International Conference on Hydroinformatics

8-1-2014

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11th International Conference on Hydroinformatics
HIC 2014, New York City, USA

RELIABILITY OF SIMULATED DISCHARGES FOR DIFFERENT GAUGE LOCATIONS IN A SEMI DISTRIBUTED RAINFALL RUNOFF MODEL

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In terms of flood forecasting in alpine environments, predictions at different gauges as well as sites with exposed infrastructure within the catchment are required. The used semi-distributed hydrological model HQsim combines runoff formation and surface runoff routines with an implemented channel routing for river reaches. This allows the estimation of discharges at selected channel segments. As a case study a large alpine catchment with a size of 890 km² is used. The uncertainty in the discharge prediction is investigated at three discharge gauges located along the main river. The basis of our experimental set-up are 15,000 samples describing the prior parameter distribution obtained by means of a Latin Hypercube sampling. Out of this, we calculated a Generalized Likelihood Uncertainty Estimation (GLUE) for the flood discharge at each gauging station. As informal likelihood a combination of different Nash Sutcliffe Efficiencies (NSE) is used covering summer season as well as flood periods containing peak discharges. Based on the behavioral parameter settings for each individual gauge, the model prediction distribution and their means for the remaining gauging stations are computed and analyzed.

INTRODUCTION

This study has been done in frame of the operational flood forecasting system of the Tyrolean River Inn (*'HoPI – Hochwasserprognose Inn'*). Within the used modular system setup tributary catchments of the River Inn are modelled using hydrological models whose output is forwarded to a 1D hydrodynamic model of the Inn. Originally the main focus was to best possible model the discharges at the catchment outlet. Still, owing to the alpine character, catchments with a high percentage of glaciation are modelled individually with the distributed Snow- and Icemelt model SES whereas unglacierized catchments are simulated with the conceptual rainfall-runoff model (CRR) HQsim [1]. Further developments towards a holistic flood forecasting require to including additional locations (mostly at gauging stations) at which forecasts are provided. These additional points of interest are to be represented in the model layout. Due to a flexible representation of river channels for flow routing is given within HQsim, the discharge simulation at different gauging stations within a tributary catchment is possible. Still, although being technically possible, the conceptual nature of HQsim requires testing the reliability of the simulated discharges at individual gauging station along the river. In general CRR simplify physically processes to various extends, trying to incorporate the most relevant (or dominant) processes. With the applied conceptual approach such as control volumes (i.e. linear storages for the saturated soil zones), variables are spatially (sometimes even temporally) averaged (i.e. the hydraulic conductivity of the soil zones of a hydrological response unit) [5]. Especially the temporal and spatial averaging leads to uncertainties within the intra-model predictions, concerning model states (snow, soil moisture, …) as well as the routed discharges. To answer the questioning of the reliability of intra-model predictions specifically for river channel segments, a refined version of the HQsim model for the Ötztal valley including three gauging locations along the river (see figure 1) is used as the experimental set-up.

METHODS

A semi distributed rainfall-runoff model of an alpine catchment, realized with HQsim is used where several gauging stations along the main river are considered. The prediction of these channel segments here are understood as intra-model prediction for the case that the HQsim simulation is optimized for the gauge Brunau (see figure 1). To estimate the uncertainty of the intra-model prediction the common used *Generalized Likelihood Uncertainty Estimation (GLUE)* method [2] is applied for each gauging station independently. In the end the gained intra-model prediction distribution as well as the model parameter distributions is compared with the results of the GLUE on Tumpen and Huben, respectively.

Experimental set-up

The study is performed for the large alpine catchment *Ötztaler Ache* (673-3762 m.a.s.l.) with its size of about 890 km² and nearly 10 percent glaciation. Figure 1 shows the location of the Ötztaler Ache as well as the experimental set-up. As mentioned before, glaciated sub-catchments are simulated by the Snow- and Icemelt model SES [9]. As the focus is on the non-glacierized part covered with HQsim, the model parameters of the model SES are not varied and its output is assumed as a fixed input series. Hourly time series from precipitation and temperature gauges (period 2000-2012) are spatially interpolation [1] to obtain the model inputs.

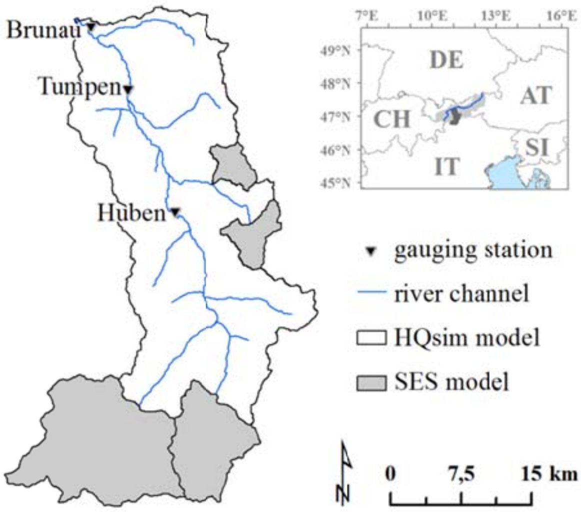

Figure 1: Overview of the Ötztal catchment with the considered gauging stations

The hydrological model HQsim

The used semi-distributed CRR HQsim is based on hydrological response units (HRUs) which aggregate areas with similar soil type, aspect and elevation. After calculating the water balance of each HRU the runoff it is transferred to the nearest reach of the channel network and routed downstream towards the catchment's outlet [1]. Processes include snow accumulation / snow melt, infiltration, evapotranspiration, interception as well as percolation and are applied at each HRU [3]. The total runoff is thereby separated for *surface flow*, *interflow* and *base flow*. The contributing area concept allows the separation between infiltrated and surface run-off, linked to a temporally varying moist content. The water content and the associated subsurface flow in the unsaturated zone (*interflow*) are described according to *Van Genuchten* [10]. The *base flow* is modelled with linear storage representing the saturated zone. Flow time if the surface flows from the HRU to the nearest channel segment is calculated according to *Morgaly and Linsley* [6]. The channels are modelled as non-linear storage cascades using an approach based on *Rickenmann* [8] to calculate the flow velocity.

Prediction uncertainty / parameter uncertainty estimation

To estimate model and parameter uncertainty of the hydrological model we decided to apply the often used and easily computable *Generalized Likelihood Uncertainty Estimation (GLUE)* of *Beven and Binley* [2]. In this study the following GLUE algorithm (see *Vrugt* [11]) is used:

1. A Latin Hypercube of 15.000 samples (θ) out of a feasible parameter space (Θ) is computed.

2. In the GLUE method the informal likelihood has only to fulfill the requirement of a monotonically increasing value by improved model performance [4] The likelihood function used in this study is the sum of the *Nash Sutcliffe Efficiency (NSE)* [7] of different time periods: (τ) the whole summer season (01.05.-30.09.) and (φ) flood events, weighted by their normalized peak runoff. In more detail the likelihood is calculated as follows:

$$L(\theta|\hat{Y}, X) = \sum_{s=1}^{S} NSE_{\tau,s} + \sum_{e=1}^{E}(w_{\varphi,e} * NSE_{\varphi,e}) \quad (1)$$

with
$S = \{2000, \ldots, 2006\}$ for calibration, $S = \{2007, \ldots, 2012\}$ for validation and
$E = \{\varphi \in S: y \geq HQ1\}$.

The terms $NSE_{\tau,s}$ and $NSE_{\varphi,e}$ are computed by,

$$NSE_{\tau,s} = 1 - \frac{\sum_{i=1}^{M}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{M}(y_i - \overline{Y_M})^2} \quad (2)$$

with $M = \{01.05., \ldots, 30.09. \in s\}$ and

$$NSE_{\varphi,e} = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{Y_N})^2} \quad ; \quad w_{\varphi,e} = \frac{\max(Y_{\varphi,e})}{\sum_{l=1}^{E}\max(Y_{\varphi,l})} \quad (3)$$

with $N = \{\varphi \in E: y_{y \geq HQ1} \pm varying\ timesteps\ (based\ on\ event\ duration)\}$.

3. To differentiate behavioral from non-behavioral parameter combinations the top 10 % of the simulations are picked out and normalized regarding their likelihood value:

$$L(\theta|\hat{Y}, X)_{norm.,b} = \frac{L(\theta_i|\hat{Y},X)_b}{\sum_{l=1}^{B} L(\theta_l|\hat{Y},X)_b} \quad (4)$$

with $B = \{l \in L(\theta|\hat{Y}, X)_b : L(\theta|\hat{Y}, X) \geq\ p\ with\ p = 0.9\}$.

4. Based on the normalized likelihoods the prediction density function of the model output predictions as well as the uncertainty intervals are computed.

The steps 2-4 in the algorithm are applied for each gauging station independently. Finally, in each case the gained model prediction distribution is compared with the intra-model prediction distribution for each time step.

RESULTS

To start with the informal likelihood values the range has to be set. In this study a combination of NSE over different periods is used. Consequential it leads to the minimal value of minus infinite and monotonically increases by improved model performance. The optimum of a perfect simulation depends mainly on the number of summer periods, whereas the sum of event's NSE is scaled to unity. Thus, an optimum simulation has a likelihood of 8 for the calibration period and 7 for the validation period. In figure 2 Box-Whisker-Plots of the likelihood function distribution from behavioral parameter settings are shown. The predictions of Tumpen lead to maximal values of 5.684 / 4.1284 (calibration / validation) for both the best simulation regarding the gauge Tumpen as well as the intra-model estimate. In the case of Huben there are slight differences. As well as the case of Tumpen both estimates leads to similar maximal values of 5.4165 but with the addition of minimal differences in the validation period. For the validation period the best simulation result of the gauge Brunau has the maximal value of 4.1342 against what the intra-model prediction reaches a slightly lower value of 4.0588. This gives rise to the question if similar likelihood values are simulated by similar parameter settings. In the case of the gauge Tumpen the question has to be denied. Each maximal value whether of the calibration or the validation period is estimated with different parameter combinations. On the other hand the maximal values of the calibration period for the intra-model prediction as well as the simulation of Brunau are results of one parameter settings as well as in the validation period.

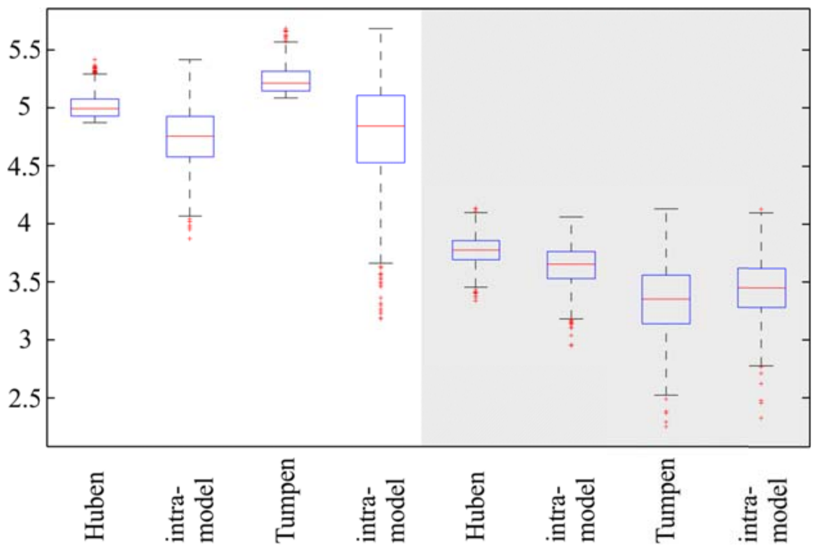

Figure 2: Box-Whisker-Plots of the informal likelihood function distribution of behavior parameter settings (with white shaded calibration and grey shaded validation period)

For comparing the different model predictions the differences of i) model prediction distribution for the individual gauges are analyzed with a χ^2-goodness-of-fit test (significance level of 5 %) and ii) similar distribution means are analyzed with a two sample t-test (significance level of 5 %) at every time step. Table 1 summarizes the percentage rejection of the hypotheses that the intra-model prediction leads to similar prediction distribution and similar predictions mean, respectively. In more than half of the time steps the hypotheses are rejected for both cases. Thereby the gauging station Tumpen shows a slightly minor rejection rate than the gauging station Huben. In general the rejection rates increase for the flood events up to 100 per cent. Figure 3 depicts chosen periods for gauging station Tumpen where periods with similar predictions mean are shaded in grey. For the hydrological year 2010 it is clearly shown that the model predictions differ from each other for periods of increased discharge. The periods at the end of April and at the beginning of July illustrate that for low flows the predictions mean and their 90%-confidence intervals do not differ much. In contrast, when runoff increases the predictions means are outside the confidence intervals of each other. Differences of the behavior parameter distribution are not as obvious as the differences in runoff prediction. Figure 4 shows the parameter density plots of all 63 varied parameter. Given that most of the behavior parameter distributions tend to be uniformly distributed these parameters cannot be identified well with the used sampling scheme. Merely the parameter ‘soil depth >20°’, ‘corr. factor’ and ‘meltfunc max’ seem to be not uniformly-distributed and thus they have a strongly pronounced high probability density region. Furthermore in many cases the parameter density distributions do not differ much of each other. A prominent example of parameter with notable differences is the ‘meltfunc max’ where the resulting distribution of the gauge Huben differs significantly.

Table 1: Percentage rejection of the null hypothesizes (χ^2-goodness-of-fit test / two sample t-test)

		Calibration (2000-2006)	**Validation (2007-2012)**
Huben	complete series	92.52 / 82.07	86.42 / 78.27
	summer season (01.05.-30.09.)	99.10 / 93.57	99.58 / 94.97
	high flow events	99.70 / 92.43	100 / 94.26
Tumpen	complete series	86.17 / 93.24	82.60 / 90.11
	summer season (01.05.-30.09.)	76.84 / 94.82	63.34 / 94.53
	high flow events	100 / 100	86.67 / 95.00

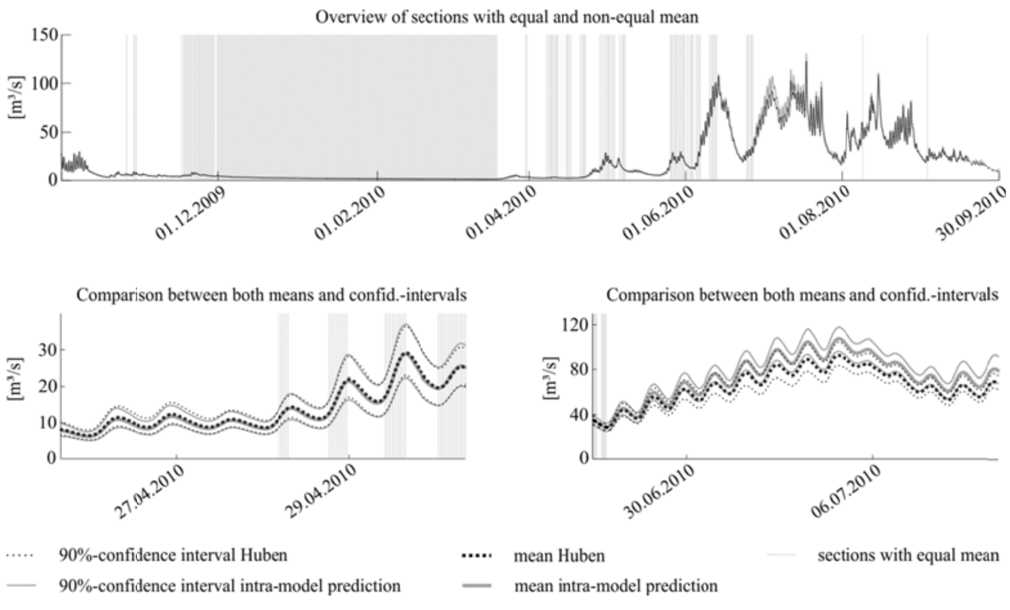

Figure 3: Generic depiction of sections with equal and non-equal mean using the example of gauging station Huben.

Figure 4: Overview of the different behavior parameter density distributions

DISCUSSION

As a result of this study it is not possible to precisely state the quality of intra-model predictions for flood forecasting. The study results indicate that different gauges within a catchments model have different global optima of the informal likelihood function. Indeed some parameter settings are found in all gained behavioral parameter settings, but they do not induce similar good likelihood values compared to the other behavior settings. Especially the case Tumpen leads to completely different parameter settings for the maximal likelihood values both for calibration and validation period. Out of this it is inadvisable to optimize a CRR at the catchments outlet and trust this parameter setting within all gauges of the catchment.

In the case of an uncertainty analysis not only the global optimum of the informal likelihood function but rather the whole distribution function of mainly the model parameter and model prediction is of interest. Therefor the hypotheses on similar model prediction distribution as well as similar prediction mean are tested. In both cases the null hypothesis was rejected in nearly all time steps. Significant differences of the model prediction distributions and their means occur when the runoff increases. By analyzing the three behavior parameter distributions the gained posterior parameter distributions of figure 4 does not differ much from a uniform distribution with a few exceptions. This suggests the assumption that no parameter can be estimated precisely by using the applied sampling scheme (Latin Hypercube sampling with 15.000 samples). So, further work is needed to confirm the hypothesis that model parameter settings are transferrable into sub-catchments and the intra-model prediction is reliable.

ACKNOWLEDGEMENTS

This work was supported by the Austrian Ministry of Science BMWF as part of the UniInfrastrukturprogramm of the Focal Point Scientific Computing at the University of Innsbruck. It has been undertaken within the frame of the alpS Project “H05 HoPI II – Enhancing Preparedness through Improved Flood Forecasting” and the Austrian Academy of Science Project HyPCC embedded in the International Strategy for Disaster Reduction (ISDR) program. The authors would like to thank the federal state of Tyrol, the Austrian Research Promotion Agency (FFG), the Austrian Academy of Science (ÖAW) and the TIWAG – Tiroler Wasserkraft AG who support the project.

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