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Parameterising hydrological models – Comparing optimisation and robust parameter estimation

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SUMMARY

In most conditions, calibration is a prerequisite for successfully applying conceptual and physically based rainfall–runoff models. The goal of this paper is to comparatively analyse the potential of both event-based automatic calibration (PEST) as described in Skahill and Doherty (2006) and robust parameter estimation (ROPE) as proposed by Bárdossy and Singh (2008). The results of our modelling study in the Rietholzbach catchment (Switzerland) show that ROPE performs better in validation of small to medium sized events. This indicates that ROPE might be better suited to parameterise models when the modellers intention is focussed on a maximising the generalisation capacity of the model, e.g. for evaluating transient process characteristics. We base our study on the hydrological model WaSiM-ETH, using a combined ROPE and automatic parameter estimation approach to investigate optimal parameter sets. The PEST algorithm used in this study outperforms the ROPE application by a factor of roughly 100 in terms of time required for computation.

1. Introduction

Generally, any model structure is merely approximating the portrayed natural processes and data is almost always a restrictive factor for setting up complex or physically based models (Wagener et al., 2003). This makes modelling rainfall–runoff processes a challenging task which calls for comprehensive efforts. If flood forecasting in small catchments is considered this challenge becomes even more difficult as the discharge behaviour is dominated by highly nonlinear dynamic processes. This, amongst other reasons, requires that models have to be adapted to a specific catchment by a parameter vector, i.e. a set of hydrological parameters needs to be calibrated. In this context, hydrological models are not yet able to equally well describe the full range of processes that drive the runoff generation. This holds both for simple conceptual models and detailed process models with physically based components. Applicability of simple empirical and conceptual models is limited to conditions represented within the data used for the calibration of their respective parameters. Process-oriented models are supposed to maintain system dynamics even beyond the range of calibration data, but often there are not enough data available to satisfy the requirements of model equations. This leads us to substituting detailed information with “effective” calibrated parameters that work best on the data that is used for calibration. This leads us to a model which works with physically based equations but which lacks process fidelity, some say it is “right for the wrong reason”. Besides missing data, one of the main reasons for lack of process fidelity is that most models are not able to describe the full range of natural dynamics. The lack of process fidelity can be partly compensated for by adapting various parameter vectors according to the actual dominant driving forces of the rainfall–runoff processes. A number of approaches address this way forward. Cullmann et al. (2008) propose an event specific classification method to enable the application of an adequate parameter vector to different classes of flood patterns. Along the same lines Fenicia et al. (2007) had proposed the combination of local models, each best describing a specific range of processes.

One of the keys to successful modelling of rainfall–runoff processes in a specific catchment is the calibration itself. In a classical way this task is formulated as a mathematical optimisation problem for a given single or multi-objective function. The result is a single best performing parameter vector, or a set of equally well performing parameter combinations. Equifinality and the missing consideration of measurement errors can lead to over-fitted models, which consequently lack the robustness (ability to generalise) required for operational purposes.

Parametrisation of hydrological models has been the subject of enormous scientific effort throughout the last decades. Event-based or subset-specific variance of best model parameter sets may result from uncertainty of input data, observation data and equifinality of the system (Beven and Binley, 1992). Merz and Blöschl (2003) improved their model by dividing floods into five classes, where different flood formation mechanisms (forces and

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runoff-generating processes) cause varying system response characteristics on the basis of indicators such as timing, storm duration, rainfall depth and catchment state. One main focus was scaling in space, i.e. finding more or less homogeneous regions to be portrayed by parameter ranges determined either by a priori knowledge or by calibration (Gupta et al., 1994; Gupta and Dawdy, 1995; Post and Jakeman, 1996). The results of these studies made a valuable contribution to our general understanding of parametrisation of both conceptual and process models.

However, experience in rainfall–runoff modelling resulted in the awareness that various best parameter sets apply to single events or periods of time (Beven and Freer, 2001). This motivates us to compare a classical optimisation procedure with an alternative methodology for model parameter estimation as described in this paper.

With this study, we intend to contribute to the ongoing research efforts in the field of model calibration. We compare the widely used PEST algorithm and ROPE for calibrating WaSiM-ETH on a consistent data set of hourly recordings from the well-observed Rietholzbach catchment. The event-based calibration results in a number of optimal parameter sets, which are analysed and compared to the results obtained with a comparable, event based application of ROPE. ROPE is based on the concept of data depth and uses information about the location of parameter vectors in n-dimensional space as a means to discriminate between possible parameterisations. Here, the goal is to search for parameter sets that perform well in terms of error criteria and which fulfil geometric criteria representing the robustness of a parametrisation. PEST is a classical search algorithm that is focused on finding minima in error surfaces. A new idea which includes additional information (the data depth) for parameterising models is benchmarked against a classical optimisation approach. Thus we are able give first estimates on additional possibilities ROPE might bring about for calibrating models in watersheds, especially in cases when process characteristics are transient. The joint application of both methodologies offers an additional means of evaluating model parameter identifiability in the context of specific event characteristics reflected by the results of automatic calibration. The analysis in this paper is restricted to selected model parameters, which are well suited to show the potential of the two methods.

2. Material and methods

2.1. Study area, data and model

The Rietholzbach drains a 3.18 km^2 hilly pre-alpine watershed with an average precipitation of 1600 mm per year, generating a mean annual runoff of 1046 mm. It is located in north-eastern Switzerland, in the centre of the Thur basin (Fig. 1), with elevations ranging from 681 to 938 m a.s.l. The land use mainly consists of pasture (67%), the rest being dominated by forest (25%) including a few settlement areas (Table 1).

The soil types range from gley soils to more permeable brown soils and regosols with relatively large soil water storage capacities. The catchment is equipped with a meteorological station, continuous time domain reflectometry (TDR) soil moisture measurements, one weighing lysimeter at a pasture site and a well-defined runoff profile at Rietholzbach gauging station. Datasets for the meteorological input parameters (temperature, humidity, wind, global radiation and precipitation) as well as for soil moisture at a single location (four TDR probes in depths of 15, 55, 80 and 110 cm) and runoff at the catchment outlet were available for the period 1981–2007 (Courtesy of ETH Zürich). In our study we focussed on the largest 24 summer runoff events that we extracted from the flow data of 27 years.

For hydrological modelling of the catchment we used the process-oriented, distributed model WaSiM-ETH (Schulla, 1997; Schulla and Jasper, 2001; Gurtz et al., 2003; Zappa et al., 2003) with a spatial resolution of 50 m. WaSiM transforms rainfall into runoff according to the scheme shown in Fig. 2. Direct runoff (Q_d) is generated at the soil surface. A variable number of soil water compartments (three in Fig. 2) process infiltration from the Green and Ampt approach. Water is transported into the respective deeper sol layers, interflow (Q_{ifl}) is generated in each soil compartment. Q_d is cellwise transferred to the basin outlet; a specific travel time is used to mimic retention. Diffusion is expressed by means of a simple bucket type function (Eq. (1)). The recession coefficient of this function is kd.

$$Qd = Qd_{i-1} \cdot e^{-\Delta t/Kd} \tag{1}$$

where Q_d is the direct runoff and $Q_{d(i-1)}$ is the runoff in the preceding time step Δt. The soil water movement through the layers is modelled by means of a discretised form of the continuity equation.

$$\frac{\Delta\Theta}{\Delta t} = \frac{\Delta q}{\Delta z} = q_{in} - q_{out} \tag{2}$$

Here $\Delta\Theta$ denotes the change in soil water content, Δt defines the time step, Δq is the change in specific flux. The fluxes q_{in} and q_{out} characterize the influx and efflux from the specific soil layer respectively. Finally, Δz defines the thickness of the soil layer. The Van-Genuchten parameters used for the solution of the Richards equation are not subject to calibration in this study. Each soil layer produces interflow (Q_{ifl}) according to (Eq. (3)), which is cellwise scaled with dr.

$$Q_{ifl} = k_s(\Theta_m) \cdot \Delta z \cdot dr \cdot \tan\,\beta \tag{3}$$

where ks = effective hydraulic conductivity as described in Schulla and Jasper (1998), Θ_m = Soil moisture of the specific layer, dr = scalar and β denotes the slope.

The interflow is again transferred to the watershed outlet by means of the flow-time grid and a second bucket type function. Herein, ki represents the recession coefficient in analogy to (Eq. (1), k_d). The soil layers are topping the compartment from which base flow is generated by means of a simple, empirical approach. More details about WaSiM are documented in Schulla (1997) and Schulla and Jasper (1998).

According to previous studies with WaSiM-ETH in the context of flood forecasting (see Cullmann, 2007; Pompe, 2008) we choose the following three conceptual model parameters to be considered for calibration: the recession coefficients for storage of direct runoff k_d and interflow k_i and a scaling parameter for the generation of interflow dr in the unsaturated zone. Reference parameters as shown in Table 2 are derived from Pompe (2008).

2.2. Event-based parameter estimation

Two approaches for parameter estimation are implemented in PEST; both methods try to minimise an objective function that is represented by least squares. PEST requires user specified parameter ranges and start values to optimise the given model. The standard method uses the Gauss–Marquardt–Levenberg (GML) algorithm. The drawback of this method is that the algorithm might converge to local minima, depending on the error surface and the start values for the optimisation run. This nonlinear parameter estimation algorithm is fast and stable as it switches between the steepest gradient search and the Gauss–Newton approach, depending on a scalar of the identity matrix (details in Mohamed and Walsh (1986)). The second method supplied with the PEST suite is the global SCEUA (shuffled complex evolution –