Requirements for case-specific calibration in urban hydrological modeling

K. Sedki[1*], U. Dittmer[1]

[1]Institute for Urban Water Management, Technische Universität Kaiserslautern, Germany

*Corresponding author email: karim.sedki@bauing.uni-kl.de

Highlights

- Requirements for calibration data depend on the aim of the model and on the specific case.
- Rainfall-runoff balances can be used to define starting parameter values for manual calibration.

Introduction

The interpretation of simulation results from urban drainage models always has to consider associated uncertainties. Potential sources of uncertainty are widely discussed in literature (e.g. Deletic et al., 2012). All of these sources have an impact on model parameters. Thus, calibration is performed efficiently if the input data are well prepared and the model parameters are set correctly.
An open question is whether these model parameters are transferable to different objectives and applications of modeling.
The aim of this work is to sum up aspects to define project-specific requirements for calibration data, particularly for long-term simulations. For this reason, in this work an auto-calibration of catchment characteristics with KALIMOD (Henrichs, 2015) was tested for a lumped model in KOSIM (itwh, 2020). The results are compared to manual calibration based on rainfall-runoff-balances.

Methodology

As case study in this work three neighboured catchments (estimated impervious areas: M62: 18.7 ha, M65: 36.2 ha, M67: 17.3 ha) were modelled in KOSIM (itwh, 2020). They are drained in combined sewer system and have a similar settlement structure as well as topography. The measured datasets include time-series of runoff and local precipitation from a campaign of about 6 months for the three catchments. Every time-series was reviewed for completeness and homogeneity with respect to the spatial distribution of precipitation using R-Language.
The measured precipitation data was separated into single events with a semi-automatic toolchain from the R-Package IETD (Duque, 2020). According to Schmitt et al. (2008) thresholds of rainfall-height and -intensity, runoff-volume and flow-depth were used to select events suitable for calibration.
Auto-calibration was performed for five model parameters, describing runoff generation and overland flow: storage count and constant (multiplicated to *TS*), wetting losses (*Vben*), swale storage (*Vmuld*), initial (*PsiA*) and final runoff coefficient (*PsiE* – constant losses) for runoff generation. To assess transferability calibration results were compared for different events at the same site as well as for different sites for the same event.
Established statistical indicators were used to rate the quality of measured data and of calibration results. The selection is based on results from Henrichs (2015). First the Nash-Sutcliffe-Efficiency (*NSE*) was calculated for overall similarity between two measured (precipitation) or measured and simulated (runoff) time series calculated from the residuals of each time step. Second is relative volume error (*PBIAS*) which was also calculated for each time step and third is deviation of peaks (*DYmax*) which was determined for events. The statistical indicators were also used as objectives for the optimization-

algorithm AMALGAM (A Multi-Algorithm Genetically Adaptive Multiobjective method) for multi-objective optimization implemented in KALIMOD.
The measured combined sewer runoff was devided into dry and wet weather flows as basis for rainfall-runoff balancing. The stormwater fraction is used to determine the parameter x_k (Schmitt et al. 2008). The parameter x_k is used to evaluate whether the estimated impervious area is over- or underestimated. It is calculated by rainfall-caused runoff volume (V_R) related to precipitation volume ($V_{N,eff}$, without initial losses) for each event: $x_k = V_R \cdot V_{N,eff}^{\ -1}$.
The resulting parameter-sets for calibrated events were used to identify limitations in the transmission of calibration results. At least x_k is compared for all calibrated events to the resulting value of the auto-calibration for the model parameter *PsiE*, to evaluate if it is possible to use x_k instead of a manual or automatic calibration.
Uncertainties were quantified for the processed calibration using a concept by Jin et al. (2010) with Average Relative Interval Length (*ARIL*) and counting the simulation-results *Within Bounds*. The GLUE-method (Generalised Likelihood Uncertainty Estimation by Beven & Binley 1992) was not applied to avoid the subjective formulation of uncertainty-distribution (Freni et al., 2009).

Results and discussion

Sensitivity analyses confirmed that *PsiE* has the strongest impact on simulation results compared to other parameters. Therefore, *PsiE* is focused in the following. The resulting parameter-values from the auto-calibration showed that calibration has to be made for every single catchment and has limitations in transferability due to catchment characteristics and in particular due to assessment of impervious area. Therefore, comparison of x_k and resulting *PsiE* for five events per studied catchment (M62, M65 and M67) showed minor deviations and confirmed the approach about importance of basics determination, especially for impervious area (Figure 1). Finally, x_k should only be used as start value for manual or auto-calibration. This approach is justified by the parameter-sensitivity which is very sensitive for *PsiE*. The uncertainty-quantification in Figure 1 shows high *ARIL*-values and mid-range values within 5-%-minimum and maximum-quantile (*Within bounds*).

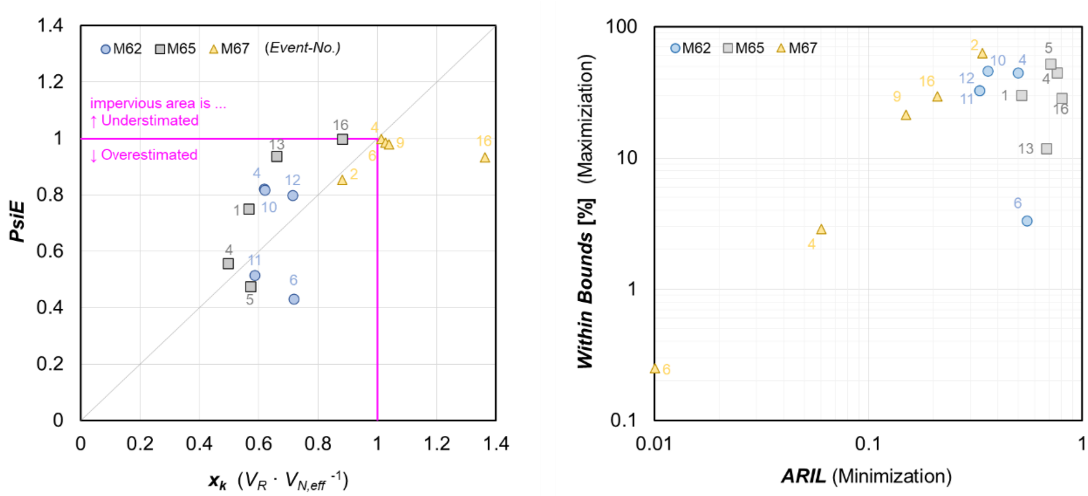

Figure 1. Calibration results of individual events (le.) for parameter *PsiE* compared to x_k for evaluation of estimated imperviousness and (ri.) for uncertainty assessment following Jin et al. (2010).

Other tested parameters were also be calibrated for optimal solutions, but the efficiency-markers used (*NSE*, *PBIAS* and *DYmax*) were not able to achieve complete congruence of measured and simulated time series. For this reason, the pareto-optimal solutions leads to the necessity of assessments of

accuracy and precision to minimize uncertainties. The selection of suitable data and an adequate model concept are essential for building reliable and robust models (e.g. Henrichs, 2015). This applies to both manual and auto-calibration.
Furthermore, differences regarding model concepts and their application according to calibration data have to be considered. In particular, lumped models (often conceptual) reproduce extreme runoff peaks due to short-term high precipitation intensities less accurate than e. g. hydrodynamic models (mostly physical models processed in a distributed way). The results of the auto-calibration show that the quality of calibration is lower for more rare events due to global extremes. For long-term simulations with continuous time series data moderate single events with return periods of less than one year are recommended for model calibration due to their estimated discharge volume.

Conclusions and future work

The rainfall-runoff balances determined as viable alternative to reduce subjectivity in manual calibration due to the similarity of the parameter x_k and the auto-calibrated *PsiE*. Therefore, x_k could be used as starting parameter value for both manual and auto-calibration.
The evaluation of the calibration results showed the need of additional visual time-series comparison. Although it has a subjective and difficult reproducible influence, expert knowledge is an important additional evaluation criterion for calibration (and validation) success because the used objective-functions do not recognize all relevant deviations. The resulting quality is also influenced by the chosen model setup. In order to achieve a given study objective, model users have to set system boundaries and select the appropriate model type. This decision depends not only on the objective of the study but also on the available data, if any data is available.
The model to be selected must contain adjustable parameters the focused process is sensitive to.
At least one main question has to be answered: Which parameters, used to describe the system and processes, can be transferred to other times and/or project-areas?
For the main goal of calibration, to approximate model responses as closely as possible to realistic system behaviour in order to simulate unmeasured outputs as realistically and thus reliably as possible, the basis can be measured or synthetically generated inputs (e.g. long-term precipitation observations). This in mind, model users need to consider the limits of transferability of calibration results, especially when dealing with neighbouring areas or areas with (very) similar characteristics. Reasons for this include the spatial distribution of precipitation and inhomogeneities in soil structure as well as in the topology of the drainage system.

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