Journal of Hydrology 555 (2017) 371–384

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

On the incidence of meteorological and hydrological processors: Effect of resolution, sharpness and reliability of hydrological ensemble forecasts

Mabrouk Abaza [a,*], François Anctil [a], Vincent Fortin [b], Luc Perreault [c]

[a] Department of Civil and Water Engineering, pavillon Adrien-Pouliot, 1065, avenue de la Médecine, Université Laval, Québec, Canada
[b] Environment and Climate Change Canada, 2121, Route Transcanadienne Dorval, Montréal, Québec H9P 1J3, Canada
[c] Hydro Québec Research Institute, 1800, Boul. Lionel-Boulet, Varennes J3X 1S1, Canada

ARTICLE INFO

Article history:
Received 1 April 2017
Received in revised form 27 September 2017
Accepted 19 October 2017
Available online 23 October 2017
This manuscript was handled by K. Georgakakos, Editor-in-Chief

Keywords:
Meteorological processor
Hydrological processor
Resolution
Sharpness
Reliability
Performance

ABSTRACT

Meteorological and hydrological ensemble prediction systems are imperfect. Their outputs could often be improved through the use of a statistical processor, opening up the question of the necessity of using both processors (meteorological and hydrological), only one of them, or none. This experiment compares the predictive distributions from four hydrological ensemble prediction systems (H-EPS) utilising the Ensemble Kalman filter (EnKF) probabilistic sequential data assimilation scheme. They differ in the inclusion or not of the Distribution Based Scaling (DBS) method for post-processing meteorological forecasts and the ensemble Bayesian Model Averaging (ensemble BMA) method for hydrological forecast post-processing. The experiment is implemented on three large watersheds and relies on the combination of two meteorological reforecast products: the 4-member Canadian reforecasts from the Canadian Centre for Meteorological and Environmental Prediction (CCMEP) and the 10-member American reforecasts from the National Oceanic and Atmospheric Administration (NOAA), leading to 14 members at each time step. Results show that all four tested H-EPS lead to resolution and sharpness values that are quite similar, with an advantage to DBS + EnKF. The ensemble BMA is unable to compensate for any bias left in the precipitation ensemble forecasts. On the other hand, it succeeds in calibrating ensemble members that are otherwise under-dispersed. If reliability is preferred over resolution and sharpness, DBS + EnKF + ensemble BMA performs best, making use of both processors in the H-EPS system. Conversely, for enhanced resolution and sharpness, DBS is the preferred method.

1. Introduction

Ensemble forecasting is a probabilistic approach that favours the use of multiple model runs with different inputs, initial conditions and/or model physics. Widely used ensemble meteorological forecasts, such as those from the CCMEP (Pellerin et al., 2003), the National Centers for Environmental Prediction (NCEP) (Toth and Kalnay, 1993), or the European Centre for Medium-Range Weather Forecasts (ECMWF) (Buizza et al., 2007), are known to often be under-dispersive and locally biased (Schaake et al., 2007). Biases occur not only in relation to the mean, but also in higher statistical moments of the predictive distribution, limiting the capacity of the ensemble to reliably depict the true uncertainty of the forecast (Eckel and Walters, 1998). As a consequence, usage of raw forecast values may not exploit the full potential of information on predictive uncertainty inherent to the models (Schaake et al., 2007). Retrieving that information requires a meteorological processor to address model biases and dispersion errors of the ensemble members.

For similar reasons, in addition to the post-processing of meteorological data, post-processing of hydrological ensemble forecasts may also be required to guarantee the issued ensemble members are unbiased and exhibit the appropriate spread (Madadgar et al., 2014). Very few studies have previously addressed the comparison between meteorological and hydrological processors (e.g. Zalachori et al., 2012; Roulin and Vannitsem, 2015).

Many popular methods for post-processing ensemble meteorological forecasts are described by Wilks (2006a). Amongst the methods compared are: ensemble Bayesian Model Averaging (ensemble BMA) (Raftery et al., 2005; Baran, 2010), Non-homogeneous Gaussian regression (NGR) (Gneiting et al., 2005), ensemble dressing (Roulston and Smith, 2003; Wang and Bishop, 2005), and logistic regression (Wilks, 2006b). Wilks concluded that

* Corresponding author.
E-mail addresses: mabrouk.abaza.1@ulaval.ca (M. Abaza), francois.anctil@gci.ulaval.ca (F. Anctil), vincent.fortin@canada.ca (V. Fortin), perreault.luc@ireq.ca (L. Perreault).

https://doi.org/10.1016/j.jhydrol.2017.10.038

the most promising methods were NGR, logistic regression, and ensemble dressing. However, ensemble BMA performed well for post-processing of multimodel ensembles. Yang et al. (2017) compared the BMA and heteroscedastic censored logistic regression (HCLR) methods for post-processing of the 11-member Global Ensemble Forecast System reforecasts, where the HCLR method slightly outperforms the BMA. Recently, Khajehei and Moradkhani (2017) used a Bayesian ensemble post-processing approach based on copula functions to improve the reliability of ensemble meteorological forecasts and this method provided a reliable and unbiased ensemble forecast. There few studies which have addressed the post-processing of ensemble hydrological forecasts (Roulin and Vannitsem, 2015; Boucher et al., 2015).

The objective of this study is to obtain hydrological ensemble forecasts with best possible performance and resolution, without reducing the reliability, through the use of both meteorological and hydrological statistical post-processors. Meteorological post-processing is performed by applying the Distribution Based Scaling method (DBS: Rana et al., 2014; Wetterhall et al., 2012), which focuses on reducing the bias of ensemble meteorological reforecasts – it is assumed here that there is no need to improve on the under or over dispersion problems, since that task is accounted by the hydrological processor. Hydrological post-processing is implemented using the ensemble BMA. Raftery et al. (2005) proposed this method to adjust forecast ensemble and generate predictive probability density functions (PDFs) for future weather quantities (Berrocal et al., 2007). The ensemble BMA predictive PDF is defined as a weighted average of predictive PDFs associated with each individual ensemble member, with weights consistent with the member's relative skill.

Two meteorological reforecast products are combined in order to operate with different meteorological ensemble prediction systems: the 4-member Canadian reforecasts from CCMEP and the 10-member American reforecasts from NOAA, leading to 14 members at each time step. Working with reforecast data allows exploration of a long time span and diverse climatic conditions.

The Ensemble Kalman Filter (EnKF), a probabilistic sequential data assimilation technique, is also applied to improve the reliability, sharpness and resolution of the ensemble hydrological reforecasts (e.g. Abaza et al., 2014a; Abaza et al., 2014b; Abaza et al., 2017), prior to hydrological post-processing. Other studies (e.g. Parrish et al., 2012; DeChant and Moradkhani, 2014; Madadgar and Moradkhani, 2014) combine ensemble data assimilation and post-processing methods in order to improve the reliability and performance and reduce the uncertainty of hydrological forecasting. They were shown to outperform applications based on a single component (data assimilation or post-processing).

This paper is organized as follows. In Section 2, we describe the data and watersheds dataset considered herein. In Section 3, the implementation procedure is explained. In Section 4, results and discussion are exposed. Finally, conclusions are presented in Section 5.

2. Material and methodology

2.1. Study area and data

Three watersheds located in the province of Québec (Canada) have been considered in this study (Fig. 1). They all drain a large area, ranging from 9 426 km^2 for the Gouin watershed to 17,109 km^2 for the Outardes-4 watershed. Strategic management decisions are based on hydrological forecasts produced for these sites, namely to prevent flooding damages and avoid operating losses. Therefore, producing skillful hydrological forecasts for these watersheds is of primary importance.

Two meteorological reforecast products are combined: the Global Ensemble Prediction System (GEPS) reforecasts, which are operationally issued by the CCMEP, based on the Global Environmental Multiscale (GEM) model (Girard et al., 2014) And the GEPS reforecasts, which consist of four 50-km members issued once a week over a 32-day horizon, for years spanning from 1995 to 2012 – this span has been extended to 2014 after the end of the calculations presented herein. The four members of the GEPS product are selected from the 20 members of the GEM simulations and member selection varies from year to year.

According to Charron et al. (2010), the deep convection parameterization in GEM is considered has an important impact on the skill and bias of the precipitation forecast. Two parameterizations of comparable skill but differing bias are used in the operational ensemble forecasting system, and each of them is used in 10 members of the 20 member ensemble: odd-numbered members use the Kuo parameterization and even-numbered members use the Kain and Fritsch parameterization (see http://collaboration.cmc.ec.gc.ca/cmc/ensemble/doc/info_geps_e.pdf). Unfortunately, computing resources are insufficient to run a 20-member ensemble reforecast; only four members are available in the reforecast dataset. To be as coherent as possible with its regular 20-member forecast product, four reforecast members are alternately chosen from the initial 20-member GEM runs, and in each case two odd-numbered and two even-numbered members are chosen. Hence, each member includes the same number of times over the years. For example, 1995 exploits members 1, 6, 11, and 16, while 1996, members 2, 7, 12, and 17. Overall, 72 reforecasts are thus issued each time: 4 members over 18 years.

The second product consists of the second generation of NOAA's Global Ensemble Forecast System (GEFS-v2): 11 members (10 + 1 control) over a 16-day horizon, issued each day from December 1984 until present (Hamill et al., 2013). The horizontal resolution of GEFS-v2 is 50 km up to day 8, and subsequently 70 km.

The daily climate input to the hydrological model (precipitation and temperature) also originates from NOAA. It has a grid resolution of about 6 km, covering most of Canada, Mexico, and conterminous U.S. (CONUS), and extends from January 1950 to December 2013 (Livneh et al., 2015). All the reforecast data defined above have been interpolated to each basin, producing an average amount for the watershed as required by the lumped model used in this study (GR4J). In the case of precipitation and temperature observation data, an average of the grid points which are inside of the basin has been used as an average of the input data.

The daily hydrological data (streamflow), provided by Hydro-Québec, extends from 1995 to 2012. It has been split evenly for the calibration and validation of the hydrological model.

2.2. Meteorological processor

A meteorological processor is often required to obtain a maximized resolution, subject to a reliable description of the forecast uncertainty (Gneiting and Raftery, 2007). A range of tools exist for this (e.g. Wilks, 2006a), such as the ensemble BMA, Ensemble Model Output Statistics (EMOS), kernel dressing, and parametric statistical methods (e.g. Scheuerer and Hamill, 2015). Considering that a hydrological processor is also used in this study, a meteorological processor was selected that would focus exclusively on the correction of the local bias: the Distribution Based Scaling (DBS) method (Yang et al., 2010). The fact that DBS does not improve the dispersion of the ensemble is not detrimental to the study since a hydrological processor is available for this purpose at the end modelling chain, if needed. The DBS approach operates directly on the precipitation outputs in order to preserve the statistical distribution of the observed precipitation for the reference period (Seaby et al., 2013). Application of the DBS consists of two steps: