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Internal validation of conceptual rainfall–runoff models using baseflow separation

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SUMMARY

An important tool in the management of floods is the use of rainfall–runoff models to predict the arrival of discharge peaks. These models generally use rainfall and potential evapotranspiration rates as input, and relate these to the catchment discharge through a number of conceptual equations. The parameters of these equations are estimated through a comparison of the modeled discharge to the observations. Only one variable, catchment discharge, is thus generally used to calibrate and validate these models. The objective of this paper is to validate the internal model dynamics of two widely used rainfall–runoff models using baseflow estimates. The baseflow time series used in this paper are obtained through the use of a physically-based digital baseflow filter. These models, the Hydrologiska Byråns Vattenbalansavdelning (HBV) model and the Probability Distributed Model (PDM), were calibrated using 1 year of hourly discharge data. The HBV model uses a linear reservoir for the modeling of groundwater flow, while the PDM uses a cubic reservoir for this purpose. In order to assess the impact of the type of reservoir choice, the cubic reservoir in the PDM was also replaced by a linear reservoir. Two different parameter estimation algorithms were used for model calibration. The Shuffled Complex Evolution (SCE-UA) algorithm minimizes the Root Mean Square Error between the model simulations and the observations, while Multistart Weight-Adaptive Recursive Parameter Estimation (MWARPE) uses the Extended Kalman Filter equations in an iterative, Monte-Carlo framework. MWARPE was found to lead to the best discharge simulations, but the differences with the results obtained from the SCE-UA algorithm were relatively small. When only the modeled discharge was analyzed, no clear picture emerged of which model produced the best results. However, it has been found that the replacement of the cubic groundwater reservoir in the PDM by a linear reservoir resulted in a strongly improved model performance with respect to the baseflow. Further, MWARPE consistently led to the best baseflow estimates for the three models, while the HBV model resulted in the best simulations of the baseflow, regardless of the calibration algorithm. The overall conclusion of this paper is that, even though it may be difficult to assess which model and calibration algorithm resulted in the best discharge estimates, the MWARPE calibration algorithm and the HBV model consistently led to the best internal model dynamics.

Introduction

Floods are among the most common natural disasters in the world. For example, in the Northern part of Belgium, eight floods causing severe economic loss occurred during the last 15 years. Among other infrastructure protecting measures, one indispensable tool to manage floods is the use of hydrologic models to predict the arrival of discharge peaks. Examples of such models are the Hydrologiska Byråns Vattenbalansavdelning (HBV) model (Linström et al., 1997) and the Probability Distributed Model (PDM) (Moore, 2007).

These operational flood forecast models schematize a catchment as a number of reservoirs (for example a subsurface reservoir and a groundwater reservoir), which are connected through a number of flows. The equations for these flows are determined empirically, meaning that they have no real physical basis. The parameters for these equations are then estimated through a comparison of the modeled discharge rates to observations, and a tuning of the parameters until a good fit has been obtained. A large number of methods have been developed for this purpose, for example the parameter estimation (PEST) method (Doherty, 2001), the Shuffled Complex Evolution (SCE-UA) algorithm (Duan et al., 1994; Yapo et al., 1998; Vrugt et al., 2003a,b), genetic algorithms (Reed et al., 2000, 2003), the Multiple Start Simplex (MSX) and local Simplex methods (Gan and Biftu, 1996), and simulated annealing (Thyer et al., 1999). In the application of these methods for operational rainfall–runoff modeling, a number of problems arise.

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One problem frequently encountered with these algorithms is that, since high flows occur relatively rarely, low flows will have an excessive weight in the parameter estimation, which will lead to model parameters that will result in a good model performance under low flow conditions, but not under high flow. A possible solution to this problem is to use two different simulations (one calibrated for high and the other calibrated for low flows), and to weigh these simulations using a seasonal index (Oudin et al., 2006). Another possible solution is the use of the Extended Kalman Filter equations in an iterative, Monte-Carlo framework (Multistart Weight-Adaptive Recursive Parameter Estimation or MWARPE) (Pauwels, 2008). A third possible solution is to calculate multiple objective functions, and to choose among the parameter combinations on the Pareto-front (Yapo et al., 1998; Madsen, 2000; Madsen et al., 2002; Vrugt et al., 2003a; Ajami et al., 2004; Vrugt and Robinson, 2007). Further, as noted by Vrugt et al. (2005), the above listed approaches assume that the mismatch between the observations and model simulations is due explicitly to errors in the model parameters, and disregard the effect of uncertainty in the forcing data, the model structure, the parameters, and the observations. Methodologies to take into account these other sources of error are Bayesian recursive parameter estimation (Thiemann et al., 2001; Kaheil et al., 2006), the combination of global optimization and data assimilation (Vrugt et al., 2005), the Integrated Bayesian Uncertainty Estimator (IBUNE) methodology (Ajami et al., 2007), and the use of the MWARPE method (Pauwels, 2008).

A second problem is that operational flood forecast models are usually calibrated and validated using only observed discharge rates, while internally they calculate a number of additional states and fluxes. More than a decade ago, Beven and Binley (1992) already showed that identical model results can be obtained using widely varying parameter combinations. This means that similar discharge rates can be modeled with very different combinations of for example baseflow and surface runoff. Although calibration and validation of rainfall–runoff models using streamflow records has been performed for decades, very few attempts have been made to use baseflow estimates for this purpose. Recently, Rouhani et al. (2007) used graphically obtained baseflow estimates to calibrate and validate the Soil Water Assessment Tool (SWAT). However, since a number of physically-based digital baseflow separation algorithms have been developed (Furey and Gupta, 2001, 2003; Huyck et al., 2005), the possibility exists to use continuous estimates of baseflow for the calibration and validation of rainfall–runoff models.

The objective of this paper is to validate two well known rainfall–runoff models, which are calibrated using discharge time series, using baseflow estimates obtained from a physically-based digital baseflow filter. In other words, the problem analyzed is which type of model leads to the most realistic internal model dynamics, if the model is calibrated in the traditional way, meaning that only discharge records were used for model parameter estimation. Since operational flood forecasting is usually performed using conceptual rainfall–runoff models, two different models of this type are used for this purpose. The first model, the HBV model, assumes a linear relationship between the saturated zone storage and the baseflow (Linström et al., 1997). A second model, the PDM, assumes a cubic relationship, meaning that the baseflow is proportional to the third power of the saturated zone storage (Moore, 2007). However, Fenicia et al. (2006) demonstrated that the groundwater reservoir is best modeled in a linear manner. For this reason, the PDM is also calibrated and validated using a linear reservoir formulation for the baseflow. In order to generalize the results, the parameters of the models are estimated using two different algorithms, more specifically the SCE-UA algorithm and MWARPE. The SCE-UA algorithm calculates the Root Mean Square Error between the modeled and observed discharge, and searches for parameter values that minimize this RMSE. MWARPE uses the Extended Kalman Filter equations in an iterative, Monte-Carlo framework in order to search for the optimal parameter values. In other words, no RMSE is ever calculated. Because of its theoretical foundation, it has been shown that this method is much less prone to the above mentioned problems (too much weight given to low flows and errors in the internal model dynamics) than traditional RMSE minimizing methods (Pauwels, 2008). Using the calibrated model parameters, the modeled baseflow rates are then compared to estimates of the catchment baseflow, obtained using a physically-based digital baseflow filter (Huyck et al., 2005). It is assessed which type of reservoir choice, model formulation, and calibration algorithm leads to the best estimate of the catchment baseflow, and consequently to the best internal model dynamics.

Site and data description

The study was performed in a subcatchment of the Dender catchment in Belgium, more specifically the Bellebeek catchment. The elevation ranges between 10 and 110 m. Soil texture is predominantly loam (75%), and the land use is predominantly agriculture (63%) and pasture (22%). The surface area of the catchment is 87.36 km^2. Fig. 1 shows the location of the catchment together with a Digital Elevation Model (DEM) of the area.

Discharge observations were continuously available at the outlet of the catchment. Precipitation rates as well as the required meteorologic data to calculate potential evapotranspiration rates according to the method of Hargreaves, were continuously measured at the meteorologic station of Liedekerke, situated near the outlet of the catchment. The Hargreaves equation, as explained in Shuttleworth (1992), can be written as:

$$E = 9.5833 \times 10^{-5} S_0 \bar{\delta}_T (T_a + 17.8) \quad (1)$$

E is the potential evapotranspiration (mm h^{-1}), S_0 the water equivalent of extraterrestrial radiation (mm h^{-1}), T_a is the air temperature (C), and $\bar{\delta}_T$ is the difference between the mean monthly maximum and minimum air temperatures (C). At the meteorological station of Liedekerke, net radiation was measured instead of solar radiation. For this reason, a regression was made between the solar and net radiation measured at a meteorological station in Gooik (approximately 2 km to the South of the catchment, for which data were available for approximately 1 year, with many data gaps). This regression yielded a value of 0.91 for the R^2, and was thus used to convert the net radiation into solar radiation. Both the discharge observations and the meteorologic data were available at a 15 min interval and were aggregated to an hourly time step.

Currently, the catchment is being used for operational flood forecasting. However, these studies all focus on matching total discharge observations. More detailed studies of water flows in the catchment have not yet been performed. For this reason, the approach using alternative validation methods developed in this paper is an attractive tool for model improvement.

Meteorological observations from August 1, 2006, through April 30, 2008, were used in this study. In order to analyze the meteorological conditions during the study period, the observations of the precipitation were compared to the statistics of 105 years of precipitation from the meteorological station in Uccle, situated close to Brussels (De Jongh et al., 2006). This 105 year data set indicates that the average precipitation in the area is 780 mm per year. For the year 2007, the only complete year in the study period, the total precipitation was 847 mm, which is relatively close to the mean. However, Table 1 lists the monthly total precipitation throughout the study period, combined with the 105 year averages. Table 1 clearly shows that, even though the annual total precipitation is