / Rhine is plotted in Fig. 12, together with the climatology (mean, selected percentiles) and the forecasts (mean, uncertainty range between the 5th and 95th percentile) based on the ESP-method, the dynamical approach (S4) and the statistical approach (MLR). Within the first half of 2015 the already ongoing meteorological drought wasn't yet visible along the Rhine and the observed values were quite close to the climatological mean, except for January. As expected, in this period the use of a climatological forecast produced good results. From July onwards, the flow dropped significantly for the rest of the year. This change was predicted most accurate by the statistical approach. In the subsequent months, all methods provided meaningful forecasts, while ESP and the dynamical approach are slightly advantaged compared to the statistical method in this particular situation. The statistically-based forecasts tended to underestimate the $MoNM_7Q$, especially the September forecast was significantly too low. While the range of the 5th and 95th percentile significantly differs in the first half of 2015 with the ESP-based forecasts

showing the widest range, the ranges converge in the second, very dry half of the year 2015 and all approaches show similar ranges.

 Figure 12. Comparison between the three navigation-related forecast approaches for the lowest seven day mean MoNM$_7$Q of the current month in the year 2015 at gauge Kaub / Rhine in relation to the observed values and the climatology (1951 – 2014).

Regarding the three-monthly forecast issued at the beginning of the particular meteorological season, the statistical approach significantly outperformed the other methods in spring (Fig. 13). For summer (JJA) and autumn (SON) the forecasts of all

10 approaches are relatively similar. But the statistical approach and the S4-driven forecast slightly outperformed the ESP-based results. For the autumn season all approaches overestimated the observed value (up to 25 %), but they at least indicate below average conditions, which is already a valuable information for the navigational users. Regarding the ranges of the 5th and 95th percentile, the statistical approach produces the sharpest forecast with the narrowest ranges. Except for DJF forecast the observed values fall in the range of the statistical approach. Although all approaches overestimated the flow in autumn, the

15 measured value still fall into the 5th to 95th percentile range of all approaches.

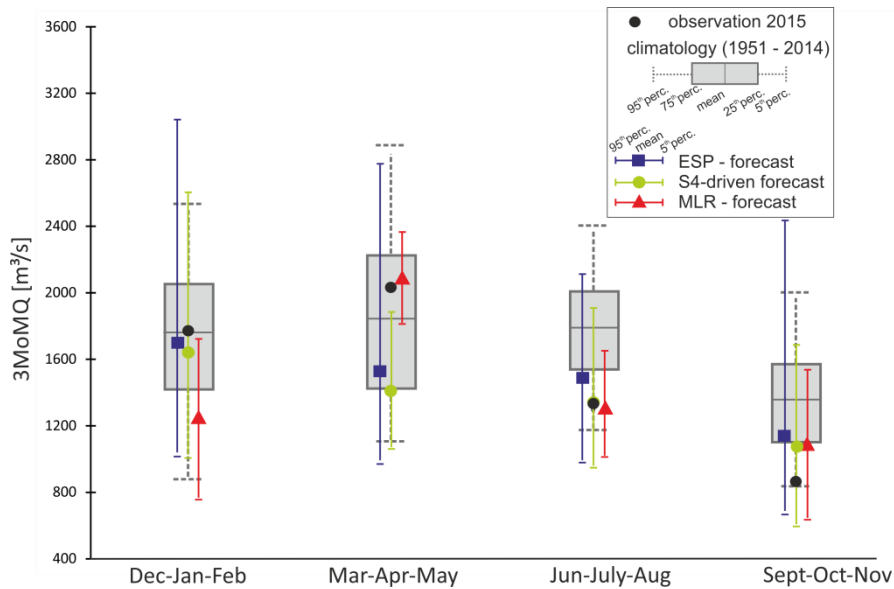



Figure 13. Comparison between the three navigation-related forecast approaches for the monthly mean flow of the next three months 3MoMQ initialized in December 2014, March 2015, June 2015, September 2015 (meteorological seasons 2015) at gauge Kaub /Rhine in relation to the observed values and the climatology (1951 – 2014).

The performance of the seasonal forecasts for the waterways Elbe and Danube is shown in Fig. 14. These results approve the long-term evaluation. The seasonal forecast results for the Elbe were markedly good, particularly for the statistical and the S4-driven approach producing nearly perfect predictions of MAM and SON flows. For JJA the flow was overestimated by all methods, but the forecasts consistently indicated below the long-term average conditions. The range between the 5th and
10   95th percentile are similar for the statistical and the S4-driven forecast, while the ESP-based forecast is significantly less sharp. For the 2015 event at the River Danube, gauge Hofkirchen, the S4-driven dynamical approach produced the best forecast results, except for the spring season. Although the dynamical approach still overestimated the flows in summer and autumn, it was a good indicator for the significant low flow situation observed. The measured value was covered by the 5th to 95th percentile range at least. Especially the statistical approach failed to predict these low values. Even the 5th to 95th
15   percentile range didn't cover the measured values in summer and autumn.

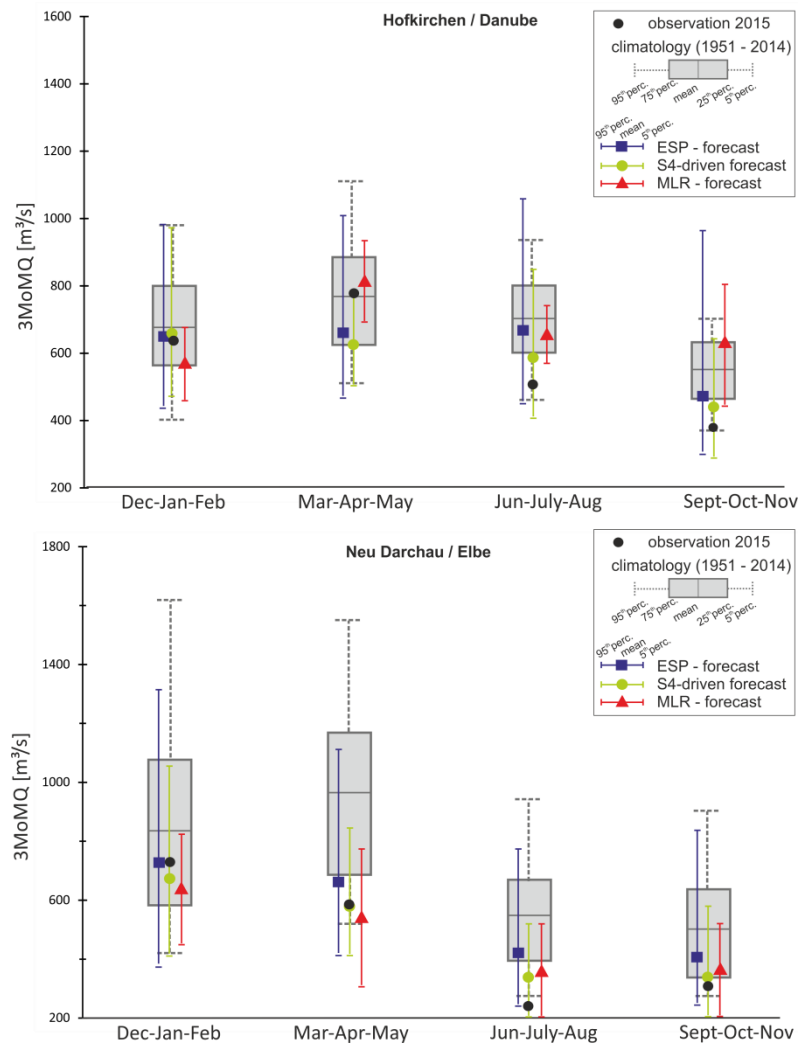



Figure 14. Comparison between the statistical forecast approaches for the monthly mean flow of the next three months 3MoMQ initialized in December 2014, March 2015, June 2015, September 2015 at gauges Hofkirchen / Danube (top) and Neu Darchau / Elbe (bottom) in relation to the observed values and the climatology (1951 – 2014).

5   Discussion

The increasing number of seasonal hydrological forecasting systems (see e.g. Zappa et al. 2014; Olsson et al. 2016; Bell et al. 2017) proves the need as well as the feasibility of long-range predictions over Europe despite the generally limited hydro-meteorological predictability when compared to other continents. Furthermore the European Flood Awareness System EFAS provides a continental-wide seasonal hydrological outlook with a lead-time of 2 months of weekly river flow anomalies and its probability for large European regions since 2016. The work presented in this paper fit into this progress and the results prove possibilities and limitations with regard to monthly to seasonal forecasting along Germany's major inland waterways. Previous findings (e.g. by Yossef et al. 2013) indicating that meteorological forcings relatively dominate initial hydrological

conditions for many European rivers beyond lead-times of 1-2 months, within specific seasons already for shorter lead-times, are fortified. Furthermore the study reveals that for setting-up a specific forecasting system tailored to particular user needs the heterogeneity within Europe requires a basin-wise as well as a use-oriented consideration of forecast sensitivities and forecast approaches. Already the differences between Rhine, Upper Daube and Elbe are significant in order to identify skilful

5 initialization months and corresponding forecast approaches (see section 4.1 and 4.2). Differences within Europe become even more apparent when comparing our findings for the German waterways with related studies in other parts of the continent. For example Olsson et al. (2016) analysed a quite similar framework of competing forecast approaches for predicting the spring-flood volume relevant for hydro power generation in a Swedish river basin. Here, none of the approaches tested (conditional ESP-approach, dynamical approach using the HBV-model forced with ECMWF's seasonal

10 meteorological forecasts, a statistical approach based on the correlation of large-scale circulation variables) consistently outperformed the ESP-based method currently applied operationally. This proves the importance of initial hydrological conditions, primarily snow pack, for this forecasting service. In contrast along the German waterways the dynamical as well as the statistical approach showed significantly higher skill (and economic value) for the majority of initialization months and lead-times than the ESP-forecasts, which mainly reveals the different effect of initial hydrological conditions for long-

15 range forecasting in both regions. For parts of Europe, like Scandinavia (Olsson et al. 2016) or the Alpine region (Fundel et al. 2013; Jörg-Hess et al. 2015), snow pack accumulated over the season prior to the initialization of a forecast could significantly dominate the predicted flow for several months, at least within specific seasons. Even for the Central European Rivers initial hydrological conditions could affect forecast skill on monthly to seasonal time-scales (see section 4.2), but compared to the aforementioned regions the signal is noticeably masked by the meteorological impact within the forecast

20 period. Furthermore over the course of the year other elements of initial hydrological conditions could have a stronger influence on flows than snow. Especially soil moisture and anthropogenic storages, along Rhine, Upper Danube and Elbe mainly dam management and lake regulation, act as buffer of the meteorological input. But in order to benefit from this "hydrological memory" in forecasting the relevant processes or information have to be included adequately in the specific approaches.

25 While for the statistical approach applied this study data on soil moisture is already used as predictor (see Table 2), no explicit information on snow pack or on any kind of anthropogenic storage or water transfer between catchments is used so far. While snow pack is at least implicitly considered via precipitation and temperature, no information on filling levels or released volumes of lakes etc. are used as input to the statistical model. For snow pack potentially useful data products are operationally available (Alverado Montero et al. 2016), this is might be more difficult for lake or dam related data due to

30 legal restrictions often imposed by hydropower companies. In order to evaluate and to demonstrate the additional predictive skill of improved data products representing initial hydrological conditions, e.g. the soil moisture, we modified the statistical approach. The results presented in the preceding sections are based on the global reanalysis product provided by NCEP (see Table 2) with a spatial resolution of 2.5°, which is relatively coarse for most of the Central European catchments with their spatial heterogeneity. Therefore we tested an alternative soil moisture information for Germany with a resolution of 4 km by

4 km, which is provided operationally by the German drought monitor (GDM, www.ufz.de/droughtmonitor) since 2014 (Zink et al. 2016). In order to evaluate the sensitivity of the forecast skill to the different soil moisture data, we evaluated the results for the forecasts of MoNM$_7$Q at gauge Kaub / Rhine solely based on the two different datasets (Table 3**Fehler! Verweisquelle konnte nicht gefunden werden.**). We have tested the model with one and two months lag, resulting in four

5   forecast models using the April and May soil moisture data of the respective source. As the metrics indicate, using the soil moisture data from the GDM could further increase the skill of the forecast considerably.

Table 3. Statistics for the forecast models based on NCEP and GDM soil moisture data for forecasted lowest seven day mean flow MoNM7Q of June at gauge Kaub / Rhine (period 1954 – 2014).

Skill measure	NCEP	GDM	NCEP	GDM
	Soil data May		Soil data April	
Pearson correlation coefficient [-]	0.43	0.71	0.50	0.60
Coefficient of determination [-]	0.19	0.51	0.25	0.36
p-value [-]	3.826×10^{-4}	6.523×10^{-11}	4.120×10^{-5}	2.248×10^{-7}
Residual standard error [m³/s]	373	290	361	332

For the dynamical approaches applied in this study snow pack and soil moisture are modelled by the hydrological model LARSIM_ME. Anthropogenic storages and water transfers, at least the most relevant ones, are implemented in the hydrological model for Rhine, Elbe and Upper Danube, too. But of course the hydrological processes like snow accumulation / snow melting are modelled in a simplified manner and the management rules had to be idealized.

15   Furthermore the real-world regulations of any measure usually differ from theoretical rules. So in this regard two important aspects to better exploit forecast skill hidden in the hydrological system exist. On the one hand the implementation of anthropogenic storages and water transfers in the hydrological model should be completed, together with a better definition of their regulation. Additionally the use of operationally available data products representing snow pack, soil moisture, lake levels etc. via data assimilation techniques is an important issue to improve the internal states of the hydrological model. The

20   amount and quality of useful data to be assimilated is continuously increasing, especially pushed by satellite missions in recent years (Jörg-Hess et al., 2015; Alverado Montero et al., 2016).

Another aspect towards an improved forecast skill, which is briefly touched on by our study and which poses a similarity to the findings by Olsson et al. (2016), is the combination of different forecast approaches. Olsson et al. (2016) tested two pragmatic ways of combining multiple forecasts in a post-processing step. This finding corresponds to a first attempt in our

25   study testing the combination of the statistical approach with the ESP-method, but in a more direct way of coupling. As shown in section 4.2 the forecast skill could noticeably increase by merging both approaches, but the added value depends on the skill of the ESP-approach. An advantage of the combination procedure we used is that by merging both forecasts forecast skill doesn't deteriorate even in case of low ESP-skill. So, we see different ways of aspects and potential ways to further improve forecast skill even within Central Europe. Additionally, the dynamical approaches using seasonal

meteorological forecasts may benefit from future improvements achieved in the area of climate and respectively seasonal meteorological forecast skill, potentially even with a disproportionate impact (Wood et al. 2016).

6 Conclusions and prospects

This paper asses the skill and economic value of a monthly to seasonal forecasting system set-up for the main European
5   waterways Rhine, Upper Danube and Elbe over a 35-year hindcast periods with a specific focus on the 2015 drought event. Inland waterway transport along these free-flowing rivers is prone to (long-lasting) droughts leading to low stream flows and respectively low water-levels, which subsequently limit the maximum cargo-carrying capacity of vessels, increase their energy consumption and their time of travel. Monthly to seasonal hydrological forecasting services are one measure to cope with these impacts and to sustainably increase IWT's efficiency as well as to support medium- to long-range waterway
10 management. Despite the overall limited hydro-meteorological predictability in Central Europe, the results of the different forecast approaches tested reveal the existence of a valuable predictability of streamflow at monthly and to some extent even up to seasonal time-scales along the major waterways in Germany. We found that the skill of the meteorological forcing has larger effect than the quality of initial hydrological conditions on seasonal forecast quality for relevant stations along the German waterways. Just for a few initialization months the initial hydrological conditions could noticeable affect forecast
15 skill for the first forecast month. Nevertheless a good estimation of the initial hydrological conditions (especially soil moisture, snow package, groundwater storage, but also human activities like regulated lakes / dams) forms basis of any monthly to seasonal hydrological forecast. Therefore the improved integration of such kind of information off-line in the course of setting-up hydrological models as well as in real-time by data assimilation techniques we have in mind for future development.

20 The more physically-based as well as the statistical approach are able to improve the predictive skills and economic value compared to climatology and the ESP-approach. The forecast intercomparison showed that the specific forecast skill along the German waterways highly depends on the forecast location, the lead-time and the season. Overall, the statistical approach currently seems to be most skilful for the three waterways investigated. The lagged relationship between the monthly / seasonal streamflow and the climatic / oceanic variables vary between one month (e. g. local precipitation and temperature,
25 soil moisture) up to six months (e.g. sea surface temperature). But we also observed that in some situations the statistical approach forecasts too extreme low stream flows while the more physically-based approaches respond more moderate. This effect needs further investigation.

Based on the present study two additional aspects will become a focal point in the near future: i) Besides improving the individual forecast methods to tap their full potential (e.g. increase of input data resolution, enhancement of the hydrological
30 model) an optimal combination, in terms of hybrid or hierarchical procedures, will be investigated systematically. ii) In close cooperation with the users monthly to seasonal forecast products have to be designed in order to push the usage of such forecast information in decision making processes and in order to communicate the value and uncertainty associated with such forecasts in a transparent way.

As such, the results shown in this paper represent the basis to setting up such an operational service, which will sustainably extend the existing forecast portfolio for waterway users and meet the growing needs in order to increase the modal share of water-borne transportation.

Code availability

5   The code used in this study is available upon request by the authors.

Data availability

The runoff data used in this study is available for non-commercial use upon request by the Federal Institute of Hydrology (datenstelle-M1@bafg.de). The climate and oceanic data used in the statistical forecast approach are publicly available:

- E-OBSv8: http://www.ecad.eu/download/ensembles/ensembles.php
10   - CDC (Climate Data Center): ftp://ftp-cdc.dwd.de/pub/CDC/
- ERSST v4: https://www.ncdc.noaa.gov/data-access/marineocean-data/extended-reconstructed-sea-surface-temperature-ersst-v4
- NCEP/NCAR Reanalysis 1: https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.surfaceflux.html
15   - CDAS-1 MONTHLY: http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP-NCAR/.CDAS-1/.MONTHLY/

In addition to the E-OBS dataset ERA-Interim dataset was used. It's a public dataset offered by ECMWF: http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/

The HYRAS dataset, used to calibrate the hydrological model LARSIM, isn't currently publicly available. It is managed by the German Meteorological service (DWD: hydromet@dwd.de). The seasonal meteorological forecasts from ECMWF are
20   not public, but depending on who you are, different ways and licenses in order to access the data are offered (http://www.ecmwf.int/en/forecasts/accessing-forecasts).

Appendices

None.

Supplemental link

25   None.

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Author contribution

Dennis Meißner and Bastian Klein designed the forecast framework presented in this paper and they carried out the forcast intercomparison. Bastian Klein set-up the dynamical forecast approaches (ESP, S4). Monica Ionita set-up the statistical
5 forecast approach. Dennis Meißner prepared the manuscript with contributions from both co-authors.

Competing interests

The authors declare that they have no conflict of interest.

Disclaimer

To be added later.

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