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Monthly water balance modeling: Probabilistic, possibilistic and hybrid methods for model combination and ensemble simulation

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SUMMARY

Multi-model (ensemble, or committee) techniques have shown to be an effective way to improve hydrological prediction performance and provide uncertainty information. This paper presents two novel multi-model ensemble techniques, one probabilistic, Modified Bootstrap Ensemble Model (*MBEM*), and one possibilistic, FUzzy C-means Ensemble based on data Pattern (*FUCEP*). The paper also explores utilization of the Ordinary Kriging (*OK*) method as a multi-model combination scheme for hydrological simulation/prediction. These techniques are compared against Bayesian Model Averaging (*BMA*) and Weighted Average (*WA*) methods to demonstrate their effectiveness. The mentioned techniques are applied to the three monthly water balance models used to generate stream flow simulations for two mountainous basins in the South-West of Iran. For both basins, the results demonstrate that *MBEM* and *FUCEP* generate more skillful and reliable probabilistic predictions, outperforming all the other techniques. We have also found that *OK* did not demonstrate any improved skill as a simple combination method over *WA* scheme for neither of the basins.

1. Introduction

Hydrologic models are simple mathematical representation of complex real world hydrologic processes and therefore they are prone to error and uncertainty in capturing reality. There is a wide range of uncertainty evaluation methods which can be grouped into the three categories: probabilistic, possibilistic and hybrid methods. Probabilistic methods typically refer to *cdf* (cumulative distribution function) or *pdf* (probable distribution function) of parameters, input or output variables (Tung, 1996; Melching, 1992; Kuczera and Parent, 1998; Beven and Binley, 1992; Thiemann et al., 2001; Krzysztofowicz, 2002; Ruessink, 2008). The second category includes the possibilistic methods with foundation in fuzzy logic (Montanari, 2007). Fuzzy tools are suitable for evaluation of conceptual/structural vagueness while statistical approaches are developed to assess probability of event occurrence (Kosko, 1990). The third category includes hybrid methods – they employ ideas from possibilistic and probabilistic methods. An example of such a method is *UNEEC* (Shrestha and Solomatine, 2006; Solomatine and Shrestha, 2009) – it uses fuzzy clustering and probabilistic descriptors of uncertainty. Further details of this classification can be found in Nasseri et al. (2013).

Despite all the efforts and resources invested in developing an accurate hydrologic model, no one can claim that any single model is better than the rest in capturing hydrological processes under all conditions and for all type of cases (Beven, 2006; Duan et al., 2007; Fenicia et al., 2007). Each conceptual platform may demonstrate strength for specific case studies and under particular conditions.

Ensemble simulation and multi-model combination techniques can dampen some of these structural flaws by providing a platform for various models with different weaknesses and strengths to be contested in order to identify the superior model at any given time. These techniques also offer some insight about the likelihood of prediction at each time step. In this paper we found useful to use the following (different) definitions for ensemble simulation and multi-model combination: model combination results in a deterministic hydrologic variables estimation based on outputs from several models, while the term "ensemble simulation" is used to

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denote experiments to estimate output uncertainty, e.g. prediction intervals. (Both of them can use the same mathematical apparatus however).

Combination of multiple models has been applied in different scientific field including economic, management and weather forecasting (Clemen, 1989). Most of the studies demonstrated that multi-model combination yields more accurate predictions than the best individual model in the ensemble set (Vislocky and Fritsch, 1995; Fritsch et al., 2000). A number of applications of multi-models in hydrology have been demonstrated; typically these are conceptual hydrological models that are combined by simple or weighted averaging (Bayesian Model Averaging also can be attributed to this class) (e.g., Georgakakos et al., 2004; Ajami et al., 2006; Duan et al., 2007). In other cases multiple data-driven models are employed to model particular aspects of the rainfall–runoff process and then combined in an optimal fashion (e.g., Solomatine and Xue, 2004; Solomatine, 2006; Jain and Srinivasulu, 2006; Corzo and Solomatine, 2007).

Apart from (linear) weighted averaging, Artificial Intelligence methods (*AI*) and Fuzzy Systems are employed for models combination as well. For example, different Artificial Neural Network (*ANN*) structures, fuzzy rule bases, Neuro-Fuzzy networks and Fuzzy regression have been used for combining results of hydrological models (Shamseldin et al., 1997; Shamseldin and O'Connor, 1999; Xiong et al., 2001; Coulibaly et al., 2005; Asefa, 2009; Araghinejad et al., 2011). Fenicia et al. (2007) and Kayastha et al. (2013) used so-called optimal fuzzy committees to combine two specialized conceptual hydrological models, each calibrated for a particular hydrological regime.

Ensemble forecasting and combination has been also used in climatic modeling (Krishnamurti et al., 1999, 2000, 2003; Kharin and Zwiers, 2002; Kumar et al., 2003; Coelho et al., 2004). Due to an increased interest to ensemble modeling and explicit accounting for uncertainty, in the last decade Bayesian Model Average (*BMA*) method (see e.g. Raftery et al., 2005) became a popular framework in combining models. It was developed for combining distributions from different models in an ensemble: the Probability Density Function (*pdf*) of forecast is calculated using weighted average of estimated *pdf* for each individual model forecasts. *BMA* is also used as the methodological basis in combining the deterministic model outputs as well (being in this case weighted averaging where higher weights are given to models with higher likelihood). Duan et al. (2007) used *BMA* to combine three daily rainfall–runoff models. They examined efficiency of the proposed method for three catchments successfully, assuming that the model results followed normal distribution. Sloughter et al. (2007) also applied the *BMA* for probabilistic quantitative precipitation forecasting in which predicted *pdf*s are not approximated by normal distribution. Zhang et al. (2009) used *BMA* to achieve the best interval response of multiple *SWAT* models, which were calibrated using Genetic Algorithm (*GA*).

Bootstraping is another technique applied for hydrologic ensemble forecasting (Sharma and Tiwari, 2009; Tiwari and Chatterjee, 2010). It is an iterative sampling-simulation method which uses nonparametric statistical analysis, and makes no statistical assumption about the distribution of the predictions (Selle and Hannah, 2010).

This study presents two novel ensemble forecasting methods which evaluate uncertainty of multi-model structures. The first method is a Bootstrap-based method – Modified Bootstrap Ensemble Modeling (*MBEM*) technique. The second method, entitled "FUzzy C-means Ensemble based on data Pattern" (*FUCEP*), couples Fuzzy C-means Regression (*FCR*) with the *UNNEC* method (Uncertainty Estimation based on local Errors and Clustering). The main novel aspects of the proposed methods can be listed as follows:

- Combination of *UNEEC* and fuzzy c-mean regression and its application in ensemble simulation and
- Combination of bootstrap technique and interval mathematics.

The paper also explores possibility of application of Ordinary Kriging (*OK*) for hydrological multi-model combination, to the best of our knowledge, for the first time. In order to evaluate the skill and strength of the newly proposed techniques in comparison to the existing model averaging techniques, their performance is compared to *BMA* and Weighted Averaging (*WA*). In this study, both uncertain interval and deterministic results have been obtained from *MBEM*, *FUCEP*, and *OK* methods and are compared with previously developed ensemble simulation and model combination techniques. Three water balance models employed to generate the hydrologic ensembles over two mountainous basins located in South-West part of Iran were used as case studies.

2. Case studies

The considered two mountainous basins are located in the South-East of Iran. The first basin is Roudzard Basin, which is a sub-basin of Jarrahi River Basin, located North of the Persian Gulf. This watershed includes four sub-basins and its total area is near 900 km^2. This basin is located between 49°39′ to 50°10′ Eastern longitude and 31°21′ to 31°41′ Northern latitude. The average elevation of the watershed is nearly 1200 masl ranging from 340 to 3300 masl. Average precipitation over the watershed is about 700 mm/yr and its runoff coefficient is about 54%. Snowmelt has noticeable contribution in the total runoff of this basin. The rainfall–runoff dataset for this basin consists of the observations in the period of September 1977–August 2009. The precipitation data used in this study include daily observed records in 8 rain gauge stations located in this basin. These stations are scattered relatively properly over the basin. In this study, Thissen polygon method is used to estimate areal average monthly precipitation time series over the basin. This dataset has also been used by Nasseri et al. (2012).

The second study area is Karoon III Basin. It is a sub-basin of the Great Karoon River basin in the southwest of Iran. This basin is one of the greatest Iranian basins and several dams have been constructed in this basin downstream of Karoon III reservoir (Pole Shaloo). It should be noted that the runoff data which has been used for this basin is not affected by any regulating structure. The basin lies within 49°30′–52° Eastern longitudes and 30°–32°30′ Northern latitudes with an area of approximately 24,200 km^2. The elevation of the basin ranges from 700 to 4500 masl. About 50% of the basin area has an altitude higher than 2500 masl and average annual precipitation of the basin is about 760 mm. The rainfall–runoff dataset for this basin consists of the observations in the period of October 1974–April 2003. The precipitation data used in this study for Karoon III basin include daily observed records in 30 rain gauge stations scattered over the basin. This dataset has also been used by Taheri Shahriaeni et al. (2012) (in daily resolution) and Nasseri et al. (2013). Thiessen polygon method has also been used to estimate areal average monthly precipitation time series over Karoon III basin.

Information about these basins has been extracted from the Iranian hydrological data bank provided by the Iranian Ministry of Energy. Brief statistical information about the hydrology of these basins is presented in Table 1. The location maps of the basins are shown in Fig. 1. For both basins, 70% of the available datasets have been used for calibration and the remaining part – for validation. In the next section of the paper, the selected monthly water balance models are described.