Performance of ensemble streamflow forecasts under varied hydrometeorological conditions

Harm-Jan F. Benninga[1,*], Martijn J. Booij[1], Renata J. Romanowicz[2], Tom H.M. Rientjes[3]

[1]Water Engineering and Management, Faculty of Engineering Technology, University of Twente, 7500 AE Enschede, The Netherlands
[2]Institute of Geophysics, Polish Academy of Sciences, 01-452 Warsaw, Poland
[3]Water Resources, Faculty of Geo-Information Science and Earth Observation, University of Twente, 7500 AE Enschede, The Netherlands
[*]Present address: Water Resources, Faculty of Geo-Information Science and Earth Observation, University of Twente

Correspondence to: Harm-Jan F. Benninga (h.f.benninga@utwente.nl)

Abstract. The paper presents a methodology to give insight in the performance of ensemble streamflow forecasting systems. We have developed an ensemble forecasting system for the Biała Tarnowska, a mountainous river catchment in southern Poland, and analysed the performance for lead times ranging from 1 day to 10 days for low, medium and high streamflow and different hydrometeorological conditions. Precipitation and temperature forecasts from the European Centre for Medium-Range Weather Forecasts serve as inputs to a deterministic lumped hydrological (HBV) model. Due to an inconsistent bias, pre- and post-processing of the meteorological and streamflow forecasts is not effective. The best forecast skill, relative to alternative forecasts based on historical meteorological measurements, is shown for high streamflow and for snow accumulation low streamflow events. Forecasts of medium streamflow events and low streamflow events generated by a precipitation deficit show less skill. To improve the performance of the forecasting system for high streamflow events, the meteorological forecasts are crucial. It is recommended to calibrate the hydrological model specifically on low streamflow conditions and high streamflow conditions. It is further recommended that the dispersion (reliability) of the ensemble streamflow forecasts is enlarged by including the uncertainties in hydrological model parameters and initial conditions, and by enlarging the dispersion of the meteorological input forecasts.

1 Introduction

Accurate flood forecasting (Cloke and Pappenberger, 2009; Penning-Rowsell et al., 2000; Werner et al., 2005) and low streamflow forecasting (Demirel et al., 2013a; Fundel et al., 2013) are important to mitigate the negative effects of extreme events by enabling early warning. Accurate forecasting becomes increasingly more important, because frequency and magnitude of low and high streamflow events are projected to increase in many areas in the world as a result of climate change (IPCC, 2014). Due to socio-economic development the impacts of extreme events further increase (Bouwer et al., 2010; Fleming, 2016; Rojas et al., 2013; Wheater and Gober, 2015).

Hydrological forecasting systems are often implemented as ensemble forecasting systems (Cloke and Pappenberger, 2009). Ensemble forecasts provide information about the possibility that an event occurs (Krzysztofowicz, 2001; Thielen et al., 2009), and allow quantification of the forecast uncertainty (Krzysztofowicz, 2001; Zappa et al., 2011). Uncertainties in streamflow forecasts originate from meteorological inputs, and hydrological model parameters, initial conditions and model structure (Bourdin and Stull, 2013; Cloke and Pappenberger, 2009; Demirel et al., 2013a; Zappa et al., 2011).

A number of studies investigated the performance of ensemble forecasting systems, e.g. Alfieri et al. (2014) for the European Flood Awareness System (EFAS), and Bennett et al. (2014), Olsson and Lindström (2008), Renner et al. (2009) and Roulin and Vannitsem (2005) for several catchments varying in size and other characteristics. These studies all found a deterioration of performance with increasing lead time. However, most studies focused either on flood forecasts (e.g. Alfieri et al., 2014; Bürger et al., 2009; Komma et al., 2007; Olsson and Lindström, 2008; Roulin and Vannitsem, 2005; Thielen et al., 2009; Zappa et al., 2011) or low streamflow forecasts (Demirel et al., 2013a; Fundel et al., 2013). The studies on non-specific ensemble streamflow forecasting systems (Bennett et al., 2014; Demargne et al., 2010; Renner et al., 2009; Verkade et al., 2013) did not evaluate the performance for different streamflow categories (i.e. for low streamflow and high streamflow events). Moreover, previous studies did not assess effects of runoff processes, like snowmelt and extreme rainfall events, on the performance of ensemble forecasts. The only study we found that touches on this is the study by Roulin and Vannitsem (2005). This study concluded that the developed high streamflow forecasting system is more skilful for the winter period than for the summer period. Next to an assessment of performance, information on the relative importance of uncertainty sources in forecasts is essential to improve the forecasts effectively (Yossef et al., 2013). A number of studies report on how errors in the meteorological forecasts and the hydrological model contribute to errors in medium-range hydrological forecasts. Demargne et al. (2010) show that hydrological model uncertainties (initial conditions, model parameters and model structure) are most significant at short lead times. The extent depends on the streamflow category: hydrological model uncertainties significantly degrade the evaluation score up to a lead time of 7 days for all flows, whereas only up to a lead time of 2 days for the very high streamflow events. Renner et al. (2009) found an underprediction of low forecast probabilities (few ensemble members over a high streamflow threshold), which they attribute to the meteorological forecasts having insufficient variability. Contrarily, the high forecast probabilities (low threshold) are overpredicted, which Renner et al. (2009) attribute to both the hydrological model and the meteorological input data. Olsson and Lindström (2008) found underdispersion of ensemble flood forecasts, which decreases with lead time. The meteorological forecasts and the hydrological model have a comparable contribution to this. In addition, Olsson and Lindström (2008) show overprediction of forecast probabilities over high thresholds, which they primarily attribute to the meteorological forecasts. Demirel et al. (2013a) concluded that uncertainty of hydrological model parameters has the largest effect, whereas meteorological input uncertainty has the smallest effect on low streamflow forecasts. Based on those studies we can say that for high streamflow forecasts uncertainties in the meteorological forecasts are dominant, whereas for low streamflow forecasts the uncertainties in the hydrological model are more important.

The objective of this study is to investigate the performance and limitations of ECMWF meteorological forecasts based ensemble streamflow forecasting for lead times up to 10 days for low, medium and high streamflow in a catchment with seasonal variation in runoff generating processes. We aim to evaluate whether performance of the forecasting system can be related to specific runoff generating processes based on hydrometeorological conditions. Further, we assess whether the main source of forecast error relates to the meteorological inputs or to deficiencies of the hydrological model, for the different streamflow categories and runoff generating processes.

2 Study catchment and data

2.1 Study area and measurement data

The Biała Tarnowska catchment in Poland serves as study area. This catchment is selected because of its large variation in streamflow and seasonal variation in runoff generating processes. The catchment (Fig. 1) is located in a mountainous part of southern Poland. Napiorkowski et al. (2014) further describe the catchment. The Biała Tarnowska River discharges into the Dunajec River, which is a tributary of the Vistula River. The length of the river is 101.8 km with a catchment area of 956.9 km^2. The mean streamflow is 9.4 m^3 s^{-1} (1972–2013). The highest measured streamflow is 611 m^3 s^{-1}. During winter and spring snow(melt) plays an important role. Comparison of the time series of precipitation and streamflow shows that the lag time between intense precipitation events and related peaks in streamflow varies between 1 and 3 days.

Precipitation and temperature measurement series are available from five meteorological stations and streamflow measurement series are available from one discharge gauging station, at a daily time interval for the period 1 January 1971 to 31 October 2013, and provided by the Polish Institute of Meteorology and Water Management. Given that meteorological stations are mostly located in valleys and precipitation and temperature vary with elevation, the catchment averages may be biased (Panagoulia, 1995; Sevruk, 1997). Following Akhtar et al. (2009), precipitation measurements are corrected using relative correction factors (in %), whereas temperature measurements are corrected using absolute correction factors (in °C). The precipitation gradient differs considerably between months. For December–February the mean precipitation gradient is 10.5 % 100 m^{-1}, while for March–November the mean precipitation gradient is 5.4 % 100 m^{-1}. Although the number of stations is small to accurately determine precipitation and temperature gradients, the calculated precipitation gradients are used because of the clear difference between the two periods. The temperature gradient does not vary much over the year and therefore the global standard temperature lapse rate of 0.65 °C 100 m^{-1} is applied. The measurements from each station are corrected for the difference between the elevation of the station and the mean elevation its respective Thiessen polygon. To represent catchment averages, the corrected measurements are weighted based on the relative coverage of their Thiessen polygon (Fig. 1). By the corrections the annual mean precipitation increases from 741.2 mm to 768.4 mm and the annual mean potential evapotranspiration decreases from 695.3 mm to 674.4 mm.

2.2 Meteorological forecast data

The meteorological ensemble forecasts by ECMWF are used, because of the good performance compared to other meteorological ensemble forecast sets (Buizza et al., 2005; Tao et al., 2014) and because the ECMWF forecasts are frequently used in hydrological ensemble forecasting (Cloke and Pappenberger, 2009). Persson and Andersson (2013) and ECMWF (2012) describe how ECMWF generates the meteorological ensemble forecasts. The ensemble forecasts consist of one control forecast (no perturbation) and 50 ensemble members. The ensemble members should represent initial condition and meteorological model uncertainty (Leutbecher and Palmer, 2008; Persson and Andersson, 2013).

The THORPEX Interactive Grand Global Ensemble (TIGGE) project, developed by The Observing System Research and Predictability Experiment (THORPEX), provides historical meteorological forecast data from 1 October 2006 onwards (Bougeault et al., 2010). The resolution of the ensemble and control forecasts is 32 km × 32 km (ECMWF, 2012). Using the TIGGE data portal we interpolated the forecasts to a regular grid (Bougeault et al., 2010) with a resolution of 0.25° × 0.25° (~17.9 km × 27.8 km at this latitude). In this study a maximum lead time of 10 days is used, following the World Meteorological Organization (WMO) that defines medium-range as forecasts with lead times from 3 days to 10 days (ECMWF, 2012). We also refer to Alfieri et al. (2014), Bennett et al. (2014), Demirel et al. (2013a), Olsson and Lindström (2008), Renner et al. (2009), Roulin and Vannitsem (2005) and Verkade et al. (2013) that use 9 or 10 days as maximum lead time for hydrological forecasting. Because we use a lumped hydrological model with a daily time step (Sect. 3.1.1), we averaged daily ECMWF forecasts according to the relative area coverage of the seven grid cells that overlay the catchment.

According to Persson and Andersson (2013) ECMWF forecasts may apply to a land elevation that significantly differs from the actual elevation in a grid and this can lead to biases. Correction for such elevation errors is ignored, because any systematic bias is accounted for in the pre-processing step (Sect. 3.1.3). ECMWF provides temperature forecasts at 00:00 hr. or 12:00 hr. This means that temperature forecasts cannot be considered as representative for one day. To obtain representative daily average temperature forecasts, we weight the temperature forecasts at 00:00 hr., 12:00 hr and 24:00 hr by 25%, 50% and 25% respectively.

3 Methods

3.1 The ensemble streamflow forecasting system

The ensemble streamflow forecasting system consists of multiple components, shown in Fig. 2. Uncertainties in meteorological forecasts, model parameters, model initial conditions and model structure affect streamflow forecasts (Bourdin and Stull, 2013; Cloke and Pappenberger, 2009; Demirel et al., 2013a; Zappa et al., 2011). To capture the full range of predictive uncertainty, uncertainties arising from all sources of error must be incorporated (Bourdin and Stull, 2013; Krzysztofowicz, 2001; Zappa et al., 2011). Bennett et al. (2014) and Cloke and Pappenberger (2009) describe that uncertainties in meteorological forecasts are the largest source of uncertainty beyond 2–3 days, and therefore only meteorological forecast uncertainty is incorporated in many studies (Bennett et al., 2014). We only include uncertainty in the meteorological forecasts to focus on the effect of ensemble meteorological forecasts on streamflow forecasts. As a consequence, underdispersion of the streamflow forecasts may be expected.

3.1.1 Hydrological model

The hydrological model we use is a lumped Hydrologiska Byråns Vattenbalansavdelning (HBV) model that we run at daily time step. The model has 14 parameters and includes a snow accumulation and melting routine (Lindström et al., 1997; Osuch et al., 2015). Daily potential evapotranspiration rates are based on air temperature using the method of Hamon (Lu et al., 2005). The HBV model has wide application in studies on ensemble streamflow forecasting (e.g. Cloke & Pappenberger, 2009; Demirel et al., 2013a, 2015; Kiczko et al., 2015; Olsson & Lindström, 2008; Renner et al., 2009; Verkade et al., 2013). The choice for a lumped model with a daily time step is the result of the spatial and temporal resolution of the available data. The available measurements of precipitation and temperature from five meteorological stations and streamflow from one discharge gauging station do not justify application of a spatially distributed hydrological model. The River Rhine forecasting suite also adopts the HBV model at a daily time step as a semi-distributed model to 134 sub catchments (Renner et al., 2009). The catchment area of Biała Tarnowska (~1000 km^2) is comparable to the area of the sub catchments in the River Rhine forecasting suite.

To calibrate the HBV model we used Differential Evolution with Global and Local neighbourhoods (DEGL), described by Das et al. (2009). The settings are adopted from the best performing variant of Das et al. (2009) (maximum number of model runs is set to 50000). The model parameters were drawn uniformly from predefined parameter ranges (Osuch et al., 2015). The objective function selected for calibration is Y, which combines the Nash–Sutcliffe coefficient (NS) and the relative volume error (E_{RV}) (Akhtar et al., 2009; Rientjes et al., 2013). According to Rientjes et al. (2013), values of Y below 0.6 indicate poor to satisfactory performance. The model is calibrated over the period 1 November 1971 to 31 October 2000, with the time series of precipitation and temperature as inputs and streamflow measurements as reference output. The validation period is 1 November 2000 to 31 October 2013. Initialization periods of 10 months and 1 year respectively ensure realistic initial conditions at the first day of the calibration and the validation period.

3.1.2 Updating of initial states

To best represent the hydrological conditions in the catchment at the forecast issuing day, hydrological forecasting system often rely on the updating of hydrological model storages by combining simulations with real-time data (Demirel et al., 2013a; Liu et al., 2012; Werner et al., 2005; Wöhling et al., 2006). A number of sophisticated techniques have been developed for data assimilation and model state updating (Houser et al., 2012; Liu et al., 2012). We apply the fairly simple and direct storage updating procedure introduced by Demirel et al. (2013a), which relies on the autocorrelation of streamflow to update model storages. The measured streamflow of the day preceding the forecast issuing day is divided in a fast and a slow runoff component to update the fast runoff reservoir and the slow runoff reservoir of the HBV model. To determine the ratio between the fast and slow runoff components, a relationship between total simulated streamflow and the fraction of fast runoff is established based on historical simulations.

3.1.3 Pre- and post-processing

Errors in the meteorological forecasts and in the hydrological models introduce biases in the mean and errors in the spread of ensemble streamflow forecasts (Cloke and Pappenberger, 2009; Khajehei and Moradkhani, 2017; Verkade et al., 2013). Several studies suggest that post-processing of streamflow forecasts is more effective to improve the forecast quality than pre-processing of meteorological input data (Kang et al., 2010; Verkade et al., 2013; Zalachori et al., 2012). Verkade et al. (2013) and Zalachori et al. (2012) found that corrections made to meteorological forecasts lose their effect when propagated through a hydrological model. Results by Zalachori et al. (2012) indicate that combined pre- and post-processing results in the best forecast quality. In this study both pre-processing of the meteorological input forecasts and post-processing of the streamflow forecasts are tested.

Many studies used (conditional) quantile mapping (QM) for pre-processing (Boé et al., 2007; Déqué, 2007; Kang et al., 2010; Kiczko et al., 2015; Verkade et al., 2013; Wetterhall et al., 2012) and post-processing (Hashino et al., 2007; Kang et al., 2010; Madadgar et al., 2014; Shi et al., 2008) to correct for bias and dispersion errors. According to Kang et al. (2010), QM generally performs well in both pre- and post-processing. Hashino et al. (2007) advise to use QM, because of the good performance regarding sharpness and discrimination and the simplicity of the method. With QM the cumulative distribution function (CDF) of the forecasts over a training period is matched to the CDF of the measurements over the same period, after which a correction function is generated (Boé et al., 2007). This means that the correction is conditional on the value of the forecasted variable itself. Boé et al. (2007), Déqué (2007) and Madadgar et al. (2014) further explain QM. The empirical CDFs of the measurements and forecasts are established on the training period 1 November 2011 to 31 October 2013 (two hydrological years) and validated on the period 1 November 2007 to 31 October 2011.

Distributions may be different for different lead times and weather patterns or seasons (Boé et al., 2007; Wetterhall et al., 2012), so three QM set-ups are tested with and without distinguishing lead times and seasons. Combining the options for pre-processing and post-processing results in four processing strategies. In strategy 0, no pre- and post-processing are applied. In strategy 1 and 2, QM is applied to pre-process the meteorological forecasts, without post-processing and with post-processing respectively. In strategy 2, the post-processing is performed based on the correction between 'observed meteorological input forecasts' (streamflow simulations with inputs from meteorological measurements) and streamflow measurements to account for hydrological model uncertainties (Verkade et al., 2013). In strategy 3, only post-processing is applied, based on the correction between streamflow forecasts generated with uncorrected meteorological forecasts and measured streamflow. In this strategy meteorological and hydrological model uncertainties are treated together (Verkade et al., 2013).

3.2 Evaluation scores of the ensemble forecasts

To measure the overall performance, we employ the frequently-used Continuous Ranked Probability Score (CRPS) (Bennett et al., 2014; Demargne et al., 2010; Hamill et al., 2000; Hersbach, 2000; Khajehei and Moradkhani, 2017; Pappenberger et al., 2015; Velázquez et al., 2010; Verkade et al., 2013). To evaluate forecast skill, we use the Continuous Ranked Probability Skill Score (CRPSS), which is the CRPS of the forecasts relative to the CRPS of alternative forecasts. The alternative forecast set is selected in Sect. 3.2.1. According to Demargne et al. (2010) and Hamill et al. (2000) a single evaluation score is inadequate to evaluate the performance of a forecasting system. Three properties of forecast quality are reliability, sharpness and resolution (Wilks, 2006; WMO, 2015).

Reliability refers to the statistical consistency between measurements and simulations (Candille & Talagrand, 2005; Velázquez et al., 2010) and whether uncertainty is correctly represented in the forecasts (Bennett et al., 2014). We evaluate reliability by rank histograms (Sect. 3.2.2) and reliability diagrams (Bröcker and Smith, 2007; Ranjan, 2009; Wilks, 2006; WMO, 2015). The five forecast probability bins that we use to establish the reliability diagrams are 0%–20%, 20%–40%, … and 80%–100%, which were also used by Demirel et al. (2013a) and Bennett et al. (2014), and the low streamflow and high streamflow thresholds considered are defined in Sect. 3.4.

Sharpness is defined as the tendency to forecast probabilities of occurrence near 0 or 1, as opposed to values clustered around the mean (climatological) probability (Ranjan, 2009; Wilks, 2006; WMO, 2015). If an ensemble forecasting system always forecasts a probability of occurrence close to climatological probability, instead of close to 0 or close to 1, the forecasting system is not useful, although it might be well calibrated (Ranjan, 2009; Wilks, 2006). To evaluate sharpness, we employ the histograms that show the sample size of the forecast probability bins used to establish the reliability diagrams (Ranjan, 2009; Renner et al., 2009; WMO, 2015).

Resolution is the ability to correctly forecast the occurrence and nonoccurrence of events (Demirel et al., 2013a; Martina et al., 2006). We employ Relative Operating Characteristics (ROC) curves to evaluate resolution (Fawcett, 2006; Khajehei and Moradkhani, 2017; Velázquez et al., 2010; Wilks, 2006; WMO, 2015). The Area Under the ROC Curve (AUC) provides a single score of performance regarding resolution (Fawcett, 2006; Wilks, 2006). A perfect ensemble forecasting system has an area of 1 under the ROC curve (100% hit rate, 0% false alarm rate for all probability thresholds), while a forecasting system with zero skill has a diagonal ROC curve with an area of 0.5 (coincides with diagonal) (Fawcett, 2006; Velázquez et al., 2010; WMO, 2015).

3.2.1 Alternative forecast set

Because in practice the CRPS converges to the average value of the evaluated variable (with the same unit), the score cannot be compared among different areas, seasons or streamflow categories (Ye et al., 2014). To eliminate the magnitude of the investigated variable, we normalize the CRPS against the CRPS of a relevant alternative forecast, a principle which is also used by Bennett et al. (2014), Demargne et al. (2010), Renner et al. (2009), Velázquez et al. (2010) and Verkade et al. (2013) to evaluate forecast skill. The CRPSS is defined as:

$$CRPSS = 1 - \frac{CRPS_{forecasts}}{CRPS_{alternative}}, \quad (1)$$

A system with perfect skill results in a CRPSS of 1 and a negative CRPSS indicates that the forecasting system performs worse than the alternative forecasts (Demargne et al., 2010; Ye et al., 2014).Forecasts that are generated without meteorological forecasts provide the alternative forecast set. It is common practice to apply hydrological persistency or hydrological climatology as alternative forecast set (Bennett et al., 2014). With hydrological persistency the most recent streamflow measurement available (i.e., from the day preceding the forecast issuing day) serves as forecast for all lead times. Regarding hydrological climatology, the average measured streamflow, after a smoothing window of 31 days, on the same calendar day over the last 20 years is used, following Bennett et al. (2013). For streamflow forecasts based on an ensemble of historical meteorological measurements, measurements on the same calendar day over the past 20 years are used, after Pappenberger et al. (2015).

The alternative forecast set with the lowest CRPS will serve as alternative forecast set to evaluate skill (Bennett et al., 2013, 2014; Pappenberger et al., 2015). We use a single alternative forecast set for all streamflow categories, so one $CRPS_{alternative}$ is calculated. The results in Fig. 3 show that the forecasts based on meteorological climatology result in the best CRPS scores and thus imply to be the most appropriate alternative streamflow forecasts, as also found in the studies of the Bennett et al. (2013), Bennett et al. (2014) and Pappenberger et al. (2015).

3.2.2 Rank histogram

The consistency condition states that the reference streamflow is just one more member of the ensemble and it should be statistically indistinguishable from the ensemble forecast (Wilks, 2006). In an ensemble forecasting system with perfect spread each ensemble member is equally likely, so all reference streamflow ranks are equally likely and the rank histogram is uniform (Hamill, 2001; Hersbach, 2000; Wilks, 2006; WMO, 2015; Zalachori et al., 2012). For backgrounds of the rank histogram, readers are referred to Hamill (2001), Wilks (2006), Velázquez et al. (2010), WMO (2015) and Zalachori et al. (2012). We use the Mean Absolute Error as flatness coefficient ε of the rank histogram, with the uniform distribution as reference:

$$\varepsilon = \frac{1}{n+1} \sum_{z=1}^{z=n+1} |f(z) - y| , \quad (2)$$

$f(z)$ = Relative frequency of reference streamflow in rank z [-]

$y = \frac{1}{n+1}$ = Theoretical relative frequency (uniform distribution) [-]

n = Number of ensemble members [-]

The rank histogram and flatness coefficient contain a random element if multiple ensemble members and the measurement have the same value, like 0 mm precipitation (Hamill and Colucci, 1998). In this case, a random rank is assigned to the measurement from the pool of ensemble members and the measurement that have the same value.

3.3 Contribution of error sources

The evaluation of ensemble streamflow forecasts is affected by errors from the meteorological forecasts, the hydrological model (including errors in the initial conditions) and errors in the measurements that serve as reference streamflow (Renner et al., 2009). By evaluation against observed meteorological input forecasts, the streamflow measurement error and the hydrological model error are eliminated, because both the ensemble streamflow forecasts and the reference streamflows contain these errors (Demargne et al., 2010; Olsson and Lindström, 2008; Renner et al., 2009). If we neglect measurement errors, evaluation against streamflow measurements ($CRPS_{meas}$) contains errors from the meteorological forecasts and the hydrological model and evaluation against observed meteorological input forecasts ($CRPS_{sim}$) exclusively contains errors from the meteorological forecasts (Demargne et al., 2010; Olsson and Lindström, 2008; Renner et al., 2009). If the ratio in Eq. (3) is low, the hydrological model errors are dominant, and if this ratio is high, the meteorological forecast errors are dominant.

$$\frac{CRPS_{sim}}{CRPS_{meas}} \sim \frac{meteorological\ forecast\ errors}{meteorological\ forecast\ errors + hydrological\ model\ errors}, \quad (3)$$

3.4 Evaluation of streamflow categories

We evaluate the forecasting system for the different streamflow categories that are defined in Table 1. A low streamflow threshold of Q_{75} (exceedance probability of 75%) guarantees that a sufficient number of events are considered in the evaluation of this streamflow category, while streamflow below this threshold still affects river functions (Demirel et al., 2013b). Similarly, we use Q_{25} as high streamflow threshold.

3.5 Evaluation of runoff generating processes

The high streamflow forecasts and low streamflow forecasts are evaluated for the specific runoff processes that can generate these events, based on hydrometeorological conditions. Medium flows are not evaluated for different runoff generating processes ,because these events commonly result from a combination of runoff generating processes under non-extreme hydrometeorological conditions.

3.5.1 High streamflow generating processes

Various runoff generating processes can result in high flows. Table 2 defines the processes and rules for classification. The rules for classification are based on rainfall observations and snowpack model simulations; at one day before the event because of the time step used in the HBV model. Figure 4a shows the distribution of high streamflow generating processes over the year following the rules for classification listed in Table 2. The distribution of processes is typical for this region.

3.5.2 Low streamflow generating processes

Processes that result in low flows are snow accumulation and the combination of low rainfall and high evapotranspiration over a period (precipitation deficit). Table 3 further characterizes and defines these processes.

Figure 4b shows that these rules for classification result in a distribution of low streamflow generating processes over the year that is typical for this region.

4 Results

4.1 Ensemble streamflow forecasting system

4.1.1 Calibration and validation of the hydrological model

Table 4 lists the calibration and validation results. The validation performance is satisfactory, indicating that the lumped model approach is plausible in this case. The updating of initial states of the fast runoff reservoir and slow runoff reservoir (Sect. 3.1.2) results in an improvement of Y from 0.75 to 0.82 over the validation period. This effect decreases with lead time, but it is still noticeable at a lead time of 10 days.

Simultaneous measurements and ECMWF forecasts are available for the period 1 November 2006 to 31 October 2013. In the hydrological year 2007 (1 November 2006 to 31 October 2007) the agreement between streamflow measurements and simulations is poor. Also with another model (Data Based Mechanistic methodology (DBM)), the performance was worse during this year (Kiczko et al., 2015). This must be the result of measurement errors and/or human influence, because it is unlikely that in this period different hydrological processes are taking place that are not captured well by both the HBV model and the DBM model. Therefore, the period 1 November 2006 to 31 October 2007 is excluded from the evaluation period.

Table 5 presents the performance of the hydrological model for different lead times and streamflow categories, including the Relative Mean Absolute Error (E_{RMA}). The NS values for the low and medium streamflow categories are negative, meaning that the averages of streamflow measurements in these categories are a better approximation of the measurements than the simulations. The scores highlight that the calibration is skewed to high streamflow conditions, which is the result of the selected objective function that includes NS (Gupta et al., 2009). Gupta et al. (2009) also found that model calibration with NS tends to underestimate the low and high streamflow peaks.

The results in Table 5 improve considerably as a result of the updating of initial storages, especially for the low streamflow simulations. The effectiveness of the updating procedure depends on the autocorrelation of daily streamflow. In low streamflow periods there is usually a high autocorrelation of daily streamflow, in contrast to high streamflow periods.

4.1.2 Pre- and post-processing strategy results

The best precipitation forecasts are obtained if QM is applied separately to each lead time, whereas the best temperature forecasts are obtained if, in addition, separate relationships for the summer and winter season are applied. The CRPS and E_{RMA} of the precipitation and temperature forecasts improve slightly and the flatness coefficients improve considerably as a result of the pre-processing.

However, for the combined pre- and post-processing strategies, the results in Fig. 5 show that strategy 0 (no pre- and post-processing) results in the best CRPS.

4.2 Forecast performance

4.2.1 Forecast skill

The streamflow forecasts are evaluated over the period 1 November 2007 to 31 October 2013, for lead times from 1 day to 10 days and for the different streamflow categories (defined in Table 1). The results are shown in Fig. 6. The CRPS increases with lead time for all streamflow categories (Fig. 6a), so the performance of the streamflow forecasting system deteriorates with lead time. For all streamflows aggregated, the CRPSS is positive for all lead times (Fig. 6b), so on average the streamflow forecasts are better than the alternative forecasts. This forecast skill is generated by the ECMWF forecasts compared to historical meteorological measurements.

Fig. 6b shows that the forecast skill is very different for the low, medium and high streamflow forecasts. The low skill of low streamflow forecasts, especially for small lead times, can be explained by the important role of the initial hydrological conditions. In low streamflow situations runoff is mainly generated by available resources in the catchment instead of precipitation input. Since the same initial model conditions are used to simulate the alternative forecasts, the result is that low streamflow forecasts cannot skilfully be forecasted for small lead times (<3 days). Also the origin of the alternative forecasts plays a role. Since low streamflow events normally occur in the same period of the year due to climatic seasonality, it can be expected that historical meteorological measurements on the same calendar day provide plausible inputs. After all, the performance of the meteorological forecasts preceding these events contributes to the low skill. The negative skill at small lead times indicates that historical meteorological measurements are even better forecasts than the meteorological ensemble forecasts by ECMWF for this category of flows. From a lead time of 3 days the accumulated meteorological forecasts are more skilful than historical meteorological measurements.

The medium streamflow forecasts do not have clear positive skill for all lead times. This can be explained by the fact that streamflow is most often close to the medium streamflow, so forecasts based on historical meteorological measurements will be a good approximation for these flows.

The system has a high positive skill in forecasting high streamflow. In general initial conditions are relatively less important for these events, because of the amount of water usually added to the system. However, we note that this depends on the responsible runoff generating process (see results in Sect. 4.4.1). As a result the streamflow forecasts and reference forecasts can easier deviate. In addition, high streamflow events will be less well captured by historical meteorological measurements, and thus the alternative forecasts will have lower quality for these events.

4.2.2 Forecast quality

Figure 7 shows the flatness coefficients. The high values indicate that the rank histograms are far from flat, especially for small lead times and low streamflow events. The rank histograms (in supplement Fig. S1) are U-shaped, which indicates underdispersion and/or conditional bias in the streamflow forecasts (Hamill, 2001). The ECMWF forecasts are also underdispersed, so this is one cause why the streamflow forecasts are underdispersed. In Sect. 5 the consequences of ignoring uncertainties in the hydrological model and initial conditions are further discussed.

The rank histograms of the different streamflow categories (Fig. S2) show that the streamflow forecasts contain a conditional bias. In general, high streamflow is underestimated by the forecasting system and this increases with lead time. Low streamflow is generally overestimated. Both observations can be the result of too coarse spatial and temporal model resolution. Using a lumped model and aggregating the meteorological inputs spatially over the catchment and temporarily over the day flattens the extreme flow events.

Also the reliability diagrams (Fig. S3) indicate low reliability of the streamflow forecasts, especially for small lead times. It appears that for low streamflow forecasts the observed relative frequencies are underestimated. Regarding the high streamflow forecasts the observed relative frequencies are overestimated, whereas the rank histograms indicate that high streamflow is underestimated. This is possible because in the rank histogram the measurements and forecasts are compared directly, whereas in the reliability diagram the measurements and forecasts are compared to a streamflow threshold.

Histograms showing the sample size in each probability bin of the reliability diagrams indicate that the sharpness of the forecasts is good, because forecast probabilities of low and high streamflow are most often close to 0 or 1, instead of forecast probabilities close to the mean probability. The sharpness decreases with lead time.

All AUC values are above 0.85, which indicates a good resolution of the streamflow forecasting system. Buizza et al. (1999) state that, for meteorological forecast systems, it is common practice to consider an area of more than 0.7 as indicative for useful prediction systems and 0.8 for good prediction systems. The ROC curves are included in Fig. S4.

4.3 Dominant error contributors

Figure 8 shows that the relative contribution of meteorological forecast errors increases and the relative contribution of hydrological model errors decreases with lead time, although the performance of the hydrological model also deteriorates with lead time (Table 5). Two effects contribute to this. First, the meteorological forecasts get worse with lead time (Fig. 5) and errors in the meteorological forecasts accumulate in the hydrological forecasting system. Second, the effect of the initial hydrological conditions at the forecast issuing day becomes smaller at larger lead times, because more water is added to the system.

For high streamflow forecasts the contribution of meteorological forecast errors is relatively more important, while in low streamflow forecasts the contribution of hydrological model errors is relatively more important. Initial conditions have relatively less influence on high streamflow (discussed in Sect. 4.2.1). In addition, the hydrological model performs better for high streamflow than for low streamflow conditions (Table 5), so meteorological forecast errors are relatively more important in high streamflow conditions.

4.4 Forecast skill for the runoff generating processes

4.4.1 High streamflow generating processes

The highest skill is obtained for short-rain floods (Fig. 9a), at small lead times (1-5 days). Two effects contribute to this. First, long-rain floods and snowmelt floods are essentially driven by the water storage conditions in the catchment whereas for short-rain floods meteorological input has more influence. Figure 9b confirms the relative importance of meteorological forecasts in these events. This results in higher potential to generate forecast skill, already at small lead times. At larger lead times the accumulation of rainfall in the forecasting system becomes important, which is confirmed by the increasing contribution of meteorological forecast errors in long-rain floods and snowmelt floods. Second, the short and heavy rain events preceding short-rain floods will be less well captured in historical meteorological measurements than the longer term processes generating long-rain floods and snowmelt floods. Long-rain floods are skilfully forecasted from a lead time of 3 days and snowmelt floods are skilfully forecasted from a lead time of 2 days. The forecast skills of short-rain floods and snowmelt floods decrease considerably from lead times of 6 days and 9 days respectively. This is the result of a decreased performance of the meteorological forecasts preceding these events. The skill of short-rain flood forecasts decreases the most.

4.4.2 Low streamflow generating processes

Figure 10a shows that the low forecast skill of low streamflow is caused by the precipitation deficit process, whereas the forecast skill of low streamflow events that are generated by snow accumulation is rather high. The low forecast skill of the low streamflow events generated by precipitation deficit can be explained by the fact that low rainfall periods often occur in the same period of the year, due to climatic seasonality, and are therefore well captured by historical meteorological measurements. Also the performance of meteorological forecast models may play a role. Meteorological models tend to forecast drizzle instead of zero precipitation (Boé et al., 2007; Piani et al., 2010) and pre-processing has not been applied to correct for this. The skill increases for larger lead times, so for larger lead times the ECMWF meteorological forecasts accumulated in the forecasting system give better predictions than historical meteorological measurements. The fact that the contribution of initial hydrological conditions at the forecast issuing day decreases for larger lead times (reflected in Fig. 10b) adds to this skill.

The forecast skill for both snowmelt floods and snow accumulation generated low streamflow events decreases from a lead time of 8 days, which indicates a decreasing skill of ECMWF temperature forecasts for large lead times.

5 Discussion

The developed methodology of analysing an ensemble streamflow forecasting system has been applied to the Biała Tarnowska catchment for a 6 year period. By this, findings of this study do not allow direct generalisation but serve ongoing discussions on improving streamflow forecasting. Also, a longer evaluation period would allow evaluation of more extreme definitions of high and low streamflow.

The best streamflow forecasts are obtained without pre- and post-processing. The effectiveness of QM depends on whether during the validation period the same bias is present between the CDF of the measurements and the CDF of the forecasts as during the training period. Figure 11 shows large differences in biases between different years and between the training period and the validation period, suggesting that bias is affected by randomness. The relatively short time series of forecasts constrains the pre- and post-processing procedures, because different weather patterns cannot be well identified and with a longer period a more consistent bias distribution could be obtained. In addition, limitations of QM, as described by Boé et al. (2007) and Madadgar et al. (2014), are expected to play a role in the ineffectiveness of the pre- and post-processing. In spite of the limitations of QM, over the training period the pre- and post-processing strategies result in an improvement of the evaluation scores (strategy 3 with seasonal distinction gives the best performance), which indicates the potential of processing with QM if a consistent bias is present. A problem in pre- and post-processing of forecasts is that the joint distribution of measurements and forecasts is often nonhomogeneous in time due to, for example, an improvement of forecasting systems over time (Verkade et al., 2013). The ECMWF meteorological forecasts in TIGGE, containing historical operational forecasts, have also undergone changes (Mladek, 2016).

Uncertainties in the hydrological model and model initial conditions have been ignored in the forecasting system. Considering the rank histogram results this affects the reliability of streamflow forecasts of short lead times and low streamflow in particular. Regarding the main effect on short lead times, Bennett et al. (2014) and Pagano et al. (2013) discuss similar findings. The lower flatness coefficients of high streamflow forecasts compared to low streamflow forecasts reflect that for high streamflow forecasts the meteorological inputs are relatively more important.

The classification of low and high streamflow generating processes is based on hydrometeorological information that is available from the HBV model and measurement series. This provides more insight in the performance of the forecasting system than a seasonal characterisation. However, some assumptions must be kept in mind when interpreting the results. It is assumed that snow accumulation before an event is embedded in the snowpack storage of the HBV model. If a snowpack is present the event is classified as snowmelt flood or snow accumulation low streamflow. The lumped model causes a simplification here, because when there is a snowpack present in the model there is not necessarily a snowpack that covers the whole catchment. If no snowpack is present, it is assumed that the low streamflow event or high streamflow event is caused by low or high rainfall. The threshold of 10 mm day^{-1} (see Table 2) is a simplification to distinguish between short-rain floods and long-rain floods. The simple character of the classification rules especially has consequences for the classification of events that are caused by a combination of processes, which often occur in practice and result in the highest floods. Another point is that only short-term information (from the day preceding the forecast issuing day) is used to classify the processes. The lag time between precipitation peaks and streamflow peaks does not necessarily match with the HBV model calculation time step and the classification rules used. Consequently, a streamflow at the day following a high rainfall event is classified as a short-rain flood, whereas the real streamflow peak might come one day later.

In the hydrological model the lag time between a rainfall event and the streamflow peak is set to 1 day. However, the timing of a rainfall event on a day will be important, especially in a small catchment. Evaluation of forecast performance in this paper indicates that the lag time is critical in the forecasting system, especially for short-rain floods. The results in Fig. 9b show that the ratio between the CRPS against observed meteorological input forecasts and the CRPS against streamflow measurements is above 100% for high streamflows, and short-rain floods in particular. This means that these forecasts are closer to the measurements than to the observed meteorological input forecasts. Analyses show that on high streamflow days on which the forecasts are closer to the measurements than to the observed meteorological input forecasts (28% at lead time of 1 day to 48% of the days at lead time of 10 days), depending on lead time, on 50% to 66% of the days the forecasts are closer to the measurement than the observed meteorological input forecast. This indicates a hydrological model deficiency, either from the rainfall-runoff relation or the flood peak timing. The precipitation peak in the measurements and the precipitation peak in the meteorological forecasts can be shifted one day with respect to each other and this may cause that the timing of the peak of the streamflow forecasts better corresponds to the streamflow measurements. Of the 97 separate peak streamflow days, on 6 days (lead time of 6 days) to 17 days (lead time of 1 day) the flood peak day of the observed meteorological input forecasts does not match to the peak day of the measurement but the peak day of the mean of the ensemble forecast does match to the peak day of the measurements. This illustrates that hydrological model deficiencies have a considerable effect on the observed meteorological input forecasts and the ensemble forecasts.

It is not trivial to compare the CRPS results to results in other studies, because the value depends on the magnitude of the evaluated variable (Ye et al., 2014). A similarity between the results in this study and previous studies is that the performance of the streamflow forecasts decreases with lead time. Because Bennett et al. (2014) use the same alternative forecast set, the CRPSS results can be compared. Although Bennett et al. (2014) use a different forecasting system and apply it to different conditions, the forecast skills are comparable to the forecast skills obtained in this study.

6 Conclusions

We developed a methodology to analyse an ensemble streamflow forecasting system. For the case study of the Biała Tarnowska catchment we conclude:

- There are large differences in forecast skill, compared to alternative forecasts based on historical meteorological measurements, for different runoff generating processes. The system skilfully forecasts high streamflow events, although the skill depends on the runoff generating process and lead time. Also low streamflow events that are generated by snow accumulation are skilfully forecasted. Since the hit rates are high compared to the false alarm rates, the system has potential to generate forecasts for these streamflow categories. Sharpness of the forecasts is good, although it decreases with lead time. Medium streamflow events and low streamflow events that are generated by a precipitation deficit are not skilfully forecasted.
- When this or any other forecasting system is (further) developed with the objective to generate more accurate high streamflow forecasts, it is recommended to focus on improving the meteorological forecast inputs because errors from the meteorological forecasts are dominant in high streamflow forecasts. This can be achieved by improving the meteorological forecasts (e.g. using the higher resolution forecasts from COSMO-LEPS (Renner et al., 2009)) or by improving the pre-processing step. Also the hydrological model performance on high streamflow must be improved, by specific calibration on flood peak timing and high streamflow conditions. To improve low streamflow forecasts, it is recommended to focus first on the hydrological model performance. In this study the calibration of the hydrological model is skewed to high streamflow conditions. An easy improvement of the forecasts can be achieved by calibrating the hydrological model specifically on low streamflow conditions. Besides improvement of the hydrological model, further research should be done to improve the meteorological forecasts, especially the precipitation forecasts (problem of forecasting of drizzle). When the forecasting system is applied exclusively on low or high streamflow forecasts, the alternative forecast set should be reconsidered.
- The ensemble streamflow forecasting system shows good resolution and sharpness, but the reliability of the streamflow forecasts must be improved. Therefore, it is recommended to include uncertainties in hydrological model parameters and initial conditions in the forecasting system. Particularly for low streamflow forecasts this is essential. Because the precipitation and temperature forecasts are also underdispersed, we recommend to investigate how the reliability of the precipitation and temperature forecasts can be improved, potentially by adding meteorological forecasts from other forecasting systems ('super-ensembles') (Bennett et al., 2014; Bougeault et al., 2010; Fleming et al., 2015; He et al., 2009) or by improved pre-processing.
- Pre-processing with QM slightly improves the meteorological forecasts, but this loses its effect after propagating through the hydrological model. Post-processing of streamflow forecasts was not effective either. A longer time series of forecasts and a retrospective forecast set would possibly promote the success of pre- and post-processing. Moreover, techniques such as a Bayesian joint probability approach (Bennett et al., 2014; Khajehei and Moradkhani, 2017), regression techniques (Verkade et al., 2013; Hashino et al. 2007), Schaake shuffle to ascribe realistic space-time variability (Clark et al., 2004), and weather typing (Boé et al., 2007; Wetterhall et al., 2012) or hydrological process typing, can improve the effectiveness of pre- and post-processing procedures.

- It is recommended to extend the study to other catchments and (if possible) with longer forecast datasets, to investigate the generality of the results and to test more extreme high and low streamflow thresholds.

The findings only apply to the study catchment and the developed system set-up, but the presented methodology of analysing an ensemble streamflow forecasting system is generally applicable. The methodology provides valuable information about the forecasting system, in which conditions it can be used, and how the system can be improved effectively.

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Figures

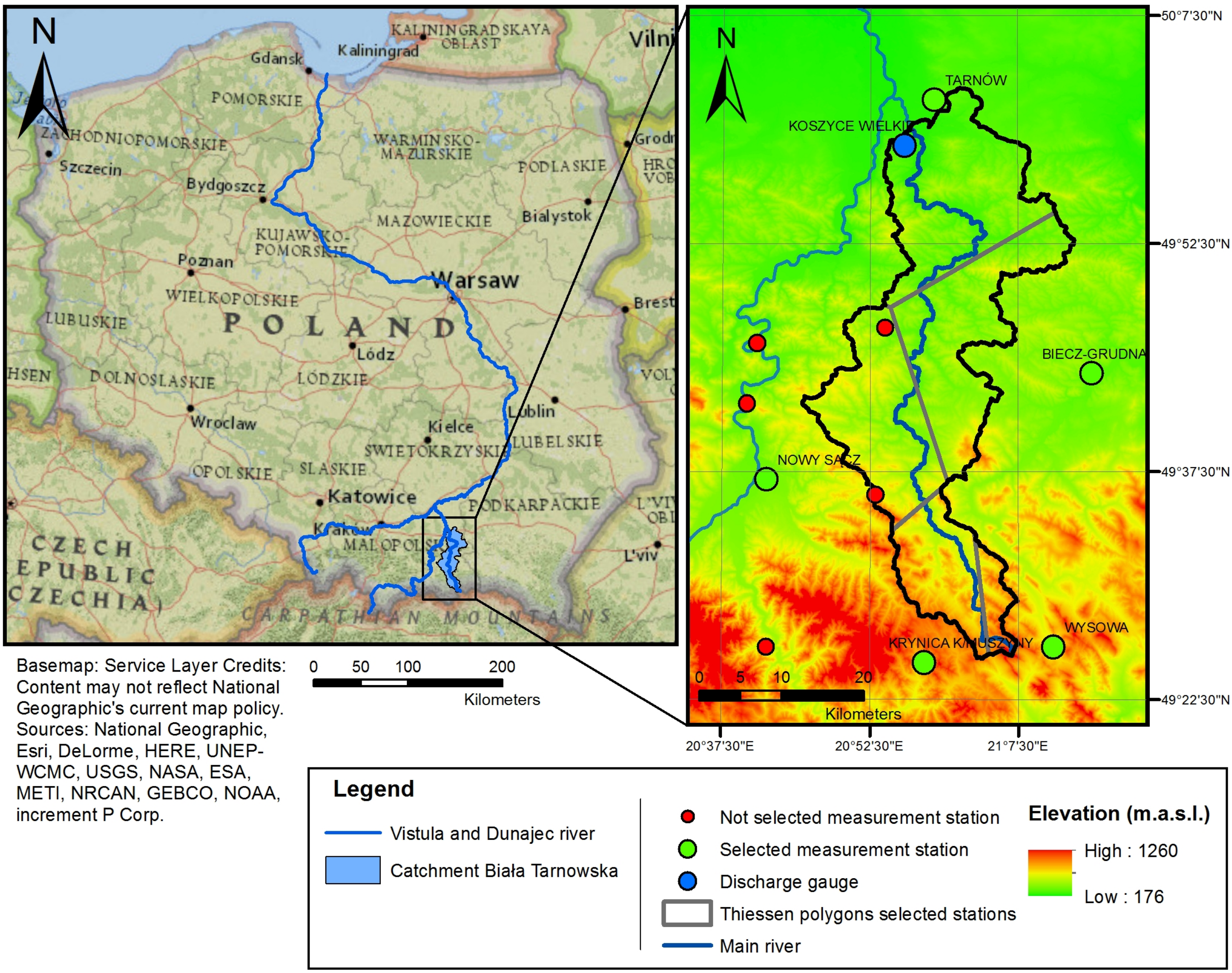

Figure 1: Location and overview of the Biała Tarnowska catchment

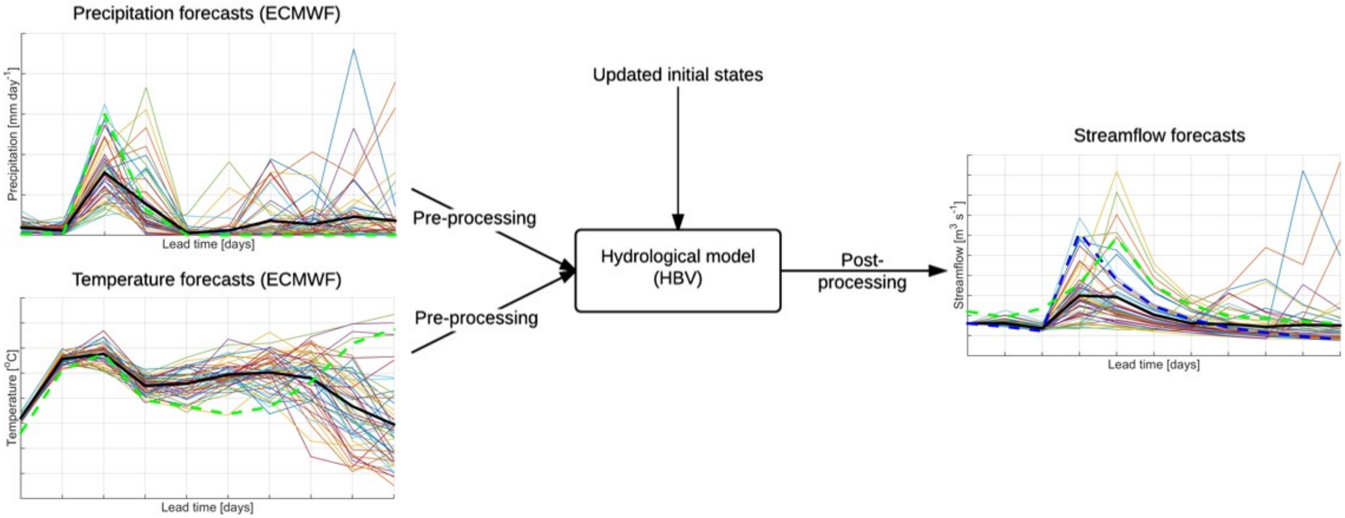

Figure 2: Structure of the ensemble streamflow forecasting system

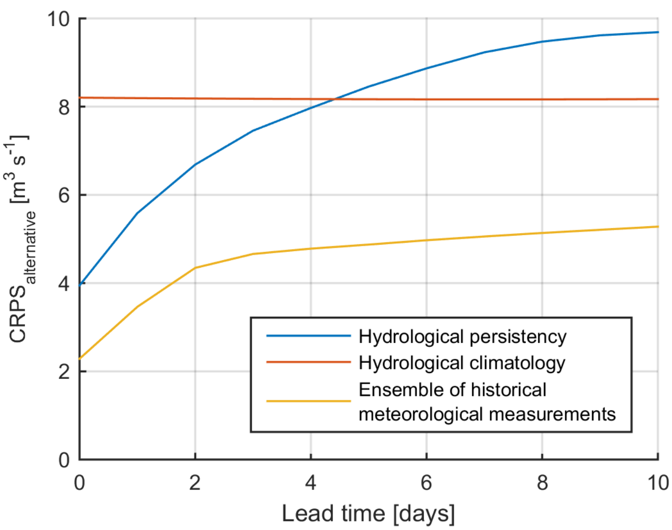

Figure 3: CRPS of three alternative forecast sets, evaluation period 2008-2013

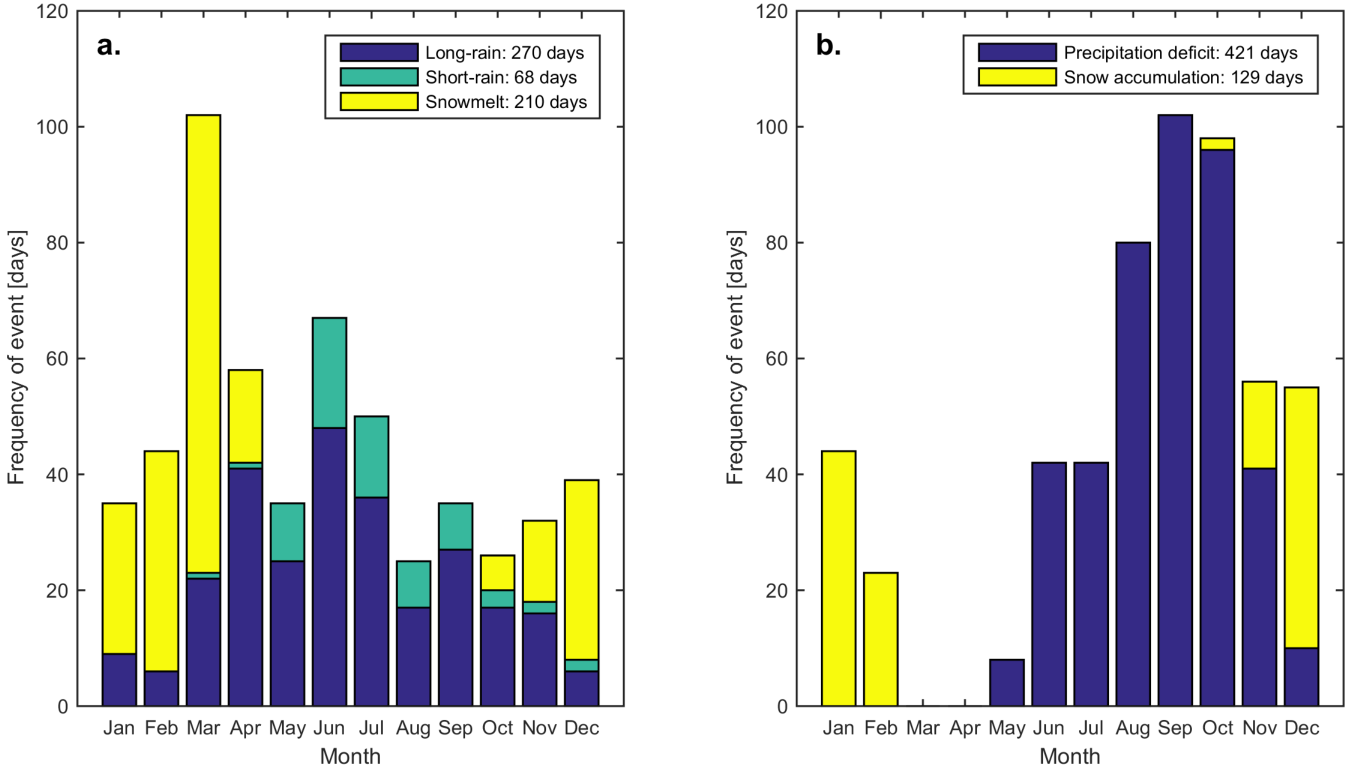

Figure 4: a. High streamflow generating processes over the year b. Low streamflow generating processes over the year, 1-11-2007 to 31-10-2013

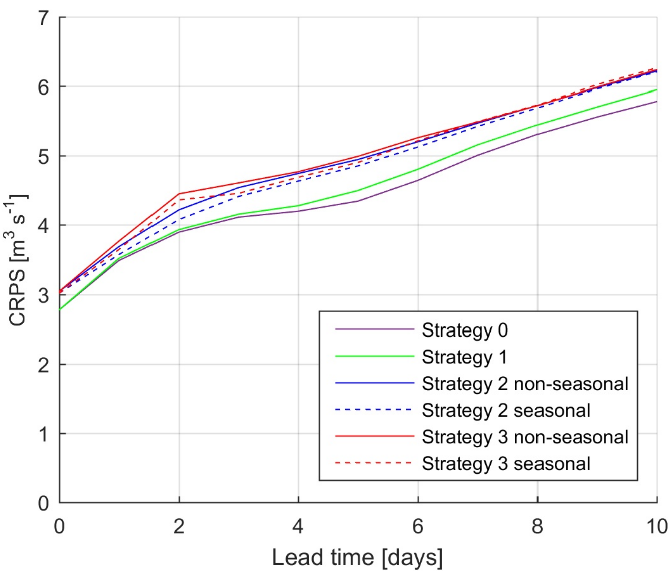

Figure 5: CRPS of streamflow forecasts over the validation period 2008-2011, by applying the post-processing strategies that are introduced in Sect. 3.1.3.

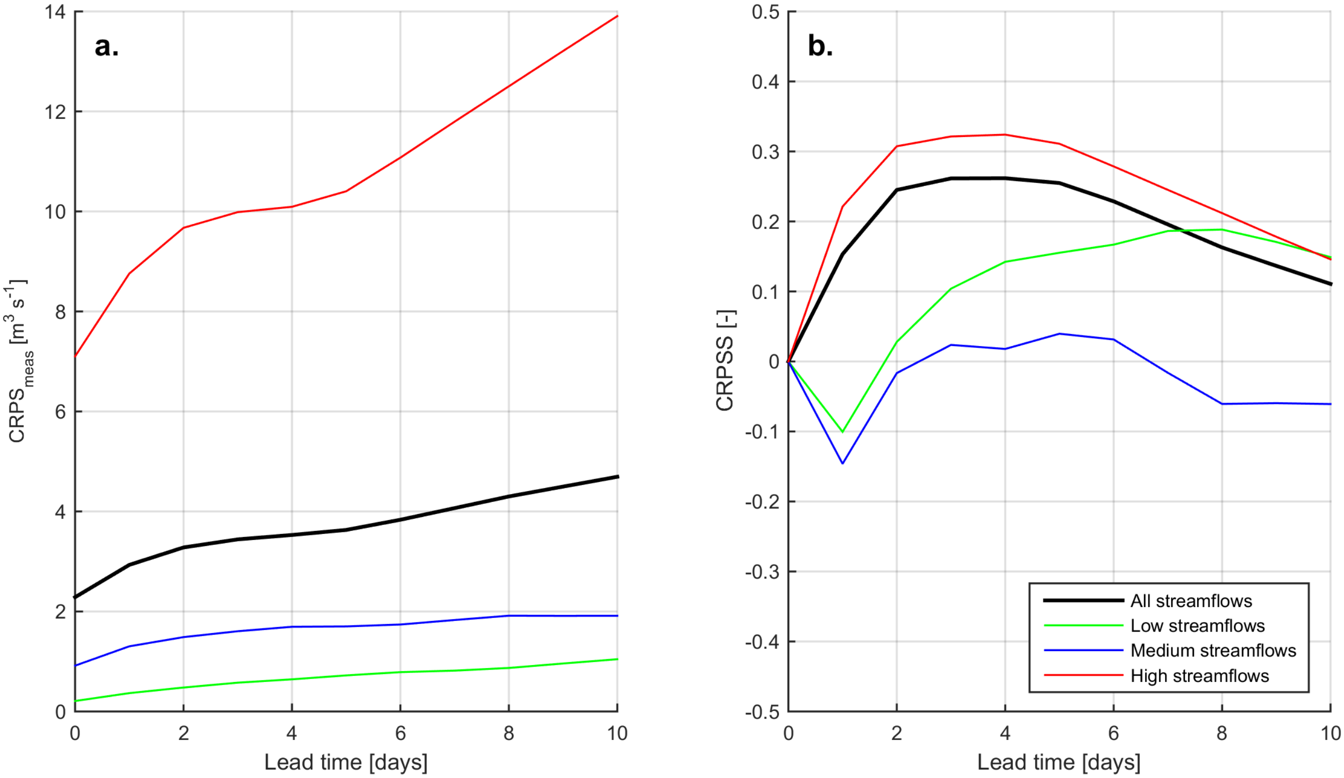

Figure 6: a. Streamflow forecasts evaluated against streamflow measurements b. Skill of the streamflow forecasts, defined in Eq. (1)

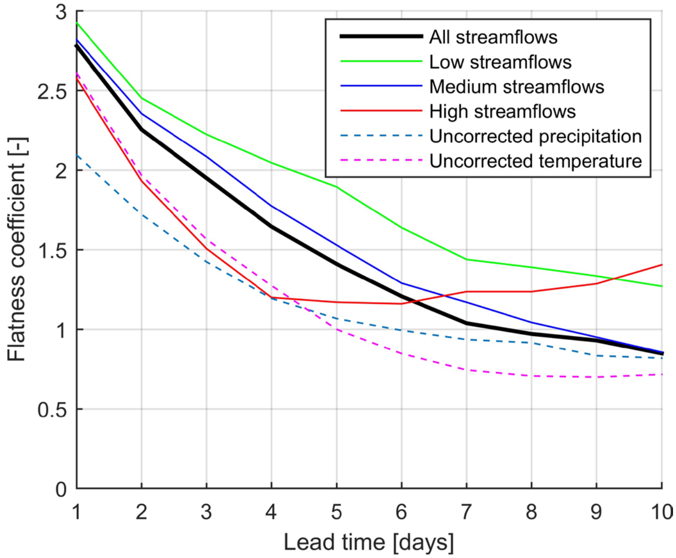

Figure 7: Rank histogram flatness coefficients. The flatness coefficients of the precipitation and temperature forecasts refer to the preceding day.

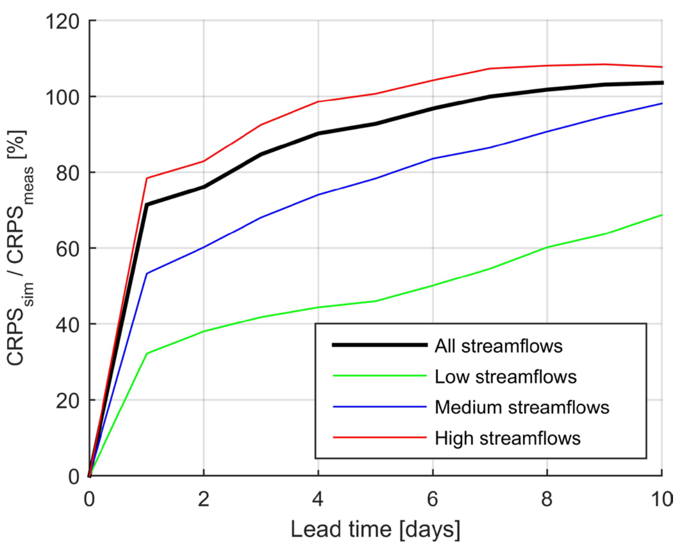

Figure 8: Ratio of errors in meteorological forecasts ($CRPS_{sim}$) to meteorological forecast + model errors ($CRPS_{meas}$)

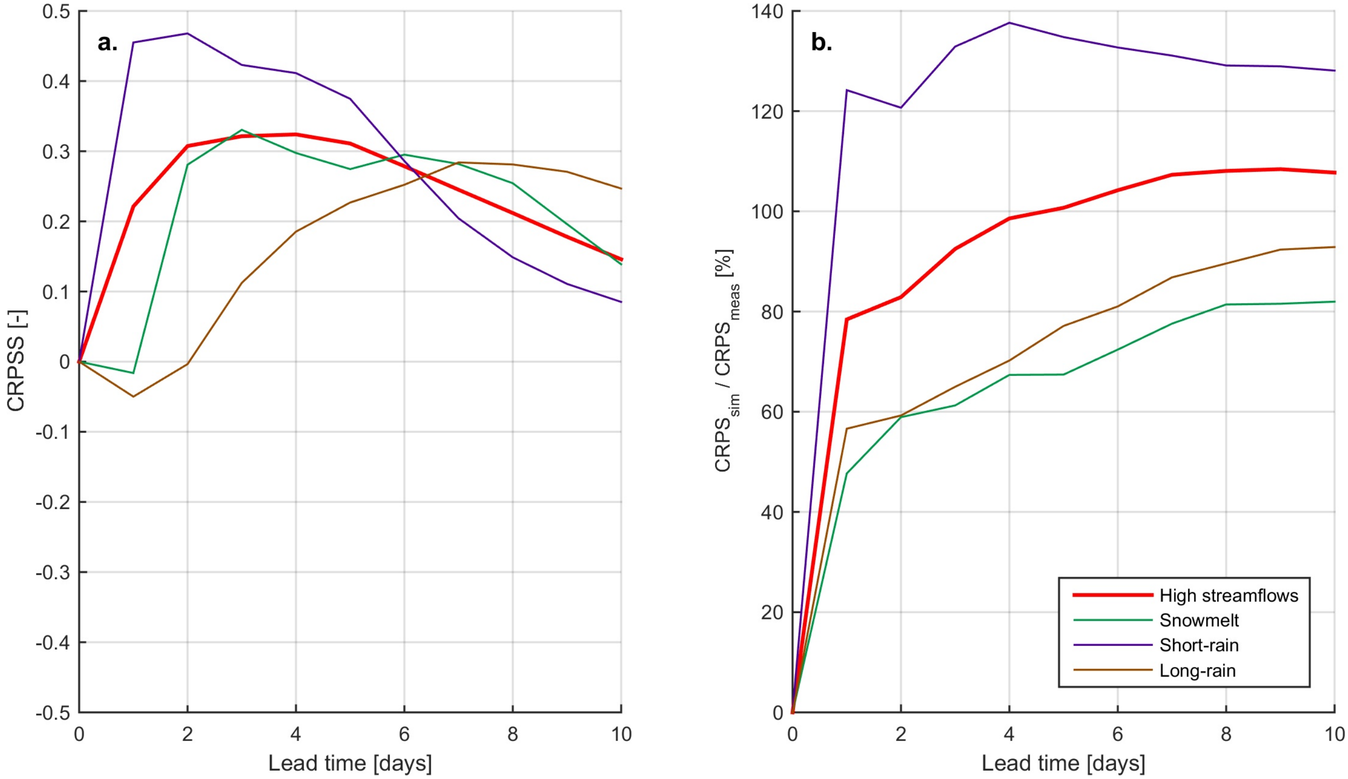

Figure 9: a. Forecast skill of high streamflow generating processes b. Ratio of errors in meteorological forecasts ($CRPS_{sim}$) to meteorological forecast + model errors ($CRPS_{meas}$).

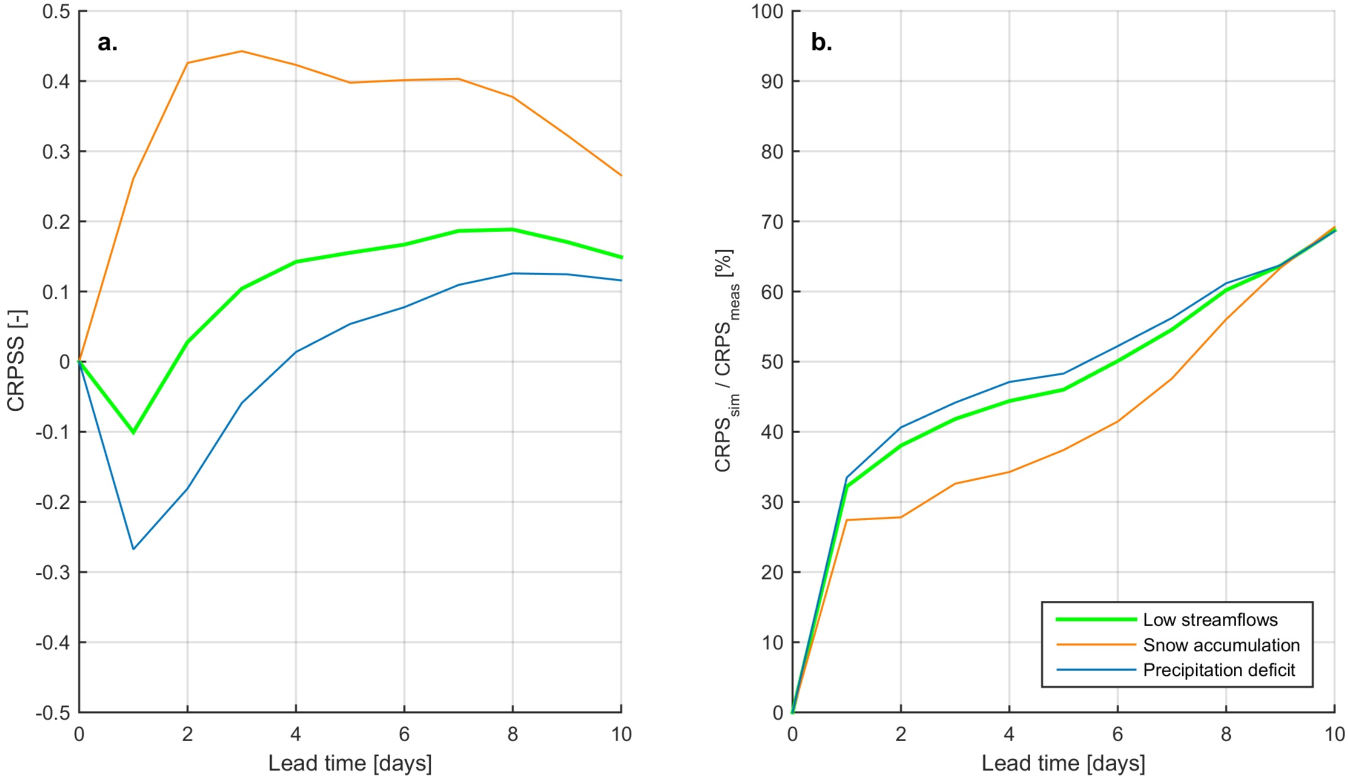

Figure 10: a. Forecast skill of low streamflow generating processes b. Ratio of errors in meteorological forecasts ($CRPS_{sim}$) to meteorological forecast + model errors ($CRPS_{meas}$).

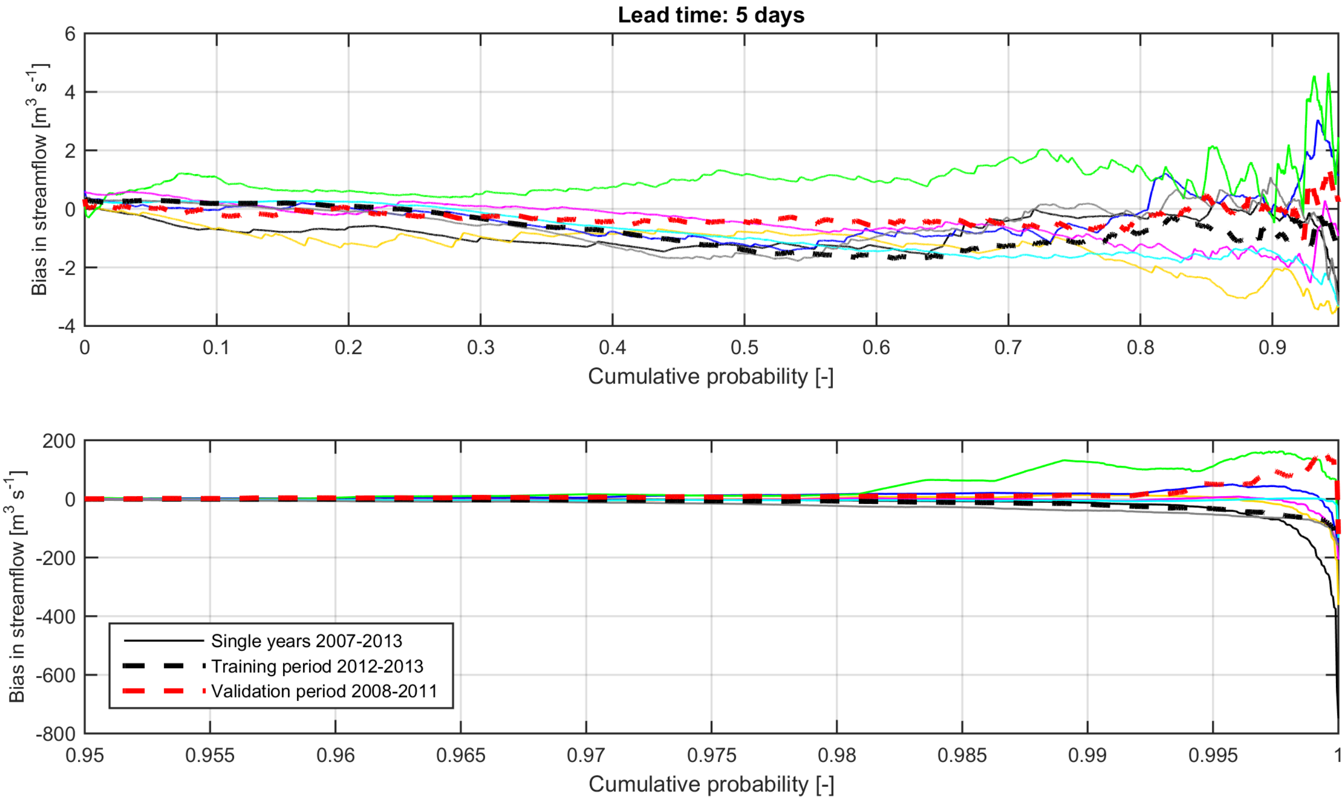

Figure 11: Difference between CDFs of the measurements and CDFs of the uncorrected streamflow forecasts per hydrological year (upper panel cumulative probability 0 – 0.95 and lower panel 0.95 – 1.0). Each thin line refers to a single year between 2007 and 2013. This figure is for a lead time of 5 days.

Tables

Table 1: Definition of streamflow categories

Streamflow category	Thresholds	Streamflow (from measurements 1-11-2007 to 31-10-2013)
Low streamflow	$Q_{obs} \leq Q_{75}$	$Q_{obs} \leq 2.76\ m^3/s$
Medium streamflow	$Q_{75} < Q_{obs} \leq Q_{25}$	$2.76\ m^3/s < Q_{obs} \leq 10.35\ m^3/s$
High streamflow	$Q_{25} < Q_{obs}$	$10.35\ m^3/s < Q_{obs}$

Table 2: Characterization of the high streamflow generating processes

Process	Characterization	Rules for classification
Snowmelt flood	Snowmelt floods and rain-on-snow floods (explained by Merz and Blöschl (2003)) are considered as one category. All high streamflow events where snow is involved are characterized as snowmelt floods, because the snowpack and/or frozen soil underneath play an important role in the runoff process.	• Snowpack (HBV) at day-1
Short-rain flood	Short-rain floods and flash floods (characterized by Merz and Blöschl (2003)) are combined. Flash floods are classed in this category as well, because only daily measurements and forecasts are available.	• No snowpack (HBV) at day-1 • Rainfall at day-1 above 10 mm: With small initial storage in the catchment (HBV), precipitation of 10 mm day^{-1} at the day preceding the streamflow event causes a streamflow event above the high streamflow threshold.
Long-rain flood	Long-rain flood processes are explained by Merz and Blöschl (2003). This category applies when a streamflow event is not directly generated by snowmelt or high precipitation.	• No snowpack (HBV) at day-1 • Rainfall at day-1 below 10 mm

Table 3: Characterization of the low streamflow generating processes

Process	Characterization	Rules for classification
Snow accumulation	If precipitation is snow and does not melt directly, accumulation occurs.	• Snowpack (HBV) at day-1
Precipitation deficit	When low rainfall and high evapotranspiration last over a prolonged period the catchment will dry out.	• No snowpack (HBV) at day-1

Table 4: Calibration and validation performances of the model

Run	Calibration (1-11-1971 to 31-10-2000)			Validation (1-11-2000 to 31-10-2013, excluding 2007)		
	Y	NS	E_{RV}	Y	NS	E_{RV}
Calibration run with input data corrected for elevation	0.81	0.81	0%	0.75	0.78	4.8%
With updating at lead time 0 days	-	-	-	0.82	0.83	1.3%
With updating at lead time 10 days	-	-	-	0.75	0.79	4.4%

Table 5: Performance over the evaluation period 2008-2013, for low, medium and high streamflow simulations (observed meteorological input forecasts). The initial states are updated at the lead time of 0 days.

Lead time [days]	E_{RV} [%] Low flows	Medium flows	High flows	NS [-] Low flows	Medium flows	High flows	E_{RMA} [-] Low flows	Medium flows	High flows
No updating	43.3	7.29	1.81	-10.9	-2.36	0.82	0.71	0.43	0.33
0	3.23	4.69	2.16	0.34	-0.14	0.86	0.11	0.16	0.25
1	6.44	7.16	2.64	-0.64	-0.53	0.84	0.19	0.21	0.29
2	8.55	8.80	2.48	-1.12	-0.88	0.83	0.23	0.25	0.31
3	11.5	9.60	2.30	-2.09	-1.07	0.83	0.29	0.28	0.32
4	13.6	10.1	2.17	-2.76	-1.15	0.83	0.33	0.30	0.32
5	15.9	10.4	2.04	-3.50	-1.33	0.83	0.37	0.31	0.32
6	18.2	10.4	1.98	-4.36	-1.43	0.83	0.41	0.32	0.32
7	19.2	10.5	2.01	-4.56	-1.53	0.83	0.43	0.34	0.32
8	20.6	10.3	2.07	-4.88	-1.62	0.83	0.45	0.35	0.32
9	22.9	10.1	2.09	-5.73	-1.70	0.83	0.49	0.35	0.32
10	24.0	10.0	2.13	-6.09	-1.77	0.83	0.50	0.36	0.32