Evaluation of a Multistart Kalman Filter Based Method for Model Parameter Estimation

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Abstract In the last few years, the importance of uncertainty in the data sets used for the estimation of model parameters has been widely acknowledged. In this presentation, an iterative model calibration method, based on the Kalman Filter equations, is developed. The advantage of this algorithm are that uncertainty in the calibration data, the parameter values, the model structure, and the model forcings are taken into account. The iteration procedure is applied to a pre-defined number of starting points, increasing the chance that the global optimum, instead of a local optimum, is found. The methodology is applied to a simple rainfall-runoff model for the Zwalm catchment in Belgium. The results are compared to widely used model calibration techniques such as the shuffled complex evolution method or simulated annealing.

1. Introduction

One of the major difficulties in the application of hydrologic models is the estimation of the value of the relatively large number of required parameters. These parameter estimates are usually obtained by applying the model for a specified calibration period, comparing the model results to observations, and adjusting the model parameter values until a reasonable fit is observed. The adjustment of the parameter values can be performed both manually and automatically. Since manual model calibration is a very labor-intensive task, of which the results strongly depend on the experience of the modeler, it is now commonly accepted that hydrologic models should be calibrated using automatic algorithms. In these methods, an objective function is calculated, which is an indication of the mismatch between the observations and the model results. This function is then optimized. For this purpose, a large number of methods have been developed, of which the Shuffled Complex Evolution (SCE-UA) algorithm [Duan et al., 1992] and Simulated Annealing (SA) [Thyer et al., 1999] are two examples. The major drawback of these methods is that they assume that errors in the model results are caused uniquely by errors in the parameter values, and thus that errors in the model structure, the model parameters, and the forcing data are negelected. Recently, a number of steps have been made towards a more integrated manner for model parameter estimation, through a combination of global optimization and data assimilation [Vrugt et al., 2005] or through the use of multimodel ensembles [Ajami et al., 2007]. The objective of this presentation is to develop a model calibration procedure, in which all the aforementioned sources of error are taken into account. The algorithm is based on Goegebeur and Pauwels [2007], in which the Extended Kalman Filter equations are used for model parameter estimation. In this presentation, this methodology is applied in a Monte-Carlo framework, increasing the chances that a global optimum is found. The results of the model parameter estimation procedure are compared to the results from two commonly used algorithms, more specifically the SCE-UA and SA methods.

2. Description of the Calibration Method

As stated above, the Extended Kalman Filter equations are used in an iterative framework. A detailed description of the algorithm and the equations can be found in Goegebeur and Pauwels [2007]. Using an initial value for all calibrated parameters, the model is applied. Then, the first derivative of all model results for which observations are available with respect to each parameter value is calculated. Using this first derivative the model parameters are updated, and the algorithm is repeated until either convergence is obtained or a predefined number of iterations has been reached. The advantage of this method is that uncertainty in the model parameters, the observations, the model structure, and the meteorological forcings are taken into account.

The major difference between this method and traditionally used methods is that in traditional methods the mismatch between observations and model results is lumped into one single number, usually the Root Mean Square Error (RMSE), which does not happen here. In this method, the algorithm does not calculate an RMSE or other objective function, and neither the first derivative thereof. The difference between the observation and the model result for each observation is explicitly taken into account.

In order to increase the chances of finding the global optimum, the methodology is applied in a Monte-Carlo framework. This means that a pre-defined number of starting points, each with different combinations of parameter values, are randomly generated, and that the iteration procedure is applied to each of these starting points.

3. Model Description

The rainfall-runoff model used in this presentation is also described in detail in Goegebeur and Pauwels [2007]. Figure 1 shows a schematic of the model.

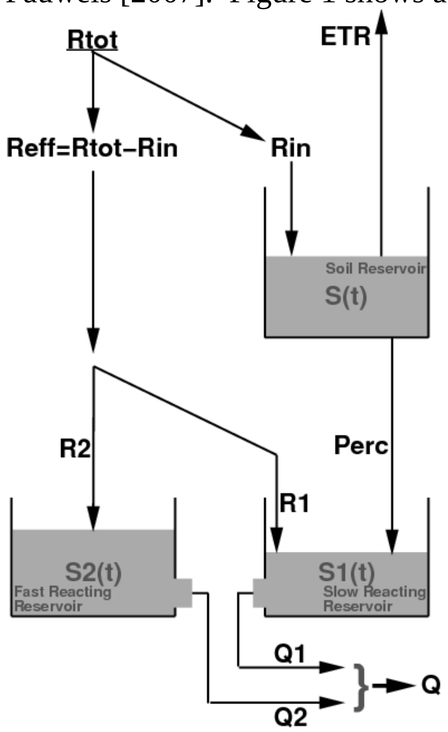

Figure 1. The rainfall-runoff model used in this study.

Meteorological inputs are the precipitation rates and the potential evapotranspiration. The precipitation is participated into infiltration and surface runoff. A part of the surface runoff enters a fast reacting reservoir, while the remaining part of it enters the slow reacting reservoir. The actual evapotranspiration and the percolation to the slow reacting reservoir are calculated using the amount of water stored in the soil reservoir. The sum of the outflows from the slow and the fast reacting reservoirs is the total discharge. For all three reservoirs the storage at the end of the time step is calculated using the initial storage and the netto sum of the incoming and outgoing fluxes. For this model, ten parameters are required, which will be estimated using the above mentioned algorithms.

4. Expected Results

The results that can be expected from this study are an assessment of the Kalman Filter-based method for model parameter estimation, and a comparison with two widely used model calibration methods.

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