Estimation of Parameter Uncertainty in the HBV Model

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Usually the HBV model is calibrated by seeking one optimal parameter set that represents the catchment. From experience we know, however, that it is hardly possible to find an unique parameter set. This is because of errors in both the model structure and the observed variables and because of interactions between the different model parameters. Therefore, there may be many sets of parameters which give similar good results during a calibration period, but their predictions may differ when simulating runoff in the future. In this study a Monte Carlo procedure was used to assess the uncertainty of the parameter estimation and to describe differences in this uncertainty for the various parameters. A fuzzy measure of model goodness was introduced to allow combination of different objective functions. Only a few of the parameters were well-defined, whereas for most parameters good results could be obtained over large ranges. Tentatively an indication of the uncertainty in model predictions arising from the uncertainty in the parameterization was given by viewing the predictions of runoff during two periods.

Introduction

The reliability of hydrological catchment models is highly dependent on the calibration procedure, which is normally the search for one optimal parameter set. On the other hand, most models are overparameterized and the parameters can not be reliably estimated (Jakeman and Hornberger 1993), since different parameter sets spread throughout the parameter space can provide almost equally good fits (*e.g.*

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Duan *et al.* 1992; Freer *et al.* 1996). Parameter uncertainty, *i.e.*, the problem to find one unique set of parameters, increases with the number of model parameters and decreases with increasing information about the system. The information which is normally available for calibration and validation, *i.e.*, time series of driving variables and discharge, often does not allow a decision which parameter set is the correct one (Sorooshian and Gupta 1983; Hornberger *et al.* 1985). Errors in both model structure and measured data together with the more or less arbitrary choice of the objective function make the expectation that any one parameter set will be the true one unreasonable (Beven and Binley 1992). Sefe and Boughton (1982), for instance, tested ten objective functions and concluded that parameter values varied with the type of objective function used for the optimization. Kuczera and Williams (1992) demonstrated that the parameter uncertainty increases when errors in the areal rainfall used in the calibration period are considered. It can be concluded that parameter uncertainty can arise from many aspects of the modelling.

The HBV model (Bergström 1976) has been applied in numerous studies, *e.g.*, to compute hydrological forecasts, for the computation of design floods or for climate change studies (Bergström 1992). The problem of parameter uncertainty within the model, however, has not yet been fully examined.

A Monte Carlo procedure was used in this study to investigate the uncertainty in parameter values using the results of a large number of model runs with randomly generated parameter sets and studying for each parameter how good simulations of the measured runoff could be achieved at best with different parameter values. Often the degree of uncertainty in calibrated parameter values is studied by testing the sensitivity of model output to changes of one parameter while keeping all other parameters constant. The procedure used in this study had the advantage that any interaction between parameters was implicitly taken into account since varying parameter sets were used instead of varying individual parameters.

Parameter uncertainty in the HBV model has been studied by Harlin and Kung (1992) using another Monte Carlo procedure described by Hornberger *et al.*(1986). They generated 1000 parameter sets choosing parameter values from uniform distributions with minimum and maximum values derived from eight model calibrations using different calibration methods and simulation periods. They divided the parameter sets into those which gave acceptable and unacceptable simulations respectively. Comparing the distributions of acceptable and unacceptable sets, they identified parameters to which the model output was sensitive by investigating how large the chance was to get acceptable simulations with a certain value for one parameter. In this study the question was put in the opposite way: How large is the interval for a certain parameter over which there is the possibility to obtain a good simulation of the measured runoff?

Parameter uncertainty is, of course, important for internal states and flows simulated by the model, but one could argue that this is not a problem for the rainfall-runoff simulations. If different parameter sets provide good fits one could just take one

of the 'good' parameter sets. This argument implies the assumption that the simulated runoff using equally good parameter sets is similar. This does not always have to be true for the calibration period and it may be completely wrong when simulating runoff during periods with different weather conditions. Therefore, amongst other sources such as natural randomness, data errors and model structure uncertainty, parameter uncertainty may be a significant source of the combined modelling uncertainty (Beck 1987; Melching *et al.* 1990). The uncertainty of the simulated discharge arising from the parameter uncertainty was addressed only briefly in this study.

Material and Methods

The HBV Model
The HBV model is a conceptual model of catchment hydrology which simulates discharge using rainfall, temperature and estimates of potential evaporation. The model consists of different routines representing snow by a degree-day method, soil water and evaporation, groundwater by three linear reservoir equations and channel routing by a triangular weighting function. Descriptions of the model can be found elsewhere (*e.g.* Bergström 1992, 1995; Harlin and Kung 1992) and in the appendix.

The version of the model used in this study, *HBV light* (Seibert 1996) corresponds to the version described by Bergström (1992) with only two slight changes. Instead of using initial states the new version uses a warming-up period, *i.e.*, the simulation period is preceded by a period during which rough estimates of the initial state values evolve into their correct values according to both atmospheric forcing and parameter values. In the original version, only integer values are allowed for the routing parameter *MAXBAS*. This limitation has been removed in the new version.

Study Catchments
Two catchments were used in this study, the Rivers Sävaån and Svartån, both located in central Sweden. Elevation differences are small and the predominant land use is forest (Seibert 1994), see Table 1. The lake percentage is higher in the River Svartån catchment and runoff is more damped (Seibert 1994). The highest specific runoff during the study period, for instance, was twice as high from the River Sävaån catchment as from the River Svartån catchment. In this study the HBV model was run on a daily time step using only one land use class and one elevation zone. The areal, corrected precipitation was calculated by Seibert (1994) from measurements at four and two stations respectively using the Thiessen polygon method and correction factors given by Eriksson (1983). Daily temperature was computed as the mean from two stations for both catchments. The monthly long-term mean potential evaporation was taken from Eriksson (1981). The simulation period was a ten-year period from September 81 to August 91 preceded by a warming-up period of eight months.

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Table 1 – Catchment characteristics

Catchment	Station	Area (km^2)	Lake (%)	Forest (%)	Open (%)	Mean precipitation (mm y^{-1}) (1981-1991)	Mean runoff (mm y^{-1}) (1981-1991)
Sävaån	Ransta	198	0.9	66.1	33	734	194
Svartån	Åkesta kvarn	730	4.0	69	27	733	276

Table 2 – Parameters and their ranges used for the Monte Carlo simulations

Parameter	Explanation	Minimum	Maximum	Unit
Snow routine				
TT	Threshold temperature	-2.5	2.5	°C
CFMAX	Degree-day factor	1	10	mm °C^{-1} d^{-1}
SFCF	Snowfall correction factor	0.4	1	-
CWH	Water holding capacity	0	0.2	-
CFR	Refreezing coefficient	0	0.1	-
Soil and evap-oration routine				
FC	Maximum SM	50	500	mm
LP	SM threshold for reduction of evaporation	0.3	1	
BETA	Shape coefficient	1	6	
Groundwater and response routine				
K_0	Recession coefficient	0.05	0.5	d^{-1}
K_1	Recession coefficient	0.01	0.3	d^{-1}
K_2	Recession coefficient	0.001	0.1	d^{-1}
UZL	Threshold for K_0-outflow	0	100	mm
PERC	Maximal flow from upper to lower GW-box	0	6	mm d^{-1}
MAXBAS	Routing, length of weighting function	1	5	d

Table 3 – Objective functions

Objective function		Value for 'perfect' fit
R_{eff}	$1 - \dfrac{\Sigma\,(Q_{obs} - Q_{sim})^2}{\Sigma\,(Q_{obs} - \overline{Q_{obs}})^2}$	1
LR_{eff}	$1 - \dfrac{\Sigma\,(\ln Q_{obs} - \ln Q_{sim})^2}{\Sigma\,(\ln Q_{obs} - \ln \overline{Q_{obs}})^2}$	1
VE	$\dfrac{\Sigma\,(Q_{obs} - Q_{sim})}{\Sigma\,Q_{obs}}$	0

Monte Carlo Procedure

For each parameter, ranges of possible values were set based on the range of cali-brated values from other model applications (Bergström 1990; Braun and Renner 1992). After initial runs the ranges were extended for those parameters where the best simulations were close to minimum or maximum. 500,000 parameter sets were generated using random numbers from a uniform distribution within the given rang-es for each parameter (Table 2). The model was run for each parameter set and the values of three different objective functions (Table 3) were computed. Only runs where the value of R_{eff} exceeded 0.7 were used for further processing.

Combination of Different Objective Functions by a Fuzzy Measure

Different objective functions judge the goodness of a certain parameter set by differ-ent aspects, this means one parameter set can give a good fit according to the R_{eff}-criterion but only a poor fit in terms of the *VE*-criterion and *vice versa*. It is difficult to combine the values of different objective functions as they are not directly com-parable. Therefore, a fuzzy measure, which allowed the combination of different ob-jective functions, was introduced in this study. Fuzzy logic allows the handling of the concept of partial truth value between completely true and completely false. A fuzzy measure varies between zero and one and describes the degree to which the statement '*x* is a member of *Y*' or, in our case, 'this parameter set is the best possible set' is true. Membership functions were defined to transform the values of the objec-tive functions into fuzzy measures (Eqs. (1a-c)) where the value one was assigned to the highest values obtained for R_{eff} and LR_{eff} ($R_{eff,max}$ and $LR_{eff,max}$) respectively and to values of 0 for *VE*

$$X_1(R_{eff}) = \max\left(0, \frac{R_{eff} - 0.8R_{eff,max}}{0.2R_{eff,max}}\right) \tag{1a}$$

$$X_2(LR_{eff}) = \max\left(0, \frac{LR_{eff} - 0.8LR_{eff,max}}{0.2LR_{eff,max}}\right) \tag{1b}$$

$$X_3(VE) = \max(0, 1-5|VE|) \tag{1c}$$

The fuzzy measure allows the three objective functions to be joined and to compute the degree of truth of the 'best possible set'-statement, F, for each parameter set (Eq. (2))

$$F = X_1 \cap X_2 \cap X_3 = \min(X_1, X_2, X_3) \tag{2}$$
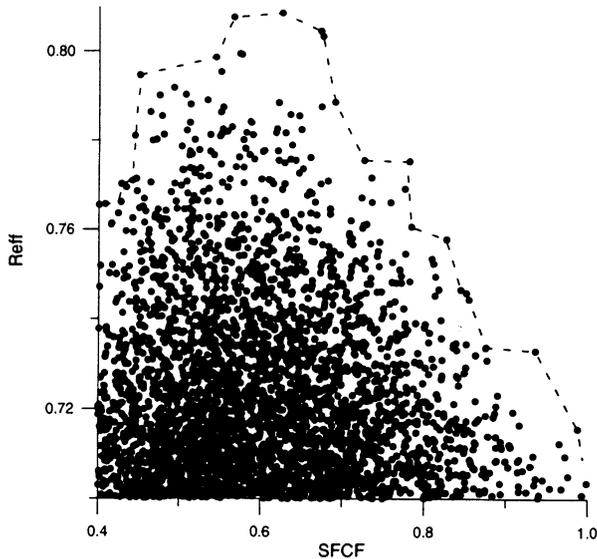
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Fig. 1. Model goodness (R_{eff}) against the values of SFCF and construction of the upper boundary curve (River Sävaån).

Uncertainty of Model Parameters

Plotting the values of model goodness against those of one parameter shows how well-defined by calibration this parameter is. For a well-defined parameter the goodness that can be obtained decreases clearly as parameter values deviate from some optimal value. If, on the other hand, good simulations could be achieved using parameter values over a wide range, this parameter is not well-defined. Note that only the best fit for a certain parameter value is of interest, since every parameter value could, of course, result in poor simulations due to the values of the other parameters. Therefore it was the upper boundary of the scattered points from the Monte Carlo runs which was of interest (Fig. 1). For well-defined parameters this upper boundary shows a distinct peak whereas there is a plateau for less well-defined parameters.

Uncertainty of Simulations

A detailed analysis of the uncertainty of the simulated runoff caused by parameter uncertainty is beyond the scope of this paper. An indication of the uncertainty of the simulated discharge caused by parameter uncertainty was assessed by comparing the simulations for two periods during 1985 for the River Sävaån catchment. The first period included the highest discharge (10.9 mm d^{-1}) which occurred during the calibration period, therefore, it may be suitable to indicate simulation uncertainty when modelling runoff larger than that which occurred in the calibration period. The other period (July 1 to July 15 1985) represented periods with very low runoff.
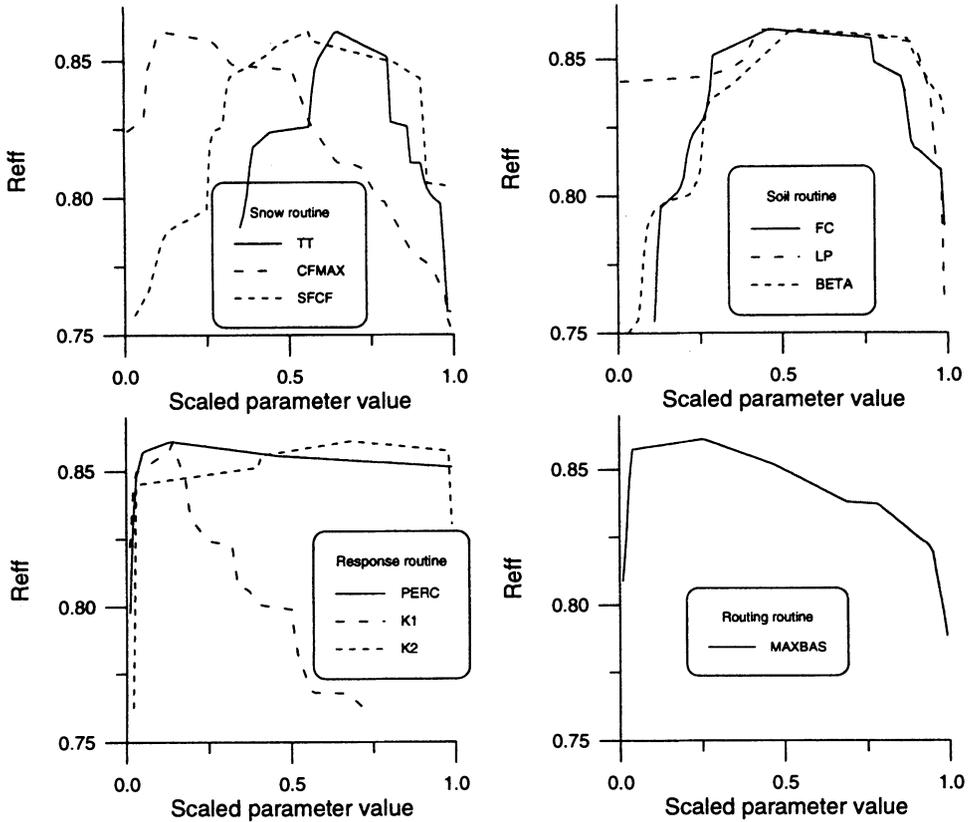
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Fig. 2. Upper boundary curves of the scatter plot of R_{eff} and parameter values for all parameters (River Svartån). To allow comparison of different parameters, their values were scaled to lie between 0 and 1 using the boundaries given in Table 2.

Results

Parameter Uncertainty

About one per cent of all model runs gave fits with R_{eff} values better than 0.7 and the highest values were 0.81 (Sävaån) and 0.86 (Svartån). For most of the best parameter sets the combination of the values for *UZL*, *PERC* and K_1 caused the upper outflow of the upper box, K_0, to be active only during extremely short periods or even not at all. In these cases, K_0 could take any value and *UZL* any value larger than some threshold value without any influence on the simulations. Therefore, the uncertainty of these two parameters could not be analysed.

For most parameters high R_{eff} values could be obtained with values varying over wide ranges (Figs. 2 and 3). The parameters K_2 and *PERC* were better defined by the LR_{eff}-criteria than by R_{eff}, which was expected since LR_{eff} is more sensitive to errors
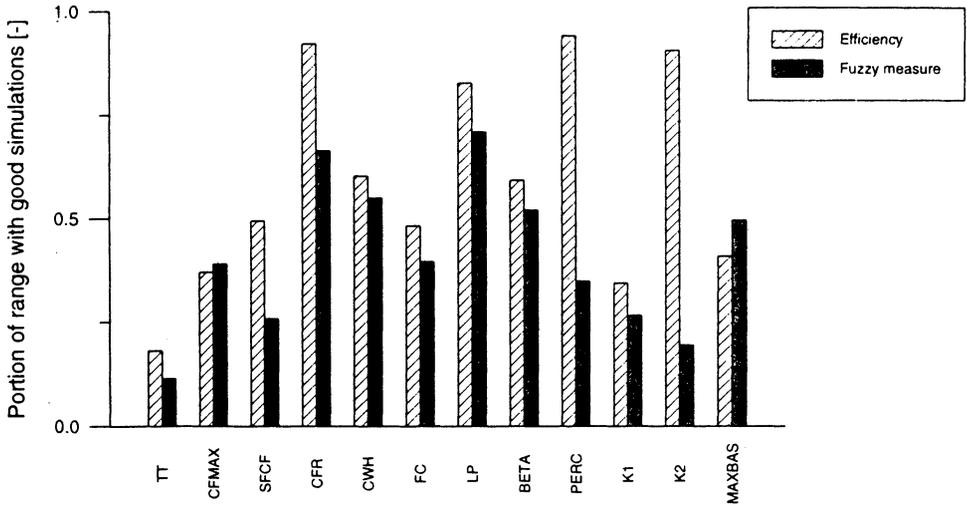
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Fig. 3. Portion of ranges (averages of both catchments) with 'good simultions' (*i.e.*, R_{eff} not more than 0.02, F not more than 0.1 less than the highest values obtained for each catchment respectively).
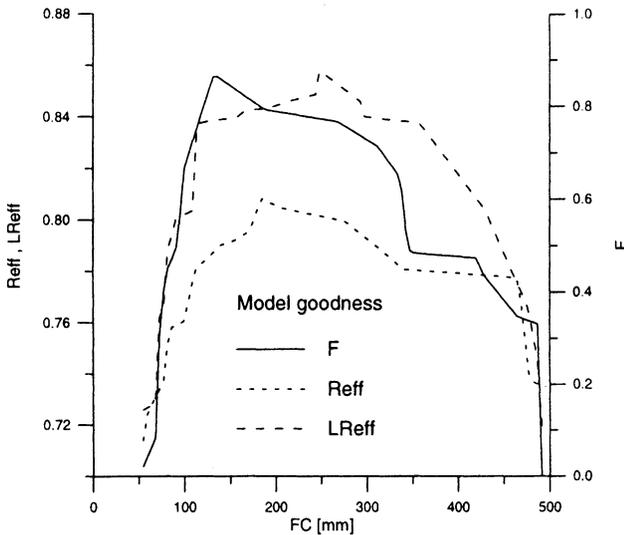

Fig. 4. Upper boundary curves of the scatter plots of model goodness and parameter values for FC (River Sävaån).

during low flow conditions. For the soil routine parameters, which are also important during low flow conditions, the LR_{eff}-criterion was only a little more sensitive than the R_{eff}-criterion. The best parameter values according to the two criteria did not always agree (Fig. 4).

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Good simulations according to the *VE*-criterion alone were obtained with parameter values over almost the entire designated range for all parameters. For the *F*-criterion, the *VE*-criterion was a supplement to the other two criteria since some simulations with high R_{eff}-values were bad according to the *VE*-criterion. The fuzzy measure, *F*, is close to unity if a good fit according to one criterion is also a good fit according to the other two criteria. The highest values of *F* were 0.87 (Sävaån) and 0.70 (Svartån), which demonstrated that model fits were judged differently by the different criteria. The R_{eff}-values of the simulations with the highest *F*-values were about 0.03 less than the maximum values (~0.04 for LR_{eff}). The parameters *PERC*, K_2 and *SFCF* were significantly better defined by using the *F*-criterion compared to the R_{eff}-criterion (Fig. 3).

Simulation Uncertainty

The shape of the spring flood hydrographs simulated using the parameter sets that gave fits with a goodness of not more than 0.02 less than the maximal value of R_{eff} varied considerably (Fig. 5). The range of simulated runoff maxima using parameter sets which had given R_{eff}-values only slightly smaller than the maximum of R_{eff} during the entire period was large (Fig. 6). The relative variations were much larger for the mean runoff during a 15-day period during July 1985 when runoff was very low (Fig. 7). The variation between simulations with the best parameter sets according to the *F*-criterion was smaller and the results were closer to the observed values (maximal runoff 10.9 mm d^{-1}, runoff volume during 15 days 1.6 mm).
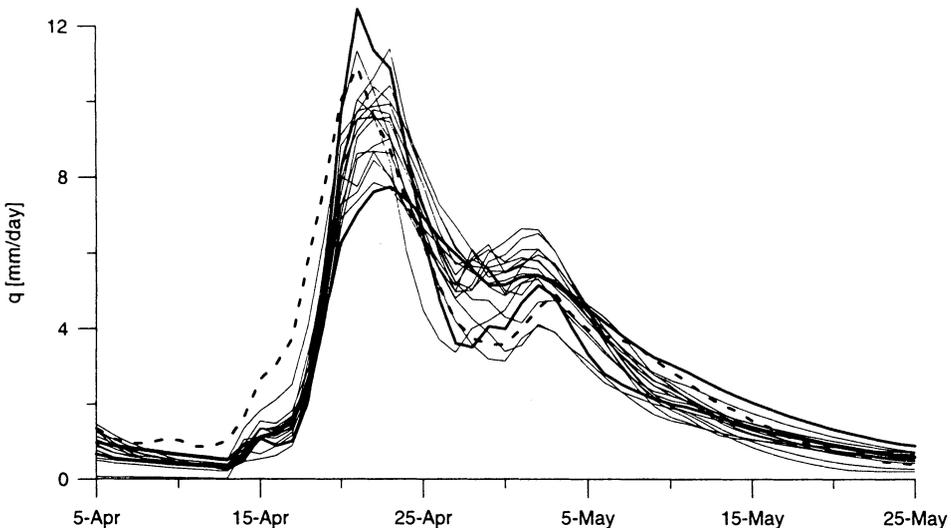

Fig. 5. Spring flood 1985 simulated with parameter sets that gave a fit with R_{eff} not more than 0.02 less than the maximal value of R_{eff}. The simulations with the lowest and highest peak discharge are shown with thick lines, the observed hydrograph is shown with the dashed line.
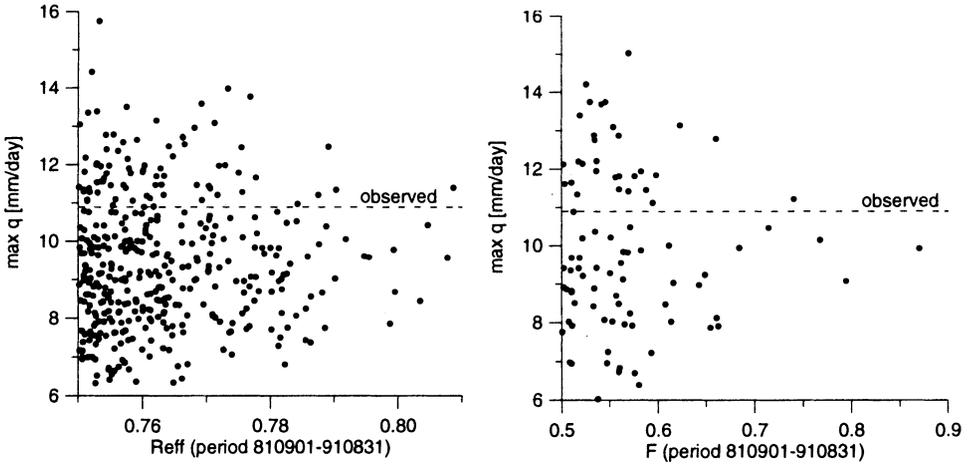
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Fig. 6. Simulated maximal runoff during the spring flood in April 1985 against model performance (left: R_{eff}, right: F) during calibration period (September 81- August 91) for different parameter sets.
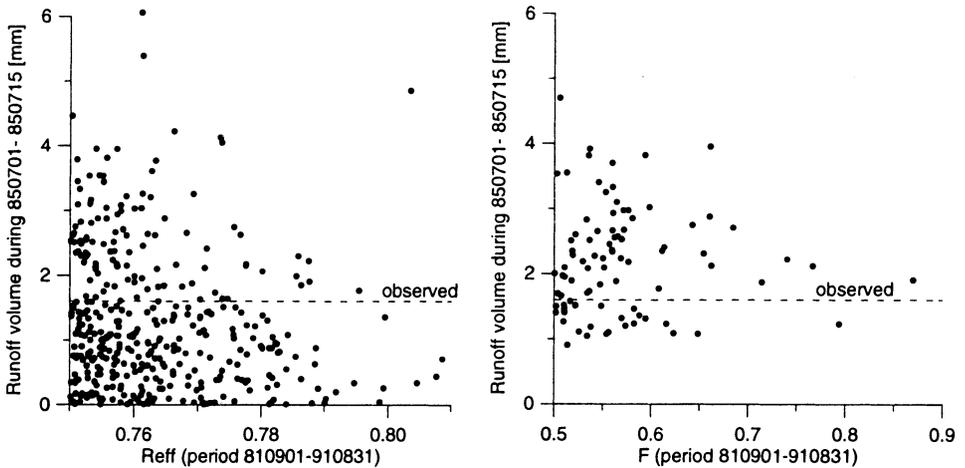

Fig. 7. Simulated runoff volume during a period of 15 days in July 1985 against model performance (left: R_{eff}, right: F) during calibration period (September 81- August 91) for different parameter sets.

Discussion and Conclusions

Only few of the model parameters were found to be well-defined, while for the other parameters good fits were obtained over broad ranges. The only parameter that could be identified clearly in both catchments was the threshold temperature, TT.

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The parameters *CFR*, *LP*, *PERC* and K_2 were found to provide good fits according to the R_{eff}-criterion over very wide ranges. The combination of different objective functions in the *F*-criterion confined these ranges for *PERC* and K_2. For the remaining parameters the range of good model performance varied between 25 and 75 per cent of the entire tested range (Fig. 3). These results may look somewhat different from those of Harlin and Kung (1992), who found model fits to be, for instance, insensitive to changes in *TT* but sensitive to changes in *SFCF*. The explanation for this apparent difference is the way they determined the minimum and maximum values of the tested parameter values. They derived these values from eight model calibrations using different calibration methods and simulation periods. Therefore, the ranges were smaller for well-defined than for badly-defined parameters because their optimized values vary less with calibration method and simulation period (*e.g.,* the range of *TT* was less than 1 °C).

If good simulations of the measured runoff could be obtained with different values for one parameter this does not necessarily mean that the simulations are not sensitive to changes in this parameter, but that changes are compensated for by other parameters. Simulations of the HBV model are very sensitive to changes of *CFMAX* or *FC*, for instance, when they are changed alone. It is therefore important to distinguish between an insensitive parameter which in practice can be set to some constant value (as is done in most HBV applications with *CWH* and *CFR*) and an uncertain parameter.

The intervals for K_1 and K_2 overlapped and thus sets with K_1 larger than K_2 were tested. This combination is often avoided in model application but has been used before (*e.g.* Braun and Renner 1992). Furthermore, there is no self-evident reason to reject this combination *a priori*. With different parameterizations of the response function the roles of the different outflows change. Larger values for *PERC*, for instance, cause an increased contribution of the lower box, which, consequently, becomes more important even during periods with high flow. However, there is hardly any objective justification that one outflow should or should not contribute during certain periods or at a certain magnitude.

The HBV model is usually calibrated manually by trial and error (Bergström 1992). Therefore, the problem of subjectivity has to be considered when judging calibration results. Usually a user will start from parameter values that gave good results in a similar catchment and try to keep them within certain ranges during calibration. Bergström (1990), for instance, found regional variations for the calibrated values of *FC* with higher values in southern Sweden. The results of this study suggest that such regional variations may be partly due to what is expected by the modeller. He/she starts with one value and as very different values of *FC* can produce good fits, it is possible to keep this value by changing other parameters. With badly-defined parameters, automatic calibration methods will often lead to different parameter sets, depending on the optimization method and start values and it is up to the user to decide which set to use (*e.g.* Kite and Kouwen 1992).

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The combination of different objective functions through a fuzzy measure did partly help to decrease the parameter uncertainty. The simulations of two shorter periods during 1985 were closer to the observations for parameter sets with high F-values than those with high R_{eff}-values. The variations between the simulations using the best parameter sets according the F-criterion were smaller than those between the simulations using the parameter sets which had the highest R_{eff}-values. This suggested that the combination of different objective functions may be suitable to judge different parameter sets which may perform more or less similarly well according to only one objective function. Furthermore, this result indicated that parameter sets with high R_{eff}-values alone may not predict runoff as well as parameter sets with somewhat lower R_{eff}-values but higher values for other objective functions.

The three objective functions used in this study are those measures most widely used in hydrological modelling to assess model performance. However, using other objective functions may alter the results. One limitation of the objective functions used in this study is that they average over the simulation period. For instance, a simulation that fits well during spring but less well during autumn and a simulation where the situation is *vice versa* thus may get the same number. Therefore, parameter uncertainty may be reduced by computing the objective functions for different parts of the years separately. Another way to reduce parameter uncertainty may be the use of additional data in the model calibration such as, for instance, snow cover, extension of saturated areas or information derived from environmental tracer studies. This may allow the user to reject parameterizations that simulate runoff correctly but with inconsistent internal variables (*e.g.* Ambroise *et al.* 1995; Franks *et al.* 1997). Furthermore, modifications of model equations may help to decrease the parameter uncertainty (Gupta and Sorooshian 1983).

The uncertainty of the simulated runoff caused by parameter uncertainty has to be studied in more detail. However, the tentative results indicated that simulated runoff during a certain period may vary considerably for parameter sets which gave almost similar good fits (according to the R_{eff}- or the F-criteria) during calibration. It should be noted that both periods were within the calibration period. Differences in the simulations are expected to be larger for periods outside the calibration period, especially when the hydrological conditions differ.

Normally, after calibration the statement 'this parameter set is the best possible set' is assumed to be true for one parameter set and false for all other sets. The results of this study, however, suggest that it would be more reasonable to think of different parameter sets, each one to a certain degree being the best one and to estimate the uncertainty of model predictions such as, for instance, the uncertainty in the volume of a design flood arising from parameter uncertainty. Consequently, a prediction should be given as a range or probability distribution (Melching *et al.* 1990; Beven and Binley 1992; Freer *et al.* 1996) rather than as a single value.

Acknowledgement

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Appendix: A Short Description of the HBV Model

The model simulates daily discharge using daily rainfall, temperature and potential evaporation as input. Precipitation is simulated to be either snow or rain depending on whether the temperature is above or below a threshold temperature, **TT** (°C) (please note that all parameters are in bold). All precipitation simulated to be snow, *i.e.,* falling when the temperature is below **TT**, is multiplied by a snowfall correction factor, **SFCF** (-), which represents systematic errors in the snowfall measurements and the 'missing' evaporation from the snow pack in the model. Snow melt is calculated with the degree-day method (Eq. (A1)). Meltwater and rainfall is retained within the snow pack until it exceeds a certain fraction, **CWH** (-), of the water equivalent of the snow. Liquid water within the snow pack refreezes according to a refreezing coefficient, **CFR** (-) (Eq. (A2))

$$\texttt{melt} = \textbf{\textit{CFMAX}} \cdot (T(t) - \textbf{\textit{TT}}) \tag{A1}$$

$$\texttt{refreezing} = \textbf{\textit{CFR}} \cdot \textbf{\textit{CFMAX}} \cdot (\textbf{\textit{TT}} - T(t)) \tag{A2}$$

Rainfall and snow melt, *P*, are divided into water filling the soil box and groundwater recharge depending on the relation between water content of the soil box (*SM* (mm)) and its maximal value, **FC** (mm), (Eq. (A3)). Actual evaporation from the soil box equals the potential evaporation if *SM/FC* is above **LP** (-), while a linear reduction is used when *SM/FC* is below **LP** (Eq. (A4)).

$$\frac{\texttt{recharge}}{P(t)} = \left(\frac{SM(t)}{\textbf{\textit{FC}}} \right)^{\textbf{BETA}} \tag{A3}$$

$$E_{\text{act}} = E_{\text{pot}} \cdot \textbf{min} \left(\frac{SM(t)}{\textbf{\textit{FC}} \cdot \textbf{\textit{LP}}}, 1 \right) \tag{A4}$$

Groundwater recharge is added to the upper groundwater box, *SUZ* (mm). **PERC** (mm d^{-1}) defines the maximum percolation rate from the upper to the lower groundwater box, *SLZ* (mm). For the lake area, precipitation and evaporation is added and subtracted directly from the lower box. Runoff from the groundwater boxes is computed as the sum of two or three linear outflow equations, K_0, K_1 and K_2 (d^{-1}), depending on whether *SUZ* is above a threshold value, **UZL** (mm), or not (Eq. (A5)). This runoff is finally transformed by a triangular weighting function defined by the parameter **MAXBAS** (*d*) (Eq. (A6)) to give the simulated runoff (mm d^{-1})

$$Q_{GW}(t) = K_2 \cdot SLZ + K_1 \cdot SUZ + K_0 \cdot \textbf{max}(SUZ - \textbf{\textit{UZL}}, 0) \tag{A5}$$

$$Q_{\text{sim}}(t) = \sum_{i=1}^{\textbf{MAXBAS}} c(i) \cdot Q_{GW}(t - i + 1)$$

$$\tag{A6}$$

$$c(i) = \int_{i-1}^{i} \frac{2}{\textbf{MAXBAS}} - \left| u - \frac{\textbf{MAXBAS}}{2} \right| \cdot \frac{4}{\textbf{MAXBAS}^2} \, du$$

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