Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-293, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 29 May 2017

Hydrology and Earth System Sciences
Discussions

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

Dennis Meißner[1], Bastian Klein[1], Monica Ionita[2,3]

[1]Federal Institute of Hydrology, Koblenz, 56068, Germany
[2]Alfred-Wegener-Institute, Bremerhaven, 27568, Germany
[3]MARUM, Bremen University, Bremen, Germany

Correspondence to: Dennis Meißner (meissner@bafg.de)

Abstract. Traditionally, navigation-related forecasts in Central Europe cover short- to medium-range lead-times linked to 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.

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 climatological forecast (ensemble of historical streamflow) and the well-known Ensemble Streamflow Prediction approach (ESP, ensemble based on historical meteorology) using common performance indicators 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, also for relevant stations along the German waterways meteorological forcings dominate initial hydrological conditions in most cases already after the first forecast month. 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 compared to climatology and the 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).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-293, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 29 May 2017

Besides improving the forecast methodology, especially by combining the individuals 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. 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.

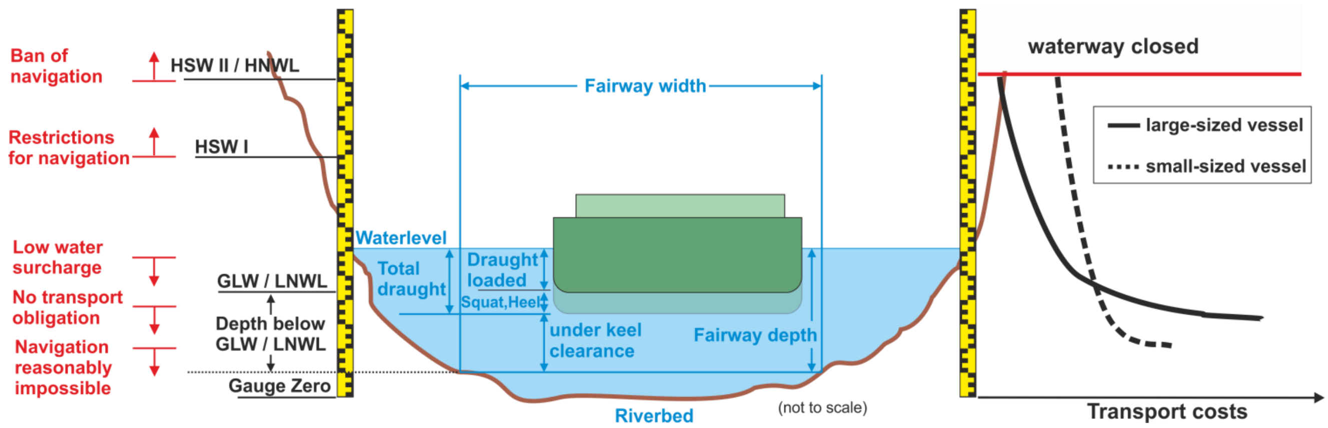


Figure 1. Schematic representation of the interaction between hydrologic conditions (water-level), waterway parameter (fairway depths), specific navigation thresholds and transport costs.

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. 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; G´amiz-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; Gelfan et al. 2015; Zappa et al. 2014). The most common objectives behind these systems are water supply, reservoir operations and hydropower. Regarding the underlying methodologies applied in seasonal hydrological forecasting two categories, aside from using observed climatology, are usually distinguished: statistical and dynamical approaches (e.g. Crochemore et al. 2016, and references therein). While the models of the first category rely on the statistical relationship between various observed predictors and the hydrological predictand, the methods of the second 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

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-293, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 29 May 2017

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 Figure 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 m^3/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 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. The River Danube, with a total length of 2,826 km, drains an area of 817,000 km^2 with a mean flow rate of approximately 6,500 m^3/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 km^2 with a mean flow rate of approximately 860 m^3/s. About 930 km are

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-293, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 29 May 2017

Hydrology and Earth System Sciences
Open Access
Discussions

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 part) visualizes the flow regime of the three waterways represented by the long-term monthly mean flow rate at selected gauges (period 1981 – 2010).

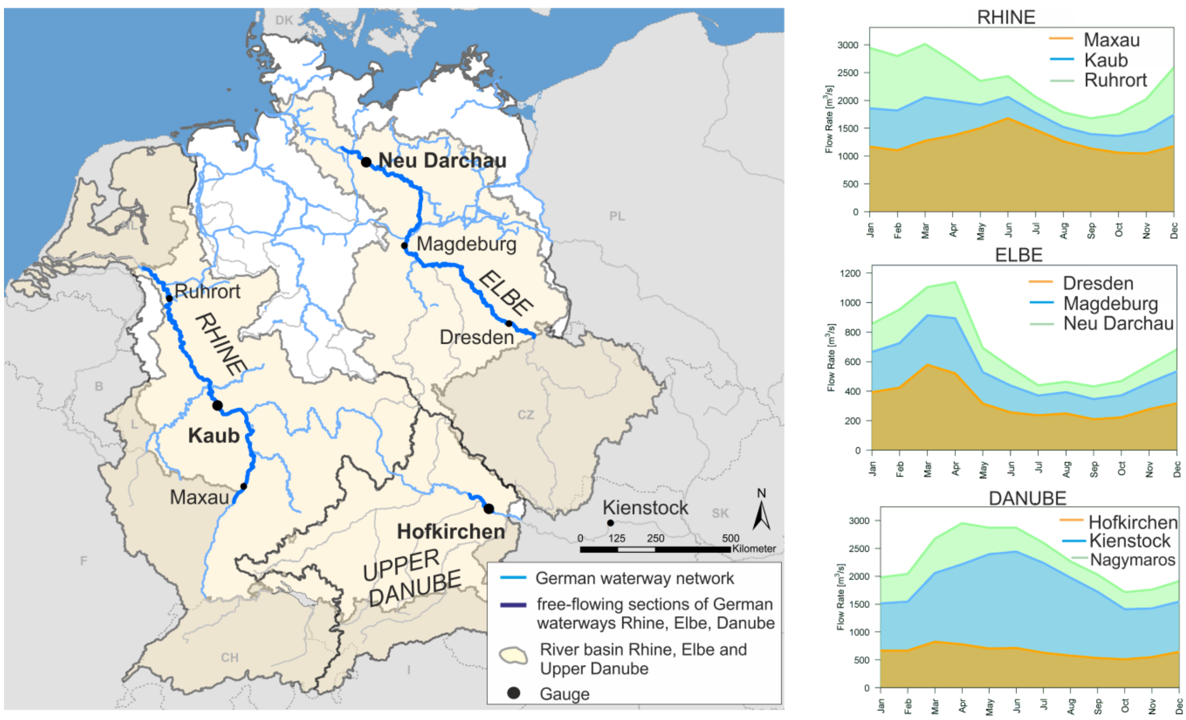


Figure 2. Map showing the German stretches of the international waterways Rhine, Danube and Elbe (left part), for relevant gauges (black dots) the long-term monthly mean flow rates (1981-2000) are visualized (right part).

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 Figure 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.

Hydrology and Earth System Sciences
Open Access
Discussions

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	799
Hofkirchen	Danube	47,518	638	301
Neu Darchau	Elbe	131,950	710	290

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 (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. Monthly linear scaling (see e.g. Lenderink et al. 2007) 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.

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

Hydrology and Earth System Sciences Discussions Open Access EGU

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 applying linear scaling. 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.

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

Dataset (Provider)	Variable(s)	Spatial coverage	Spatial resolution	Reference
E-OBSv8 (ECA&D Project, KNMI)	precipitation temperature	global	0.25° x 0.25°	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) sea level pressure	global	2.5° x 2.5°	Kalnay et al. 1996

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 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 temperature HRU could be further subdivided in elevation zones for the simulation of the snow processes. 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 domain. 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. Afterwards the parameter means and parameter spans have been derived for the clusters and 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 of the Upper Danube, the Elbe and the River Rhine.

Figure 3 shows 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 boxplots, as well as the correlation r and Nash-Sutcliffe Efficiency (NSE). All gauges show NSE > 0.8 and r > 0.9. 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 focus in the future model developments of LARSIM-ME.

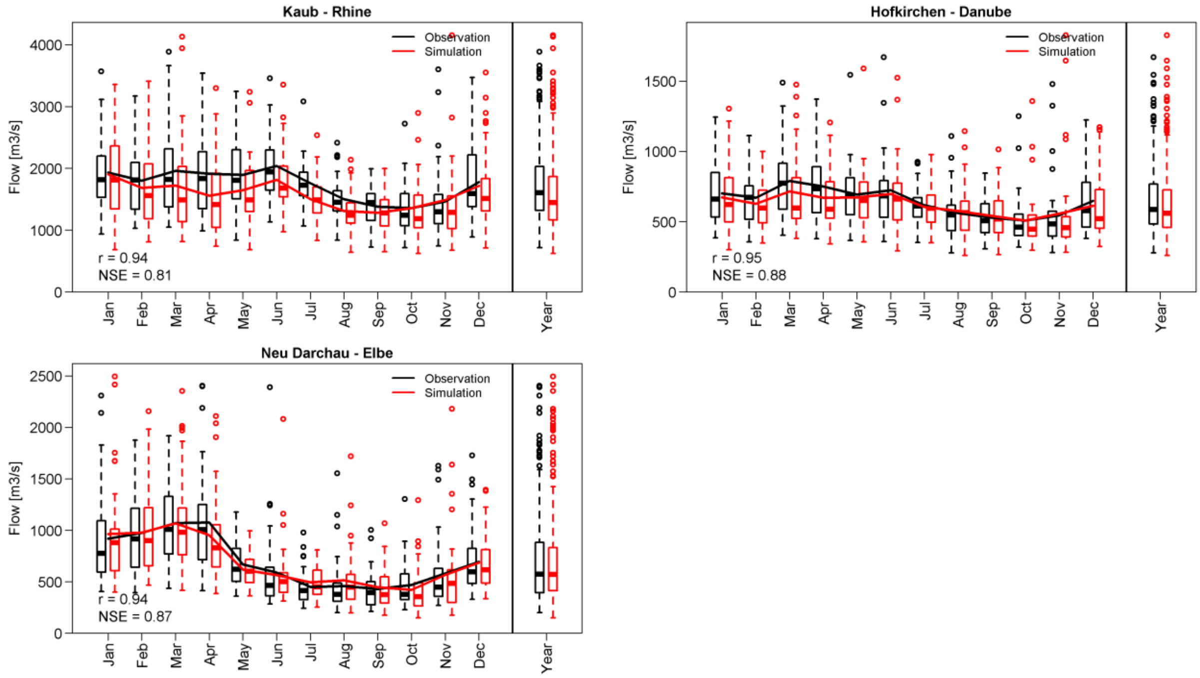


Figure 3. Comparison of the simulated (red) and observed (black) long-term (1981-2015) monthly mean streamflow and the distribution of the simulated and observed monthly mean streamflow within the different months and for the whole year illustrated as box-plots of the gauges Kaub - Rhine (top left),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

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_7Q) 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, NM_7Q is a variable primarily used as low flow indicator in the context of hydrological monitoring or ecological purposes. Low NM_7Q values imply the existence of a long-lasting drought period (Klein and Meißner 2016). Furthermore, the NM_7Q is a robust indicator, because it is insensitive to distorting singularities like short-term fluctuations due to natural or anthropogenic errors. 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) the measured discharges at the forecasting gauges representing the real-world situation and 2) the simulated discharges at the forecasting gauges generated by the hydrological model LARSIM-ME based on 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.

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 Figure 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

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 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 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 as predictors instead of climate indices. 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 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 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. The correlation is considered to be stable for those spatial units where the current streamflow and previous months' climate variables are significantly correlated at 90% level or 80% level for more than 80 % of the moving window. Regions / grid cells showing a positive, stable correlation will be represented as red (90 %) / yellow (80 %) on a global map, while areas with a negative and stable correlation will be represented as blue (90 %) and green (80 %). Figure 4 illustrates this procedure of identifying stable predictors: streamflow and SST from grid point (a) are positively correlated for all 31-year windows covering the period 1901-2002 and above the 90 % significance level for more than 80% of the windows. The streamflow and SST from the grid point (b) is positive and above 80% significance level for more than 80% of the windows. Therefore, these grid points are stable correlated with streamflow and are represented on the stability map of correlation as red and orange, respectively. The streamflow and SST from the grid-points (c) and (d) are negative and above 80% and 90% significance level correlated, respectively, for more than 80% of the windows. These grid points are represented on the stability correlation map as purple and blue respectively. Grid points significantly correlated for less than 80% windows are defined as "unstable" (white colour on the stability correlation map).

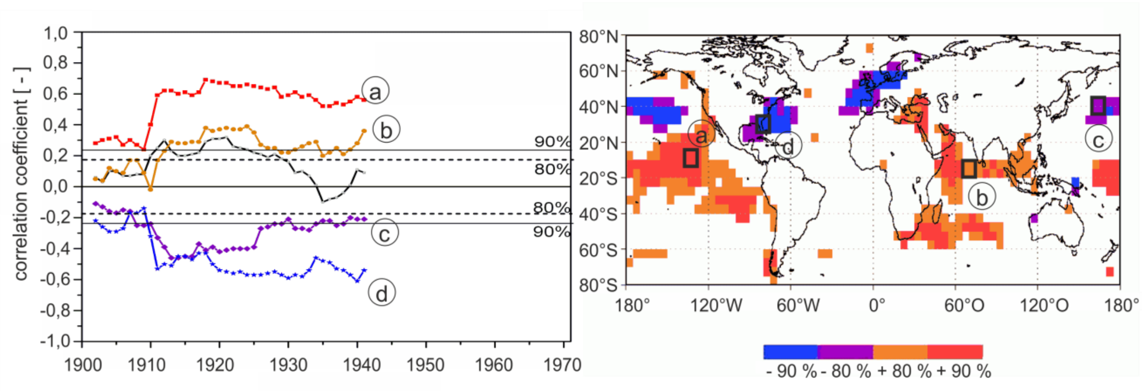


Figure 4. Example of a stability correlation map. Left: correlation between streamflow and SST of a 31-year moving window for selected grid areas; right: map showing the areas with stable positive or negative correlations.

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 **Fehler! Verweisquelle konnte nicht gefunden werden.** shows the forecast results with and without using measured discharges as predictor for June's (month with the highest NM_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), 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 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-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:

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

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 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):

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

with H = Hit rate

F = False alarm rate

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} 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 (Figure 9 and Figure 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).

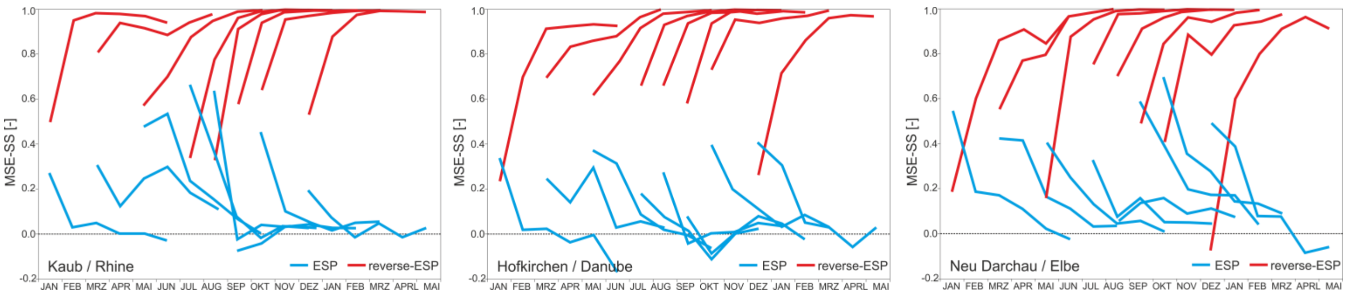


Figure 5. MSE-SS of the ESP (blue) and reverse ESP (red) forecast (reference: simulated to the MSE from using a climatology) for the gauges Kaub / Rhine, Hofkirchen / Danube and Neu Darchau / Elbe over a lead-time of 6 months (verification period 1981 – 2014).

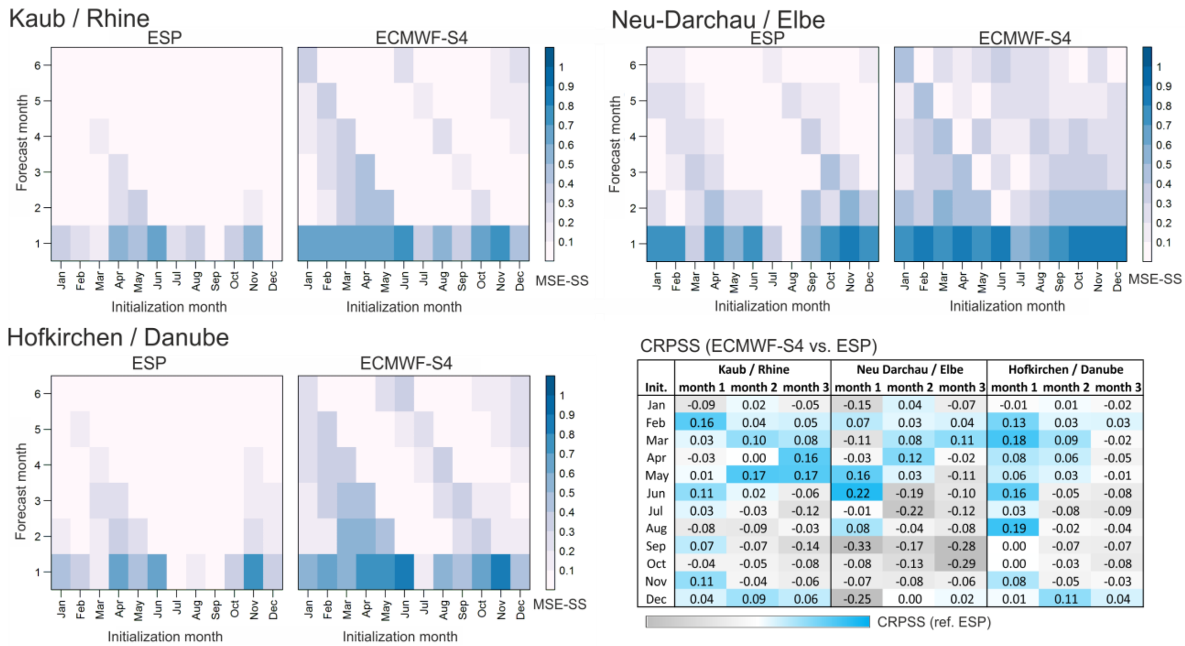
Figure 5 clearly indicates that the differences in flow regime, climate region and catchment characteristics at the waterways (see Sect. 2) sustainably affect the relative importance of the predictability sources within the seasonal cycle. But despite all differences amongst the gauges / waterways, the 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). Based on these results 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’s well known that the skill of seasonal meteorological forecasts is limited over Central Europe, 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

Hydrology and Earth System Sciences
Discussions
Open Access

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).



Init.	Kaub / Rhine month 1	Kaub / Rhine month 2	Kaub / Rhine month 3	Neu Darchau / Elbe month 1	Neu Darchau / Elbe month 2	Neu Darchau / Elbe month 3	Hofkirchen / Danube month 1	Hofkirchen / Danube month 2	Hofkirchen / Danube month 3
Jan	-0.09	0.02	-0.05	-0.15	0.04	-0.07	-0.01	0.01	-0.02
Feb	0.16	0.04	0.05	0.07	0.03	0.04	0.13	0.03	0.03
Mar	0.03	0.10	0.08	-0.11	0.08	0.11	0.18	0.09	-0.02
Apr	-0.03	0.00	0.16	-0.03	0.12	-0.02	0.08	0.06	-0.05
May	0.01	0.17	0.17	0.16	0.03	-0.11	0.06	0.03	-0.01
Jun	0.11	0.02	-0.06	0.22	-0.19	-0.10	0.16	-0.05	-0.08
Jul	0.03	-0.03	-0.12	-0.01	-0.22	-0.12	0.03	-0.08	-0.09
Aug	-0.08	-0.09	-0.03	0.08	-0.04	-0.08	0.19	-0.02	-0.04
Sep	0.07	-0.07	-0.14	-0.33	-0.17	-0.28	0.00	-0.07	-0.07
Oct	-0.04	-0.05	-0.08	-0.08	-0.13	-0.29	0.00	-0.03	-0.08
Nov	0.11	-0.04	-0.06	-0.07	-0.08	-0.06	0.08	-0.05	-0.03
Dec	0.04	0.09	0.06	-0.25	0.00	0.02	0.01	0.11	0.04

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).

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 Figure 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.

As second forecast approach the multiple linear regression model (MLR) based on the stability analysis (Sect. 3.3) was implemented. In Figure 7 all three forecast approaches currently implemented in the forecast framework are compared by different skill metrics 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 Figure 7 it is evident that the statistical approach is able to further improve forecast quality of the dynamical 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 ESP	Kaub / Rhine S-4	Kaub / Rhine MLR	Neu Darchau / Elbe ESP	Neu Darchau / Elbe S-4	Neu Darchau / Elbe MLR	Hofkirchen / Danube ESP	Hofkirchen / Danube S-4	Hofkirchen / Danube 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	

Initialization Month	Score	Kaub / Rhine ESP	Kaub / Rhine S-4	Kaub / Rhine MLR	Neu Darchau / Elbe ESP	Neu Darchau / Elbe S-4	Neu Darchau / Elbe MLR	Hofkirchen / Danube ESP	Hofkirchen / Danube S-4	Hofkirchen / Danube MLR
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	0.10	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	0.37		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 next month (verification period 1981 – 2014).

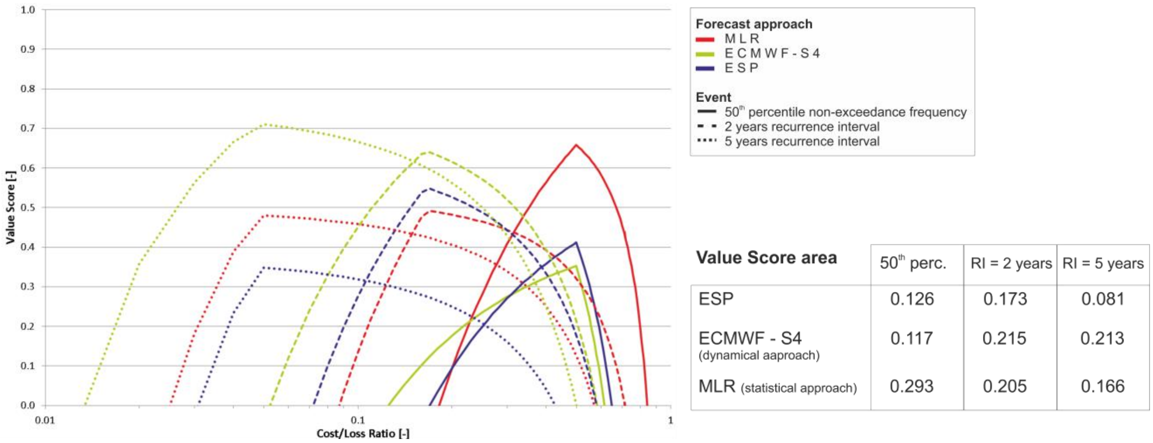
The results for the seasonal forecasts (3-monthly mean discharge of the upcoming meteorological season) shown in Figure 8 confirm the findings described above. While forecast skill based on ESP and S4 at Rhine und especially Danube is comparatively low when compared to climatology, the skill for the 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 ESP	Kaub / Rhine S-4	Kaub / Rhine MLR	Neu Darchau / Elbe ESP	Neu Darchau / Elbe S-4	Neu Darchau / Elbe MLR	Hofkirchen / Danube ESP	Hofkirchen / Danube S-4	Hofkirchen / Danube 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).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-293, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 29 May 2017

The inter-comparison of the forecast approaches, based on the relative economic value, was conducted for $MoNM_7Q$. 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_7Q of the particular month the forecast is issued for (period 1951 – 2014), the NM_7Q 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 Figure 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.

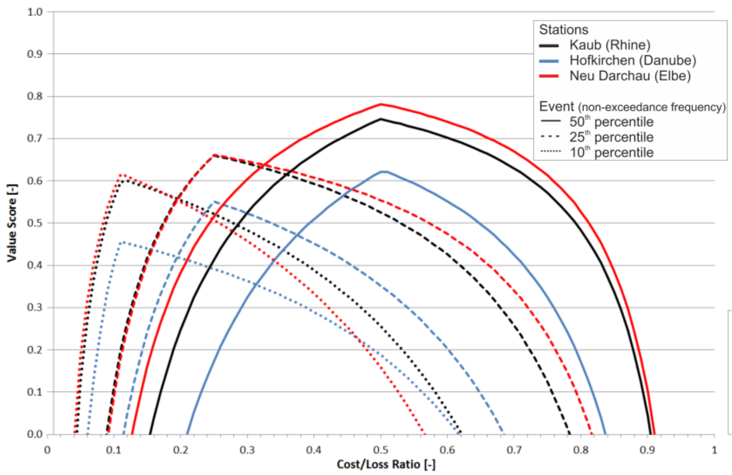


Value Score area	50th perc.	RI = 2 years	RI = 5 years
ESP	0.126	0.173	0.081
ECMWF - S4 (dynamical aapproach)	0.117	0.215	0.213
MLR (statistical approach)	0.293	0.205	0.166

Figure 9. Economic value score plotted against cost-loss ratio for three forecast approaches predicting the lowest seven day mean $MoNM_7Q$ of the next 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. 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 Figure 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 Figure 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).



Value Score area	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 next 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 Figure 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 Month	Score	Kaub / Rhine 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 next 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). 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 Figure 12, together with the climatology (median, selected percentiles) and the forecast 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 median, 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.

Hydrology and Earth System Sciences
Open Access
Discussions

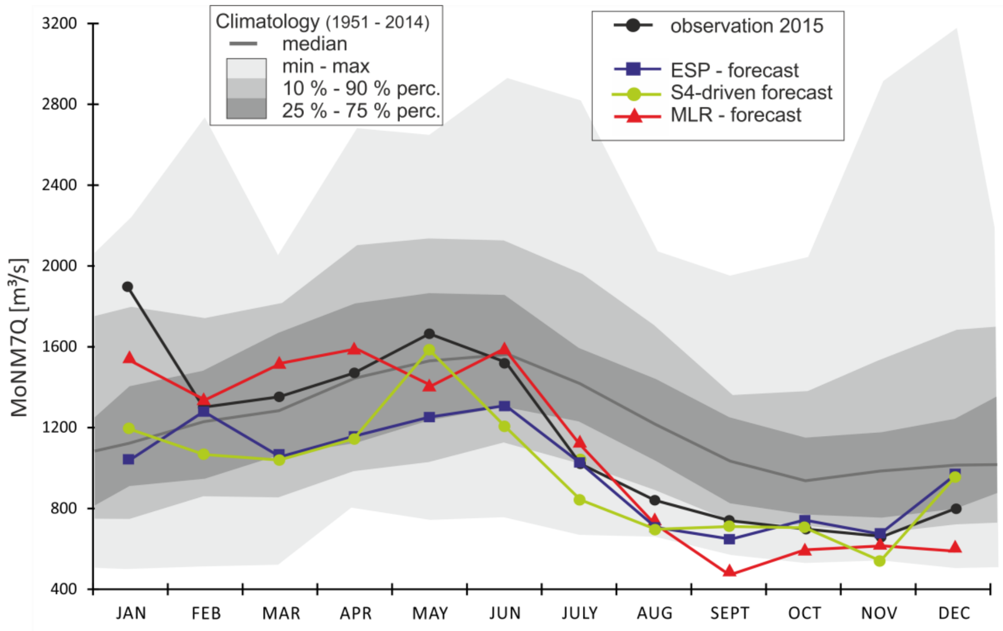


Figure 12. Comparison between the three navigation-related forecast approaches for the lowest seven day mean $MoNM_7Q$ of the next month in the year 2015 at gauge Kaub / Rhine in relation to the observed values and the climatology (1951 – 2014).

Regarding the three-monthly forecast issued at the beginning of the particular meteorological season, the statistical approach significantly outperformed the other methods in spring (Figure 13). For summer (JJA) and autumn (SON) the forecasts of all approaches assimilate. But the statistical approach and the S4-driven forecast 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.

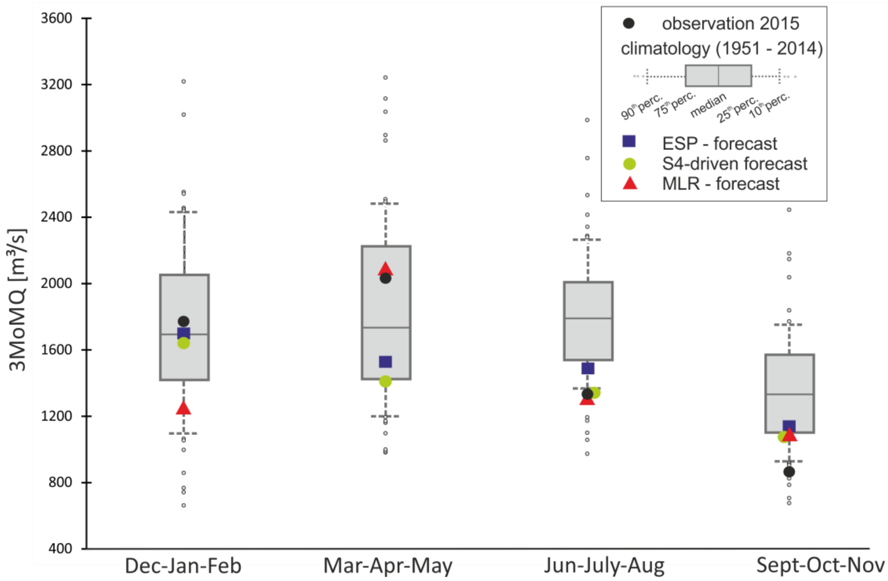


Figure 13. Comparison between the three navigation-related forecast approaches for the monthly mean flow of the next three months 3MoMQ initialized in December 2014, March 2015, June 2015, September 2015 (meteorological seasons 2015) at gauge Kaub /Rhine in relation to the observed values and the climatology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

The performance of the seasonal forecasts for the waterways Elbe and Danube is shown in Figure 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. 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. Also the dynamical approach still overestimated the flows in summer and autumn, it was a good indicator for the significant low flow situation observed. Especially the statistical approach failed to predict these low values.

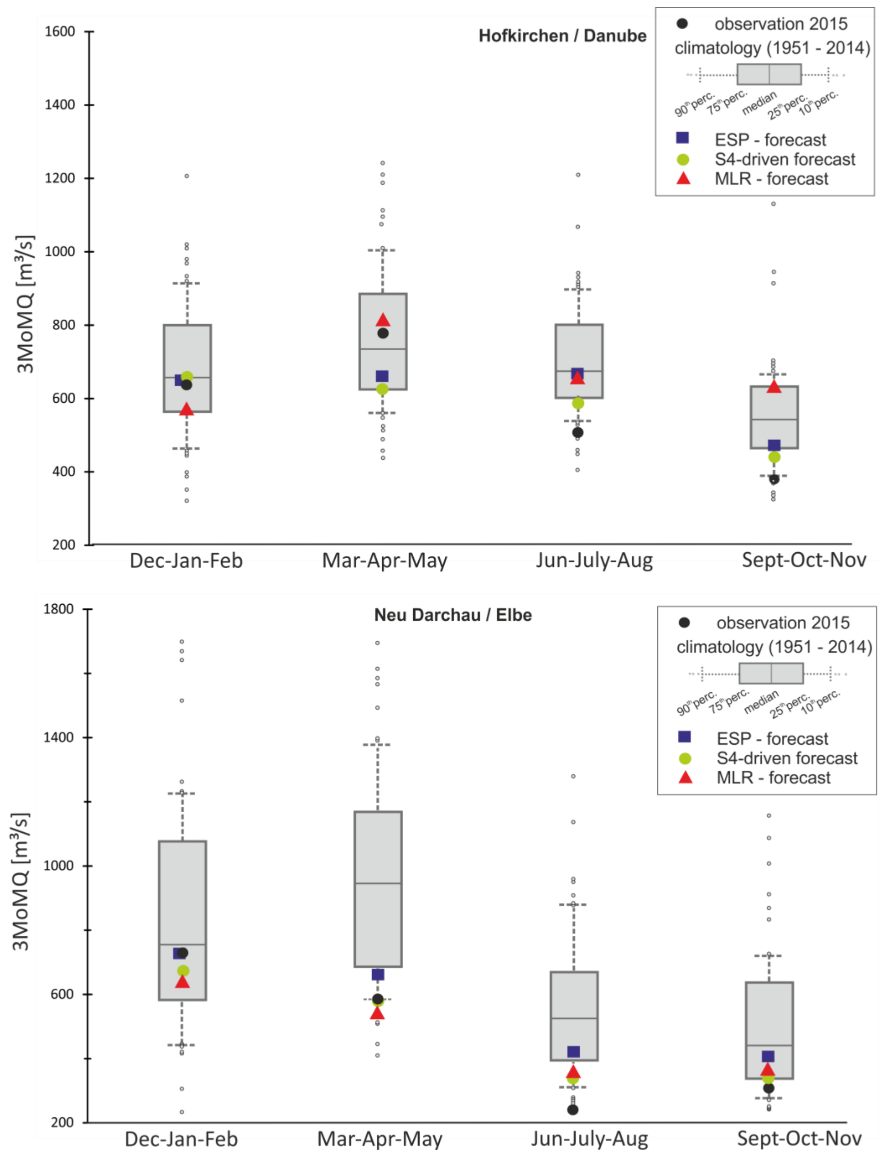


Figure 14. Comparison between the statistical forecast approaches for the monthly mean flow of the next three months 3MoMQ initialized in December 2014, March 2015, June 2015, September 2015 at gauges Hofkirchen / Danube (top) and Neu Darchau / Elbe (bottom) in relation to the observed values and the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

5 Conclusions and prospects

This paper assesses the quality and value of a monthly to seasonal forecasting system set-up for the rivers Rhine, Upper Danube and Elbe, which are important Central European waterways. As inland waterway transport, an economic sector which often plays a minor role in studies related to hydrological forecasting, is the focal point of this forecasting system, low flow situations leading to restrictions for water-borne transportation are of major relevance in this study. 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 up to seasonal time-scales along the major waterways in Germany.

Based on the present study two aspects will be addressed in the near future: i) in close cooperation with the users the monthly to seasonal forecast products have to be designed in order to allow for the usage of these forecast in decision making processes and in order to avoid misinterpretations and ii) several experiments have been started in order to tap the full potential of the approaches in place and to further increase the forecast skill of the final service. One direction towards further skill improvements is the increase of precision / spatial resolution of the input data, e.g. the soil moisture data used in 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 $MoNM_7Q$ at gauge Kaub / Rhine solely based on the two different datasets (Table 3). We have tested the model with one and two months lag, resulting in four 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

Besides improving the individual forecast methods and their optimal combination, in terms of hybrid or hierarchical procedures dependent on the basin characteristics, the focal point in the further steps is towards a monthly to seasonal forecasting service tailored to the waterway transport sector. 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

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
- 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
- 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 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

None.

Team list

Dennis Meißner, Federal Institute of Hydrology, meissner@bafg.de
Bastian Klein, Federal, Institute of Hydrology, klein@bafg.de
Monica Ionita, Alfred Wegener Institute, Monica.Ionita@awi.de

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 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.

Acknowledgements

This work was supported by the Research & Development Project "Seamless Prediction" financed by the German Federal Ministry of Transport and Digital Infrastructure and the EU-Horizon 2020 project IMPREX (grant agreement 641811, www.imprex.eu). M. Ionita was funded by the Polar Regions and Coasts in the Changing Earth System (PACES) program of the AWI and the Helmholtz Climate Initiative REKLIM.

Furthermore we acknowledge the E-OBS dataset from the EU-FP6 project ENSEMBLES (http://ensembles-eu.metoffice.com) and the data providers in the ECA&D project (http://www.ecad.eu). Surface Solar Radiation Downwards from the ERA-Interim data was provided by courtesy ECMWF. Streamflow and water-level data was provided by the Federal Waterways and Shipping Administration (WSV), respectively the Federal Institute of Hydrology (BfG) (gauges Maxau, Kaub, Ruhrort, Hofkirchen, Dresden, Magdeburg-Strombrücke, Neu-Darchau), ViaDonau (gauges Kienstock and Wildungsmauer), and the Ministry of Interior, respectively the General Directorate of Water Management, Republic of Hungary (gauge Nagymaros).

References

CCNR: Annual Report 2016 - Inland Navigation in Europe - Market Observation, Central Commission for the Navigation of the Rhine, Strasbourg, France, 2016.

Crochemore, L., Ramos, M. H., and Pappenberger, F.: Bias correcting precipitation forecasts to improve the skill of seasonal streamflow forecasts. Hydrol. Earth Syst. Sci., 20, 3601–3618, doi:10.5194/hess-20-3601-2016, 2016.

Day, G. N.: Extended streamflow forecasting using NWSRFS, J. Water Resour. Plann. Manage., 111, 157–170, 1985.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Holm, E. V., Isaksen, L., Kallberg, P., Kohler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thepaut, J. N., and Vitart, F.: The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society 137(656), 553-597, 2011.

Domeisen, D. I. V., Butler, A. H., Fröhlich, K., Bittner, M., Müller, W.A., and Baehr, J.: Seasonal Predictability over Europe Arising from El Niño and Stratospheric Variability in the MPI-ESM Seasonal Prediction System. Journal of Climate, Volume 28, DOI: 10.1175/JCLI-D-14-00207.1, 2015.

DWD: Deliverable D.1.7 Gridded 20 yr dataset of surface solar radiation, cloud albedo, cloud fraction and surface albedo derived from MVIRI (SEVIRI) using the Heliosat method (0.05°res), EU funded project EURO4M, 2013.

European Commission: White paper – European transport policy for 2010: time to decide. COM(2001) 370, 2001.

G´amiz-Fortis, S., Pozo-V´azquez, D., Trigo, R.M., and Castro-D´ıez, Y.: Quantifying the predictability of winter river flow in Iberia. Part II: seasonal predictability Journal of Climate 21: 2503–2518, 2008.

Gelfan, A.N., Motovilov, Yu. G. Motovilov, and Moreid, V. M.: Ensemble seasonal forecast of extreme water inflow into a large reservoir. Proc. IAHS, 369, 115–120, doi:10.5194/piahs-369-115-2015, 2015.

Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones, P.D., and New, M. A.: European daily high-resolution gridded dataset of surface temperature and precipitation. J. Geophys. Res (Atmospheres), 113, D20119, 2008.

Hersbach, H.: Decomposition of the continuous ranked probability score for ensemble prediction systems, Weather Forecast., 15, 559–570, 2000.

Huang, B., Banzon, V.F., Freeman, E., Lawrimore, J., Liu, W., Peterson, T.C., Smith, T.M., Thorne, P.W., Woodruff, S.D., and Zhang, H.-M.: Extended Reconstructed Sea Surface Temperature version 4 (ERSST.v4): Part I. Upgrades and intercomparisons. Journal of Climate, 28, 911–930, doi:10.1175/JCLI-D-14-00006.1, 2014.

Ionita, M., Lohmann, G., and Rimbu, N.: Prediction of Elbe discharge based on stable teleconnections with winter global temperature and precipitation. Journal of Climate, 21, 6215-6226, 2008.

Ionita, M., Lohmann, G., Rimbu, N., and Chelcea, S.: Interannual Variability of Rhine River Streamflow and Its Relationship with Large-Scale Anomaly Patterns in Spring and Autumn. Journal of Hydrometeorology 13(1): 172-188, 2012.

Ionita, M., Dima, M., Lohmann, G., Scholz, P., and Rimbu, N.: Predicting the June 2013 European Flooding based on Precipitation, Soil Moisture and Sea Level Pressure. Journal of Hydrometeorology, doi: 10.1175/JHM-D-14-0156.1, 2014.

Ionita, M., Tallaksen, L. M., Kingston, D. G., Stagge, J. H., Laaha, G., Van Lanen, H. A. J., Scholz, P., Chelcea, S. M., and Haslinger, K.: The European 2015 drought from a climatological perspective, Hydrol. Earth Syst. Sci., 21, 1397-1419, doi:10.5194/hess-21-1397-2017, 2017.

Klein, B. and Meißner, D.: Vulnerability of Inland Waterway Transport and Waterway Management on Hydro-meteorological Extremes. Deliverable 9.1, IMPREX - Improving Predictions of Hydrological Extremes - Grant Agreement Number 641811, 2016.

Lenderink, G., Buishand, A., and van Deursen, W.: Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. Hydrology and Earth System Sciences 11(3), 1143-1159, 2007

Lohmann, G., N. Rimbu, and Dima, M.: Where can the Arctic Oscillation be reconstructed? Towards a reconstruction of climate modes based on stable teleconnections, Clim. Past Disc., 1, 17–56, 2005.

Ludwig, K. and Bremicker, M.: The Water Balance Model LARSIM –Design, Content and Applications. 22. C. Leibundgut, S. Demuth and J. Lange (Eds), Freiburger Schriften zur Hydrologie, Institut für Hydrologie, Universität Freiburg im Breisgau, Freiburg, 141 pp, 2006.

Maurer, E. P. and Lettenmaier, D. P.: Predictability of seasonal runoff in the Mississippi river basin, J. Geophys. Res., 108(D16), 8607, doi:10.1029/2002JD002555, 2003.

Meißner, D. and Klein, B.: Probabilistic Shipping Forecast. In: "Handbook of Hydrometeorological Ensemble Forecasting". Editors: Duan, Q., Pappenberger, F., Thielen, J., Wood, A., Cloke, H.L., Schaake, J.C. (Eds.). Springer. ISBN 978-3-642-39924-4, 2017, DOI: 10.1007/978-3-642-40457-3_58-1, 2016.

Murphy, A. H.: What Is a Good Forecast? An Essay on the Nature of Goodness in Weather Forecasting. Weather and Forecasting 8(2), 281-293, 1993.

Nilson, E., Lingemann, I., Klein, B., and Krahe, P.: Impact of hydrological change on navigation conditions. Deliverable 1.4 ECCONET - Effects of climate change on the inland waterway transport network, 2012.

Rauthe, M., Steiner, H., Riediger, U., Mazurkiewicz, A., and Gratzki, A.: A Central European precipitation climatology - Part I: Generation and validation of a high-resolution gridded daily data set (HYRAS). Meteorologische Zeitschrift 22(3), 235-256, 2013.

Olsson, J., Uvo, C. B., Foster, K., and Yang, W.: Technical Note: Initial assessment of a multi-method approach to spring-flood forecasting in Sweden. Hydrol. Earth Syst. Sci., 20, 659–667, doi:10.5194/hess-20-659-2016, 2016.

Richardson, D. S.: Skill and relative economic value of ECMWF ensemble prediction system. Q.J.R. Meteorol. Soc., 126, 649 – 667, 2000.

Richardson, D. S.: Economic Value and Skill. In: Joliffe, S. B., I. [Hrsg.]: Forecast Verification: A Practitioner's Guide in Atmospheric Science, Second Edition, 167-184. John Wiley & Sons, Ltd., 2012.

Rimbu, N., Dima, M., Lohmann, G., and Stefan, S.: Impacts on the North Atlantic Oscillation and the El Niño–Southern Oscillation on Danube river flow variability, Geophys. Res. Lett., 31, L23203, doi:10.1029/2004GL020559, 2004.

Rimbu, N., Dima, M., Lohmann, G., and Musat, I.: Seasonal prediction of Danube flow variability based on stable teleconnection with sea surface temperature, Geophys. Res. Lett., 32, doi:10.1029/2005GL0242412005.

Robertson, D. E., Pokhrel, P., and Wang, Q. J.: Improving statistical forecasts of seasonal streamflows using hydrological model output, Hydrol. Earth Syst. Sci., 17, 579–593, doi:10.5194/hess-17-579-2013, 2013.

Roulin, E.: Skill and relative economic value of medium-range hydrological ensemble predictions. Hydrol. Earth Syst. Sci., 11, 725-737, 2007.

Svensson, C.: Seasonal river flow forecasts for the United Kingdom using persistence and historical analogues, Hydrol. Sci. J., 61(1), 19 – 35, doi:10.1080/02626667.2014.992788, 2016.

Trigo, R. M., Pozo-Vázquez, D., Osborn, T. J., Castro-Diez, Y., Gamiz-Fortis, S., and Esteban-Parra, M. J.: North Atlantic Oscillation influence on precipitation, river flow and water resources in the Iberian Peninsula, Int. J. Climatol., 24, 925–944, 2004.

Van Lanen, H. A. J., Laaha, G., Kingston, D. G., Gauster, T., Ionita, M., Vidal, J.-P., Vlnas, R., Tallaksen, L. M., Stahl, K., Hannaford, J., Delus, C., Fendekova, M., Mediero, L., Prudhomme, C., Rets, E., Romanowicz, R. J., Gailliez, S., Wong, W. K., Adler, M.-J., Blauhut, V., Caillouet, L., Chelcea, S., Frolova, N., Gudmundsson, L., Hanel, M., Haslinger, K., Kireeva, M., Osuch, M., Sauquet, E., Stagge, J. H., and Van Loon, A. F.: Hydrology needed to manage droughts: the 2015 European case. Hydrol. Process., doi: 10.1002/hyp.10838, 2016.

Wang, E., Zhang, Y., Luo, J., Chiew, F. H. S., and Q. J. Wang: Monthly and Seasonal Streamflow Forecasts Using Rainfall-Runoff Modeling and Historical Weather Data. Water Resources Research, 47, 5, W05516, doi:10.1029/2010WR009922, 2011.

Wilby, R. L., Wedgbrow, C. S., and Fox, H. R.: Seasonal predictability of the summer hydrometeorology of the River Thames, UK. Journal of Hydrology 295: 1–16, 2004.

Wilks, D. S.: A skill score based on economic value for probability forecasts. Meteorol. Appl. 8, 209–219, 2001.

Wood, A. W., Maurer, E. P., Kumar, A., and Lettenmaier, D. P.: Long-range experimental hydrologic forecasting for the eastern United States. Journal of Geophysical Research-Atmospheres 107(D20), 2002.

Wood, A. W. and Lettenmaier, D. P.: An ensemble approach for attribution of hydro-logic prediction uncertainty. Geophysical Research Letters, 35, L14401, 2008.

Wood, A. W., Hopson, T., Newman, A., Brekke, L., Arnold, J. and Clark, M.: Quantifying Streamflow Forecast Skill Elasticity to Initial Condition and Climate Prediction Skill. Journal of Hydrometeorology, 17, 2, 651–68, doi:10.1175/JHM-D-14-0213.1, 2016.

Yossef, N. C., Winsemius, H., Weerts, A., van Beek, R., and Bierkens, M. F. P.: Skill of a global seasonal streamflow forecasting system, relative roles of initial conditions and meteorological forcing, Water Resour. Res., 49(8), 4687 – 4699, doi:10.1002/wrcr.20350, 2013.

Zappa, M., Bernhard, L., Spirig, C., Pfaundler, M., Stahl, K., Kruse, S., Seidl, I., and Stähli, M.: A prototype platform for water resources monitoring and early recognition of critical droughts in Switzerland, Proc. IAHS, 364, 492-498, doi:10.5194/piahs-364-492-2014, 2014.

Zink, M., Samaniego, L., Kumar, R., Thober, S., Mai, J., Scäfer, D. and Marx, A.: The German drought monitor. Environ. Res. Lett. 11 (2016) 074002, doi:10.1088/1748-9326/11/7/074002, 2016.