Adv. Geosci., 31, 67–74, 2012
www.adv-geosci.net/31/67/2012/
doi:10.5194/adgeo-31-67-2012
© Author(s) 2012. CC Attribution 3.0 License.

Advances in Geosciences

Evaluation of different calibration strategies for large scale continuous hydrological modelling

M. Wallner, U. Haberlandt, and J. Dietrich

Institute of Water Resource Management, Hydrology and Agricultural Hydraulic Engineering, Faculty of Civil Engineering, University Hannover, Germany

Correspondence to: M. Wallner (wallner@iww.uni-hannover.de)

Abstract. For the analysis of climate impact on flood flows and flood frequency in macroscale river basins, hydrological models can be forced by several sets of hourly long-term climate time series. Considering the large number of model units, the small time step and the required recalibrations for different model forcing an efficient calibration strategy and optimisation algorithm are essential.

This study investigates the impact of different calibration strategies and different optimisation algorithms on the performance and robustness of a semi-distributed model. The different calibration strategies were (a) Lumped, (b) 1-Factor, (c) Distributed and (d) Regionalisation. The latter uses catchment characteristics and estimates parameter values via transfer functions. These methods were applied in combination with three different optimisation algorithms: PEST, DDS, and SCE. In addition to the standard temporal evaluation of the calibration strategies, a spatial evaluation was applied. This was done by transferring the parameters from calibrated catchments to uncalibrated ones and validating the model performance of these uncalibrated catchments. The study was carried out for five sub-catchments of the Aller-Leine River Basin in Northern Germany.

The best result for temporal evaluation was achieved by using the combination of the DDS optimisation with the Distributed strategy. The Regionalisation method obtained the weakest performance for temporal evaluation. However, for spatial evaluation the Regionalisation indicated more robust models, closely followed by the Lumped method. The 1-Factor and the Distributed strategy showed clear disadvantages regarding spatial parameter transferability. For the parameter estimation based on catchment descriptors as required for ungauged basins, the Regionalisation strategy seems to be a promising tool particularly in climate impact analysis and for hydrological modelling in general.

1 Introduction

The use of hydrological models for answering questions in water resources management is nowadays the technical standard, not only in sciences. In many cases the modeller has to handle catchments on large scales ranging from 100 km^2 to more than 10 000 km^2. On this scales it is not possible to describe the hydrological cycle of this subsystem (catchment) in physical detail (Chow et al., 1988). There is a number of different process oriented models (some are called physically based), whose parameters are closely related to the physical properties of the catchment. These parameters are inherently uncertain. Moreover, the availability of the required data to estimate the parameters is often a problem considering the scales hydrologists are working on. For example it is hardly possible to get a sufficiently detailed description of the soils. In practice this means that at least some of the parameters have to be estimated via calibration (Beven, 2001) what is done automatically in this study. Taking all parameters of a distributed- or semi-distributed-model into account the dimension Ψ of the parameter search space can be described as:

$$\Psi = N_\mathrm{s} \cdot N_\mathrm{p}, \tag{1}$$

where N_s gives the number of catchment units (normally subbasins or grid cells) and N_p stands for the number of parameter per unit (Pokhrel and Gupta, 2010; Samaniego et al., 2010). The high dimensional parameter search space leads to the problem of equifinality which means, that there are many different parameter sets which will result in comparable solutions with respect to the model performance (Beven, 2001). Generally the dimension of the search space for the calibration should be reduced, for example by eliminating N_s in Eq. (1), in order to make the parameter estimation more robust. Pokhrel and Gupta (2010) achieved good results by reducing the dimension of the calibration problem. Other studies are dealing with the Regionalisation of model parameters, which may lead as well to a more robust model performance. One common approach of Regionalisation is to relate parameters of the model to catchment characteristics. Usually, the hydrological model is calibrated for some selected catchments independently and then the parameters are related to catchment descriptors via (multiple-) regression analysis (Haberlandt et al., 2001; Merz and Bloeschl, 2004). This procedure does not consider the parameter equifinality problem. Another idea is to calibrate parameters for different catchments simultaneously via optimisation of transfer functions which relate the parameters to the catchment characteristics. By reducing the risk of equifinality this approach showed good results in some studies (Hundecha and Bárdossy, 2004; Samaniego et al., 2010). Besides the calibration strategy the selected optimisation method plays an important role in the calibration process of hydrological models. Local search algorithms are fast but are prone to trap into local minima (Abbaspour et al., 2001). One often applied local optimisation tool is PEST (Kim et al., 2007). Sophisticated global search algorithms will more likely find a global optimum (Blasone et al., 2007). Typical candidates are the Shuffled-Complex-Evolution (SCE) method (Duan et al., 1993a) and the Dynamically Dimensioned Search (DDS) algorithm (Tolson and Shoemaker, 2007).

This research is part of a climate impact study. The focus is on long-term continuous hydrological modelling with the well known conceptual model HEC-HMS (Feldman, 2000) at an hourly time step for subsequent flood frequency analyses. For a number of catchments within a macroscale region, several sets of climate data will be used as forcing. Considering the large spatial scale, the small time step and the required recalibrations for different model forcing an efficient calibration strategy and optimisation algorithm are essential. Using a subset of catchments and data the main objective of this study is to find such a strategy together with a suitable optimisation algorithm. In such a framework not only the model performance for single catchments is of interest, but especially the estimation of robust models. Here, the model was considered as robust if its parameters can be transferred to ungauged catchments using a relation between catchment descriptors and model parameters without a significant decrease in model performance. Four different calibration strategies were combined with three different optimisation algorithms. First, a temporal evaluation of all model performances was done via a split sampling of the time series. In a further step a spatial evaluation was carried out, regionalising and applying the calibrated parameters for uncalibrated catchments.

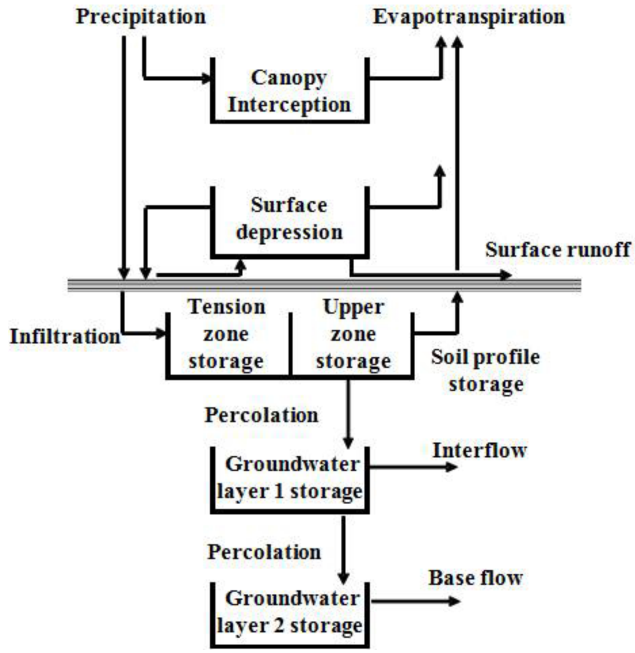

Fig. 1. Structure of the HEC-HMS Model (Bennett and Peters, 2000).

2 Methods

2.1 Hydrological model

The hydrological model used in this investigation was the Hydrological-Modelling-System Version 3.3 from the Hydrologic Engineering Center (HEC-HMS) of the US Army Corps of Engineers (Feldman, 2000). HEC-HMS is a semi-distributed model with horizontal structure realized via subbasins. Figure 1 shows the structure of HEC-HMS (Bennett and Peters, 2000). For runoff generation a Soil Moisture Accounting scheme is used. The runoff concentration of the surface runoff is calculated with Clark's Unit Hydrograph, the interflow and baseflow are calculated with linear reservoirs. All flows in the channel are routed with the Muskingum method. The calculation of the potential evapotranspiration is carried out with the Priestley-Taylor method, the snow melt with the Temperature-Index method. All meteorological input data were interpolated using Ordinary-Kriging for precipitation, External-Drift-Kriging (elevation as secondary information) for temperature and Inverse-Distance for net radiation. The model was run in a continuous mode on an hourly time step.

2.2 Optimisation algorithm

Optimisation algorithms can be generally distinguished between local search algorithms and global search algorithms. In this study both types were used, where PEST (Doherty, 1994) is a local optimisation and SCE (Duan et al., 1994)

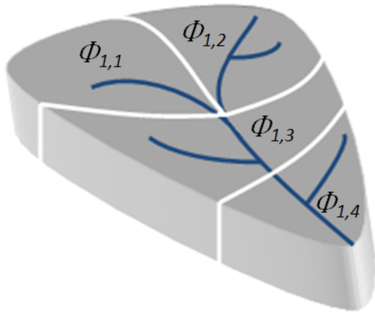

Fig. 2. Typical parameter set up for a semi-distributed model. Every $\Phi_{i,j}$ stands for one parameter value (i = parameter, j = subbasin).

and DDS (Tolson and Shoemaker, 2007) are global optimisation algorithms. PEST uses the Gauss-Marquardt-Levenberg method for nonlinear parameter estimation. One condition for the application of PEST is that the adjustable parameters must be continuously differentiable (Doherty, 1994). The SCE algorithm builds on four well proved concepts: first the combination of random and deterministic, second the concept of clustering, third the concept of systematic evolution and fourth the concept of competitive evolution. The SCE algorithm was created to solve a broad class of problems such as finding solutions for a multi parameter space which is not even continuous (Duan et al., 1993b). The DDS is a stochastic based global search algorithm. For each iteration a set of parameters is selected which are then perturbed by values randomly sampled from a normal distribution. The number of dimensions decreases with an increasing number of iterations, so that the solver searches more globally at the beginning and more locally at the end of the optimisation procedure (Tolson and Shoemaker, 2007).

2.3 Calibration strategies and validation

There are many different approaches for automatic calibration of watershed models. The simplest one is the use of the same parameter value for all subbasins. This strategy is named Lumped (LUM) parameter estimation here. In Fig. 2 a sketch of a semi-distributed model is shown. For each subbasin the parameters $\Phi_{i,j}$ need to be estimated, where the index i stands for the parameter and the index j for the subbasin. For the Lumped method all particular parameter values are equal:

$$\Phi_{i,1} = \Phi_{i,2} = \Phi_{i,3} = \Phi_{i,4} \quad ; \quad i = 1, \ldots, N_\mathrm{p}. \tag{2}$$

This implicates that the dimension of the search space depends only on the number of different parameters N_p. By eliminating the number of subbasins N_s in Eq. (1) the dimension Ψ becomes:

$$\Psi = N_\mathrm{p}. \tag{3}$$

Employing the Lumped method as we do here, the spatial variability of the climate forcing is still represented due to the attribution of time series to the subbasins, but the spatial variability of the parameters is lost. To avoid this, the 1-Factor (1-F) method is introduced. Initial parameter values are defined in a pre-processing step based on basin characteristics such as soil, landuse and topography. As a result spatially variable initial values for the parameters are obtained:

$$\Phi_{i,1} \neq \Phi_{i,2} \neq \Phi_{i,3} \neq \Phi_{i,4} \quad ; \quad i = 1, \ldots, N_\mathrm{p}. \tag{4}$$

Due to the conceptuality of the hydrological model used in this study the prior parameter estimation does not provide reliable values but is more an indicator of the spatial variability of the parameters. In the next step one factor is created for each parameter. These factors are calibrated and then multiplied with the particular parameter values (Pokhrel and Gupta, 2010). The dimension of the search space is independent of the number of subbasins, like for the Lumped strategy, and Eq. (3) is valid. Both strategies are limiting the variability of the parameter values. Either there is no spatial variability (LUM) or the variability is given by pre-processing which depends on the modeller's subjective assessment of the catchment.

Hence a further Distributed calibration strategy (DIS) is applied which considers all parameters for all subcatchments independently. Since each single parameter value is calibrated, the dimension of the parameter search space is the product of the number of subbasins N_s and the number of parameters N_p (Eq. 1) and is generally much larger than for the other methods.

As last calibration strategy the Regionalisation method (REG) is introduced, assuming that the parameters of the hydrological model can be related to basin characteristics. Each parameter value is calculated via transfer functions which have to be pre-defined and should include the main catchment characteristics affecting the particular parameter. The following structure of such a function is used here:

$$\Phi_{i,j} = \sum_{n=1}^{k} \alpha_{i,n} \cdot S_{j,n} + \sum_{m=1}^{u} \beta_{i,m} \cdot L_{j,m} + \gamma_i \cdot \mathrm{Area}_j + \ \ldots$$
$$i = 1, \ldots, N_\mathrm{p};\ j = 1, \ldots, N_\mathrm{s}, \tag{5}$$

where $S_{j,n}$ and $L_{j,m}$ are relative areas of soil- and landuse classes, respectively and k and u are the number of different soil/- landuse classes defined for each subbasin. It is important to note, that not the parameters themselves are calibrated but the coefficients of the transfer function ($\alpha_{i,n}$, $\beta_{i,m}$, γ_i, ...). Further details of this strategy can be found in Hundecha and Bárdossy (2004). The soil classes $S_{j,n}$ were described via fuzzy numbers (Fig. 3). In a first step the main physical descriptor has to be estimated for each parameter (e.g. parameter: maximum infiltration → descriptor: hydraulic conductivity). The estimation of the specific values for these physical descriptors for each soil is based on (Finnern et al., 1994). With these values the fuzzy numbers were set up. For

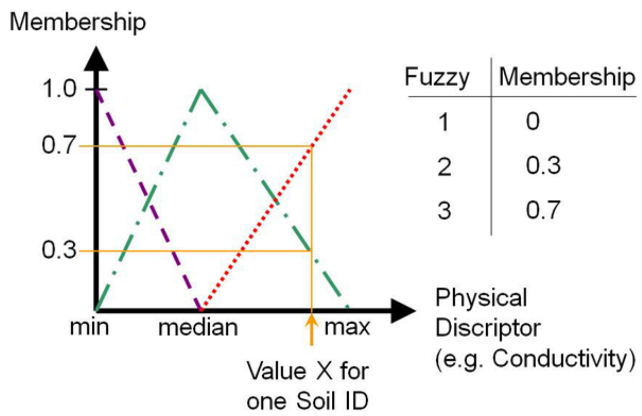

Fig. 3. Example for the definition of the fuzzy numbers for one physical basin descriptor (fuzzy number 1 dashed line; fuzzy number 2 dotted dashed line; fuzzy number 3 dotted line).

each single soil a membership to the fuzzy numbers can be defined. The upscaling of this information to the subbasin was simply done by averaging. The Regionalisation method allows calibrating an arbitrary number of catchments simultaneously with constant dimension of the parameter search space. It uses physical basin characteristics and hydrological information from different sites. In addition, this procedure alleviates the equifinality problem in model parameter regionalisation.

Beside the standard evaluation of the calibration strategies via a temporal split sampling, a spatial split sampling was introduced (only for the DDS calibration). This was done by transferring the parameters from calibrated donor catchments to uncalibrated ones and validating the model performance for these uncalibrated catchments. For the Lumped, 1-Factor and the Distributed method, multiple regressions with the structure of the transfer functions (Eq. 5) were fitted on the calibrated catchments. Then for the uncalibrated catchments the parameters were estimated using these regressions and the catchment characteristics (cf. Eq. 5).

To evaluate the model performance three different objective functions were used. The squared error (SqE):

$$\mathrm{SqE} = \sum_{t=1}^{N} \left(Q_{\mathrm{Obs}}(t) - Q_{\mathrm{Sim}}(t)\right)^2 \quad \rightarrow \quad \mathrm{Min}, \tag{6}$$

the Nash-Sutcliffe efficiency coefficient (NSE) (Nash and Sutcliffe, 1970):

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{N} \left(Q_{\mathrm{Obs}}(t) - Q_{\mathrm{Sim}}(t)\right)^2}{\sum_{t=1}^{N} \left(Q_{\mathrm{Obs}}(t) - \overline{Q_{\mathrm{Obs}}}\right)^2} \quad \rightarrow \quad \mathrm{Max}, \tag{7}$$

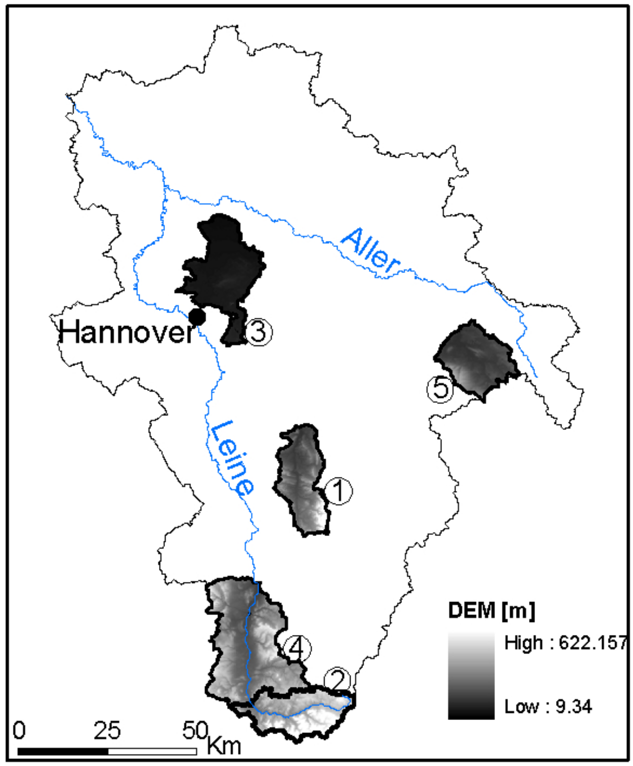

Fig. 4. Aller-Leine River Basin with catchments used for hydrological simulations. The indicated numbers correspond to the catchment ID's in Table 1.

and the volume-error (VoE):

$$\mathrm{VoE} = \frac{\sum_{t=1}^{N} Q_{\mathrm{Obs}}(t) - \sum_{t=1}^{N} Q_{\mathrm{Sim}}(t)}{\sum_{t=1}^{N} Q_{\mathrm{Obs}}(t)} \quad \rightarrow \quad \mathrm{Min}, \tag{8}$$

where $Q_{\mathrm{Obs}}(t)$ and $Q_{\mathrm{Sim}}(t)$ are observed and simulated discharge for each time step, respectively, $\overline{Q_{\mathrm{Obs}}}$ is the mean observed discharge and N is the number of time steps. To combine the NSE and the VoE a multi criteria objective function (ObjFunc) was implemented:

$$\mathrm{ObjFunc} = \sqrt{(1 \cdot (1 - \mathrm{NSE}))^2 + (1.4 \cdot (0 - \mathrm{VoE}))^2} \rightarrow \mathrm{Min}, \tag{9}$$

giving more weight on the volume error.

3 Study area and data

The Aller-Leine river basin covers most of the south-eastern part of Lower Saxony in Germany (Fig. 4). For this investigation five subcatchments with a size between 300 km^2 and 1000 km^2 and with subbasin sizes from 20 km^2 to 40 km^2

Table 1. Characteristics of the catchments (mean values for precipitation, temperature and runoff).

ID	Catchment/Gauge	Area [km^2]	Elevation [m]	Pcp. [mm/yr]	Temp. [°C]	Runoff [m^3 s^{-1}]	No. Subbasins
1	Nette/Derneburg	309	206	872	9.29	2.8	10
2	Leine/Reckershausen	319	340	771	8.61	2.3	10
3	Wietze/Wieckenberg	411	50	722	10.20	2.0	11
4	Leine/Leineturm	990	272	752	8.95	7.8	36
5	Schunter/Glentorf	290	137	727	9.56	1.5	10

were chosen. Some of the basin characteristics are given in Table 1. The climate data for the Aller-Leine catchment (provided by the German Weather Service DWD and Meteomedia) include 100 precipitation stations with a high temporal resolution (≤1 h), 244 precipitation stations with a daily resolution, 38 temperature stations with a high temporal resolution (≤1 h) and 20 other stations for which net radiation was calculated on a daily time step. However, from the large number of recording precipitation stations only 11 stations had an observation period of more than 10 years. The soil map (BüK 1000) with a scale of 1:1 000 000 was provided by the Federal Institute for Geosciences and Natural Resources (BGR), as land cover map CORINE 2000 was used and a digital elevation model (DEM) with a resolution of 10×10 m was provided by the Lower Saxony Water Management, Coastal Defence and Nature Conservation Agency (NLWKN). Discharge time series were obtained for streamflow gauges at the outlets of the five catchments in high temporal resolution (≤1 h). Three of the catchments with gauges: Derneburg, Reckershausen and Wieckenberg, were used for temporal split sampling and all five, including the other two with gauges: Leineturm, Glentorf, for spatial split sampling. The whole study was based on continuous rainfall runoff simulations with an hourly resolution. The calibration period was three years (2004/2007/2008), the validation period two years (2005/2006). The first year (2003) was used as spin-up period to determine the initial conditions for the model.

4 Analysis and results

4.1 Evaluation by temporal split sampling

In addition to the evaluation of the model performance, the efficiency of the different combinations of calibration strategies and optimisation algorithms were investigated. This was done by limiting the number of iterations to 1000 for each catchment and comparing the model performance after applying the different optimisation algorithms. In a first step the squared error (Eq. 6) was used as objective function for the calibration. For the Regionalisation method the standardised objective function (Eq. 9) was implemented. In Fig. 5 the Nash-Sutcliffe efficiency and the volume error (VoE) are illustrated for three catchments, calibrated with the Lumped calibration strategy in combination with the PEST optimisation algorithm. Comparing calibration and validation performances, for all catchments a small decrease of the NSE can be recognised. But the VoE for Derneburg stays nearly the same, and for Reckershausen it even increases. To evaluate these results for all combinations of calibration methods the average of the objective function (Eq. 9) for all three catchments, Derneburg, Reckershausen and Wieckenberg, was calculated and subtracted from 1.00. The closer the results are to 1.00, the better is the model performance. Figure 6 illustrates the results for all combinations. In all cases the performance of the validation period decreased compared to the calibration period. The Lumped method as well as the 1-Factor method showed good results for all three optimisation algorithms in the calibration period. Considering that both methods handle the same dimension of the parameter search space (42 dimensions for all three catchments) the slightly better performance of the 1-Factor method might be due to a good estimation of the spatial variability of the initial parameter set. For the Lumped and 1-Factor method there were no significant differences in performance between

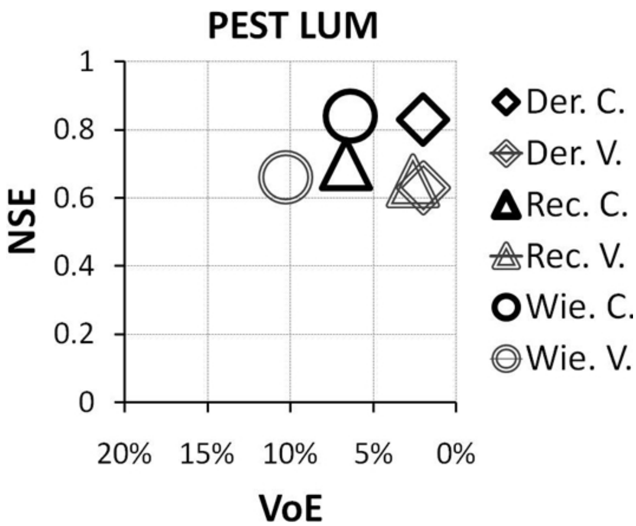

Fig. 5. Model performance for the Lumped calibration strategy in combination with the PEST optimisation algorithm. The ideal point with an NSE = 1 and a VoE = 0 is shown in the top right corner. (Der. = Derneburg; Rec. =Reckershausen; Wie.= Wieckenberg; C. = calibration (years 2004, 2007–2008); V. = validation (years 2005–2006)).

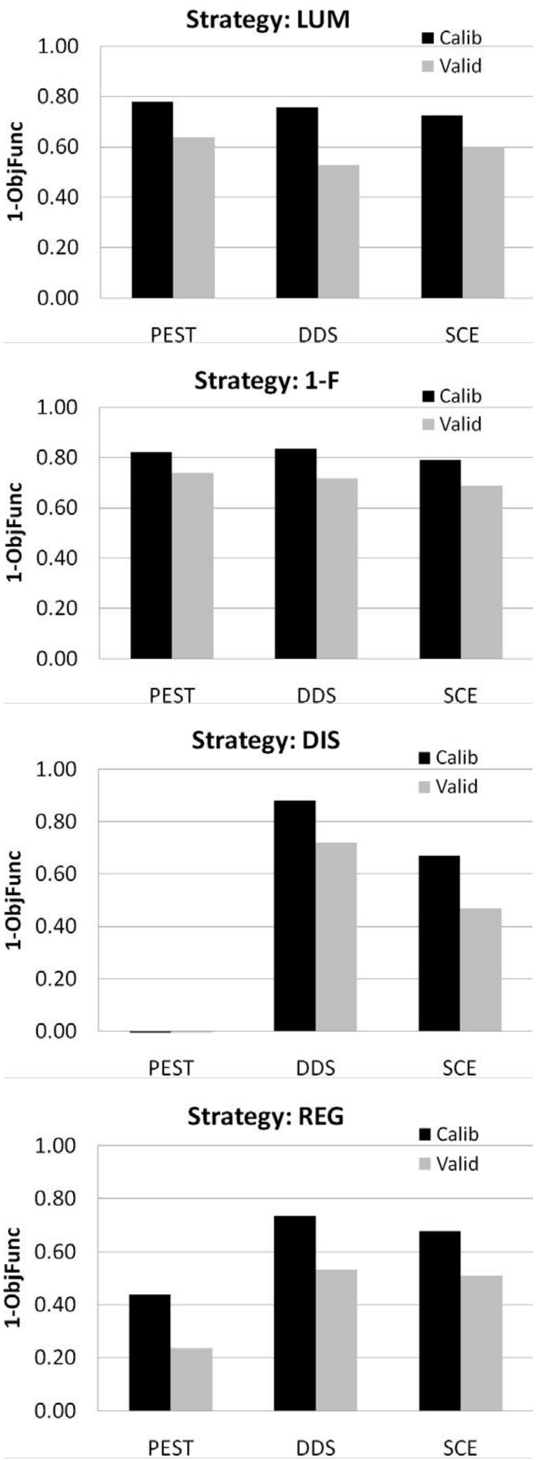

Fig. 6. Mean model performance calculated as 1.00 minus the average over the objective function values (Eq. 9) for the three catchments, Derneburg, Reckershausen and Wieckenberg for all combinations of calibration strategies and optimisation algorithms. The optimum result would be 1.00.

the different optimisation algorithms. However, considering the Distributed and Regionalisation methods it seemed that the PEST algorithm is not able to solve these more complex problems. In this study it was not possible to obtain acceptable results using PEST with those methods. In both cases the DDS algorithm outperformed the SCE algorithm for calibration and validation. An indicator of the robustness of the model is the difference in performance between calibration and validation, where the 1-Factor strategy showed the best results. The overall best performance was obtained using the Distributed strategy, calibrated with the DDS algorithm. So far the Regionalisation method led to the least performance of all calibration strategies. This may be attributed to the following reasons: the development of the transfer function used for the Regionalisation is just in its first phase and different catchments were calibrated simultaneously which sets more restrictions on the parameter estimation. The parameter dimensions of the Regionalisation strategy were 33 whereas the Lumped and the 1-Factor method had 42 dimensions and the Distributed method even had 416 dimensions (as sum over all calibrated catchments). All results are listed in Table 2.

4.2 Evaluation by spatial split sampling

Beside the common temporal evaluation of model performance criteria a special focus was given to the spatial transferability of parameter values, described in Sect. 2.3. Therefore the parameters of the three donor catchments, calibrated with the DDS algorithm, were transferred to the two validation catchments. Due to some changes in the transfer functions the results of the Regionalisation method in this chapter are not directly comparable with those from Sect. 4.1. The upper diagram of Fig. 7 illustrates the model performance, averaged for the three calibration respectively the two validation catchments, in the calibration period. Although the Regionalisation method showed the poorest performance for the calibration catchments, this method outperformed the other ones considering the validation catchments. Surprisingly, the Lumped strategy showed good results as well. Similar results were obtained for the validation period (lower diagram in Fig. 7). The Lumped as well as the Regionalisation method showed a better model performance for the validation catchments than the other two strategies. As mentioned before the transferability of parameters is a clear indicator of model robustness. Comparing the 1-Factor and the Lumped method the results differed considerably from each other. This might be explained by the transfer of a locally estimated spatial distribution of the parameter set for the 1-Factor method, which is not necessarily representative for other catchments.

In the spatial evaluation, the performance of the Distributed method noticeably decreased compared to the temporal evaluation to. This can be explained by the high dimensional parameter search space, which allowed a most flexible

Table 2. Nash-Sutcliff efficiency and volume error for the calibration and validation of the different catchments and the different optimisation algorithms (gauges: Der. = Derneburg; Rec. = Reckershausen; Wie. = Wieckenberg). The calibration years are 2004, 2007 and 2008. The validation was done for 2005 and 2006.

		Lumped				1-Factor				Distributed				Regionalisation			
		Calib.		Valid.		Calib.		Valid.		Calib.		Valid.		Calib.		Valid.	
	Gauge	NSE	VoE	NSE	VoE	NSE	VoE	NSE	VoE	NSE	VoE	NSE	VoE	NSE	VoE	NSE	VoE
PEST	Der.	0.83	0.02	0.63	0.02	0.82	0.09	0.70	0.02	0.75	0.19	0.56	0.17	0.49	0.38	−0.22	0.17
	Rec.	0.70	0.07	0.65	0.03	0.78	0.01	0.71	0.00	−2.71	0.17	−1.65	0.06	0.50	0.14	0.51	0.09
	Wie.	0.84	0.06	0.66	0.10	0.90	0.03	0.84	0.09	−0.11	0.00	−0.41	0.07	0.52	0.05	0.45	0.01
DDS	Der.	0.77	0.06	0.31	0.05	0.81	0.01	0.71	0.01	0.86	0.05	0.69	0.05	0.69	0.10	0.37	0.18
	Rec.	0.69	0.02	0.61	0.02	0.79	0.02	0.69	0.00	0.86	0.03	0.67	0.02	0.71	0.01	0.62	0.02
	Wie.	0.84	0.07	0.69	0.09	0.91	0.01	0.82	0.15	0.94	0.01	0.82	0.07	0.83	0.00	0.65	0.07
SCE	Der.	0.76	0.08	0.68	0.14	0.75	0.12	0.64	0.10	0.70	0.24	0.41	0.22	0.70	0.12	0.57	0.21
	Rec.	0.67	0.02	0.60	0.02	0.75	0.01	0.67	0.03	0.64	0.07	0.57	0.08	0.65	0.01	0.53	0.02
	Wie.	0.77	0.04	0.59	0.13	0.91	0.00	0.83	0.13	0.80	0.04	0.53	0.17	0.72	0.04	0.50	0.06

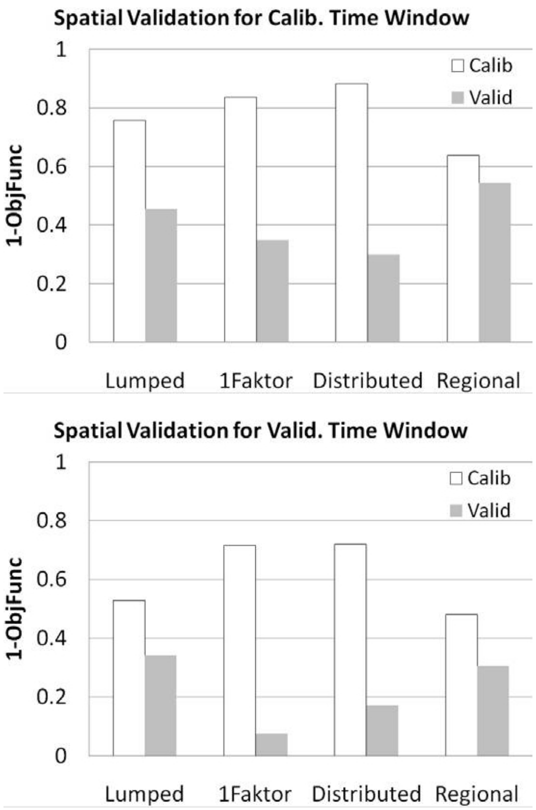

Fig. 7. Mean model performance calculated as 1.00 minus the average over the objective function values (Eq. 9) of the respective catchments for the spatial evaluation in the calibration period (left figure) and in the validation period (right figure). The white bars show the mean performance for the three calibrated catchments (gauges: Derneburg, Reckershausen, Wieckenberg) and the grey bars represent the mean performance for the two validation catchments (gauges: Leineturm, Glentorf).

fitting of the parameters to the hydrograph of the calibration catchment, but is prone to the problem of equifinality.

5 Conclusions

This study focused on the comparison of different calibration strategies in combination with different optimisation algorithms. It was shown, that depending on the complexity of the optimisation problem, the performance of different optimisation algorithms can vary significantly. The local search algorithm PEST found good solutions for the simple calibration strategies, Lumped and 1-Factor. With increasing complexity, the performance of PEST significantly decreased. The DDS algorithm slightly outperformed the SCE algorithm. The restriction of 1000 iterations per catchment certainly plays an important role for this result. Both global optimisation algorithms showed that, even with this tough restriction, they were able to solve complex problems with an adequate performance.

Comparing the calibration strategies purely for temporal evaluations, the Regionalisation was the method with the least performance. Taking the spatial evaluation into account the Regionalisation method indicated the most robust models, closely followed by the Lumped method.

It is important to find a general way to define parameters for hydrological models. This can be done via catchment classification, which can assist the regionalisation of the parameters. Therefore the dominant controls of catchment structures must be understood (Wagener et al., 2007). Further work is necessary regarding the improvement of transfer functions, the optimal selection of catchment descriptors, the suitable definition of multiple criteria objective functions and applications to a larger number of catchments.

Acknowledgements. The authors thank all supporters who gave comments to this work. Particularly we want to thank our student assistant Felipe Teixeira, furthermore Dr. Brian Tolson for some advices in using the DDS and Dr. William Scharffenberg for his support using the HEC-HMS model. We want to thank DWD and Meteomedia for providing precipitation time series and NLWKN for providing runoff time series. The study was supported by the Ministry for Science and Culture of Lower Saxony within the network KLIFF – climate impact and adaptation research in Lower Saxony.

Edited by: R. Ludwig, K. Schulz, and M. Disse
Reviewed by: two anonymous referees

References

Abbaspour, K. C., Schulin, R., and Genuchten, M. T. V.: Estimating unsaturated soil hydraulic parameters using ant colony optimization: Adv. Water Resour., 24, 827–841, 2001.

Bennett, T. H. and Peters, J. C.: Continuous Soil Moisture Accounting in the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS), edited by: Rollin, H. H. and Michael, G., Vol. 104, ASCE, 149–159, 2000.

Beven, K. J.: Rainfall-Runoff Modelling: The Primer, John Wiley & Sons, Ltd, 360 pp., 2001.

Blasone, R.-S., Madsen, H., and Rosbjerg, D.: Parameter estimation in distributed hydrological modelling: comparison of global and local optimisation techniques, Nord. Hydrol., 38, 451–476, 2007.

Chow, V. T., Maidment, D. R., and Mays, L. W.: Applied Hydrology, McGraw-Hill Book Company, 572 pp., 1988.

Doherty, J.: PEST – Model-Independent Parameter Estimation User Manual: 5th Edition User Manual: 5th Edition, Watermark Numerical Computing, 1994.

Duan, Q. Y., Gupta, V. K., and Sorooshian, S.: Shuffled Complex Evolution Approach for Effective and Efficient Global Minimization, J. Optimiz. Theory App., 76, 501–521, 1993a.

Duan, Q., Sorooshian, S., and Gupta, V. K.: Optimal use of the SCE-UA global optimization method for calibrating watershed models, J. Hydrol., 158, 265–284, 1994.

Feldman, A. D.: Hydrological Modeling System HEC-HMS – Technical Reference Manual, US Army Corps of Engineers, 2000.

Finnern, H., Grottenthaler, W., Kühne, D., Plächen, W., Schraps, W.-G., and Sponagel, H.: Bodenkundliche Kartieranleitung, Bundesanstalt für Geowissenschaften und Rohstoffe und den Geologischen Landesämtern in der Bundesrepublik Deutschland, 1994.

Haberlandt, U., Klöcking, B., Krysanova, V., and Becker, A.: Regionalisation of the base flow index from dynamically simulated flow components – a case study in the Elbe River Basin, J. Hydrol., 248, 35–53, 2001.

Hundecha, Y. and Bárdossy, A.: Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model, J. Hydrol., 292, 287–295, 2004.

Kim, S. M., Benham, B. L., Brannan, K. M., Zeckoski, R. W., and Doherty, J.: Comparison of hydrologic calibration of HSPF using automatic and manual methods, Water Resour. Res., 43, W01402, doi:10.1029/2006WR004883, 2007.

Merz, R. and Bloeschl, G.: Regionalisation of catchment model parameters, J. Hydrol., 287, 95–123, 2004.

Nash, J. E. and Sutcliffe, I. V.: River Flow Forecasting through Conceptual Models - Part I - A Discussion of Principles, J. Hydrol., 10, 282–290, 1970.

Pokhrel, P. and Gupta, H. V.: On the use of spatial regularization strategies to improve calibration of distributed watershed models, Water Resour. Res., 46, W01505, doi:10.1029/2009WR008066, 2010.

Samaniego, L., Kumar, R., and Attinger, S.: Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale, Water Resour. Res., 46, W05523, doi:10.1029/2008WR007327, 2010.

Tolson, B. A. and Shoemaker, C. A.: Dynamically dimensioned search algorithm for computationally efficient watershed model calibration: Water Resour. Res., 43, W01413, doi:10.1029/2005WR004723, 2007.

Wagener, T., Sivapalan, M., Troch, P., and Woods, R., 2007, Catchment Classification and Hydrologic Similarity: Geography Compass, v. 1/4, p. 901–931.