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HYDROLOGICAL MODELLING OF SMALL ALPINE WATERSHEDS WITH THE NAM MODEL

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Abstract: Analysis of long-term hydrometeorological data in the Alps shows an increasing number of rainfall and flood related natural hazards. Beside decreasing return periods of high-flow events, the intensity of hydro-meteorological disasters has been increasing. Weather risks of this type may result in higher material and economic losses, thus prevention and protection from floods becomes a major challenge, where forecasting has an indisputable role. A great number of hydrological models are now available with a wide range of data requirement and usability. The aim of this paper is to verify the applicability of the MIKE 11 rainfall-runoff model on the watershed of Lake Mondsee, a small Alpine catchment located in Salzkammergut, Austria. The NAM (Nedbør-Afstrømnings-Model) is a lumped and conceptual model with an autocalibration algorithm providing a timesaving option for the adjustment of the great number of free variables included in the system. The simulated runoff and long-term accumulated runoff results of the modelling achieved a variance above 86% with a proper model structure, matching the characteristics of the studied watershed, and a set of parameters provided by a systematic calibration-validation process focusing step-by-step on low flow, high flow parts of the runoff and on the overall RMSE. The model proved to be applicable to the Mondsee catchment and is expected to work in similar catchments as well, and could serve as a useful tool for runoff estimation on unmonitored catchments.

Keywords: Hydrology; Northern Alps; conceptual modelling; Mondsee; rainfall-runoff

1 INTRODUCTION

Analysis of long-term hydro-meteorological data shows the increasing number of rainfall and flood related natural hazards (Alfieri et al., 2015, Arnell 1999, JACOB et al., 2008, Stagl & Hattermann 2015). Besides decreasing return frequencies of high-flow events, the intensity of weather-related hazards has also been increasing (Anderson et al., 2008, Beniston et al., 2007, Stagl & Hattermann 2015). This results in high economic losses; thus, prevention and protection from floods have become a major challenge, where forecasting plays an indispensable role (Alcamo et al., 2007). Forecasting of floods refers to the thorough understanding of catchment-scale hydrologic processes and its behaviour under extreme meteorological and hydrologic circumstances. On a monitored catchment where a long-term record of water level, discharge, precipitation, temperature, evapotranspiration data is available, in addition to ground water table elevation and water management data (such as manipulation of hydraulic structures, pumps, known and monitored extractions), modelling is based on the processing of these data. However, modelling and forecasting on an unmonitored catchment is much more challenging (Blöschl 2005). Focusing on small watersheds and flash floods, many studies indicate that this type of inundation hazards have been becoming more and more frequent in Hungary and Eastern-Central Europe (Fábián et al., 2009, Torma et al., 2014, Lóczy 2010; Czigány et al., 2010, Czigány et al., 2013), however the numerical simulation of these events especially on small Alpine type catchments is an unexamined question. In these few published cases the lack or incompleteness of fundamental hydrological data is common. Modelling without data questions the reliability of distinct results, but may provide an estimated spectrum of the expected behaviour. To build a numerical model based on such information requires the model to be heavily simplified, robust, yet detailed enough to provide useful results for decision makers. Sensitivity analysis and ensemble modelling are the tools to compensate lower accuracy in case of model studies (Hegedűs et al., 2013).

A great number of hydrological models are available nowadays with a wide range of data requirement, calculation capacity, accuracy and usability: empirical models (e.g. unit hydrograph method, regression equations), conceptual rainfall-runoff models (e.g. NAM, HEC-HMS, HBV, SIMHYD, GAPI/TAPI), physically based models (e.g. SHE, TOPOG, DIWA) (Wagener et al., 2004, Götzinger & Bárdossy 2005, Van Leeuwen et al., 2016, Rahim et al., 2012, Huang et al., 2005, Karim, et al., 2016, Bakonyi & Bartha 1988). The general objective of this paper is to test the applicability of the MIKE 11 NAM rainfall-runoff model on a Salzkammergut watershed in Austria. Our hypothesis is that to simulate the response of the catchment with a conceptual method precipitation, temperature and evapotranspiration data is enough and the calibration of free variables is possible towards the observed outflow. The analysis will show whether the complexity of the model and the temporal resolution of the data have direct and proportional effect on the model performance on such a small watershed. A secondary objective is to find an optimal strategy for the autocalibration procedure and compare its effectiveness with the results of manual calibration. The model performance (Nash & Sutcliffe 1970) is measured with the coefficient of determination (R^2) throughout the paper and with the Nash-Sutcliffe efficiency (NSE) for the final results, and NSE > 80% is considered a satisfactory result (Moriasi et al., 2007). Obtaining a well performing rainfall-runoff model using just a minimal set of data and the simplest structure would serve as a useful tool for operative runoff estimation. In a flood forecasting system, where the number of delineated subcatchments is significant, it is an obvious advantage to a have fast calculating, easily adjustable runoff model. The best strategy of autocalibration serves the purpose of labour-free calibration of multiple catchments, where the method of similar catchments is widely used despite its substantial simplifications.

2 METHODS

2.1. Case study area

The Mondsee catchment is one of the “Long Term” Ecosystem Research (LTER) sites belonging to its international research framework ILTERNET, it is located in the Salzkammergut region of Upper-Austria, between the Central and Lower Eastern Alps separating the Alpine and pre-Alpine regions, the sedimentary and intrusive ranges (Mirtl et al., 2015). The area of the catchment is 248 km^2 and is characterised by a very dense river and stream system of about 2 km/km^2, embedded in steep slopes and heavy soils causing fast surface runoff (Klug 2010, Klug & Jenewein 2010). Numerous studies on the hydrology and meteorology of the catchment have been published, among them Swierczynski et al., 2013, Klug & Oana 2015, and Lauterbach et al., 2011. The GIS information of the catchment and all the data used for the modelling were exported from the EHYD hydrographic archive database of the hydrographic service of Austria and provided by ZAMG.

The dataset used for the calculations includes precipitation time series from 1961 to 2013 at Mondsee (no. 105346 at 13°22’-47°51’, operated by ZAMG) station, temperature time series from 2000 to 2013 also from Mondsee station. The discharge time series was observed at station See am Mondsee (no. 206185, 13°27’-47°48, operated by HD-Oberösterreich) from 1977 to 2012.

2.2. The applied model

For the numerical modelling of the Mondsee Catchment we selected the lumped NAM rainfall-runoff model. The model is integrated into the MIKE 11 1-dimensional hydrodynamic model developed by DHI. It also functions as a standalone hydrological model, which has been used globally (Doulgeris et al., 2012, Anderson et al., 2008, Makungo et al., 2010, Keskin et al., 2007, Thompson et al., 2004, Odiyo et al. 2012, Ostojski 2013, Hafezparast et al., 2013, Singh et al., 2014, Ahmed 2014, Amir et al., 2013), and compared to other rainfall-runoff models, its advantages and drawbacks have been pointed out in several studies (Vansteenkiste et al., 2014, Lidén & Harlin 2000).

Having set the target to calculate the total outflow at the watershed’s outlet section, a lumped model has been chosen. A conceptual model is able to simulate the behaviour of the catchment, describe the processes even on a long simulation period (Madsen 2000). The NAM model uses a relatively simple operational scheme (Fig. 1). The vertical layers of the catchment are separated into storages: snow storage, surface storage, lower zone storage and the groundwater storage. The essential inputs include precipitation rate and evapotranspiration, but further data may also be necessary such as temperature, irrigation data, etc. The water is conveyed by the simplified representation of physical processes: snow accumulation, snow melting, interception, evaporation, transpiration, capillary fluxes. The output of the model is the total runoff consisting of three main components. These components are the overland flow, interflow and baseflow. A NAM model has multiple parameters where the number is dependent on the processes included, such as irrigation, vertical zoning, and groundwater pumping.

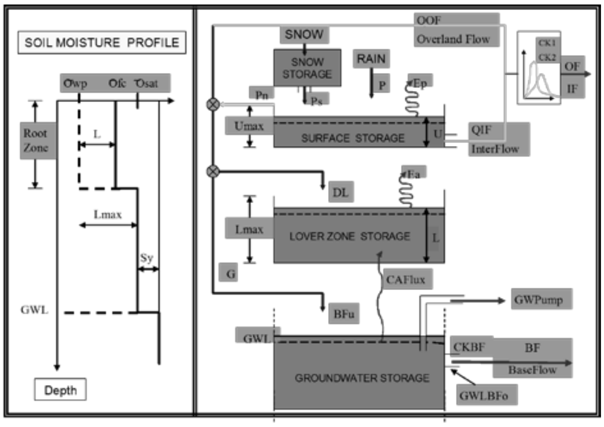

Figure 1. NAM model schematics (DHI 2014)

2.3. Calculating potential evapotranspiration

The NAM model requires evapotranspiration data for the simulation. The general empirical evapotranspiration calculation methods are erroneous and are specialised for a certain type of study area. To simplify this data generation and not to bias the simulations with additional calculations not considering the same modelling accuracy, we used a monthly averaged mean after Thornthwaite (1948) to obtain annual evapotranspiration data. The method correlates potential evapotranspiration with only mean monthly temperature, and it lacks variables like wind speed, humidity, and radiation. The method was derived from the water budget of natural watersheds and from controlled experiments in the humid Northeastern United States, that are of similar characteristics as our selected case study area. The unadjusted potential evapotranspiration in millimetres is calculated with equation 1:

$$PET = 16\left(\frac{L}{12}\right)\left(\frac{N}{30}\right)\left(\frac{10T_a}{I}\right)^a \quad , \qquad (1)$$

where T_a = average monthly mean temperature, N = number of days in the month, L = average length of daytime in the month, where I = annual heat index according to equation 2:

$$I = \sum\left(\frac{T_a}{5}\right)^{1.514} \quad , \qquad (2)$$

where T_a = monthly mean temperature;

These monthly values are then adjusted for possible hours of sunlight and the number of days in the actual month. However, the method tends to over- and underestimate potential evapotranspiration (Chen et al., 2005, Cruff & Thompson, 1967) as it does not incorporate regional and seasonal characteristics, it is still widely used for a general assumption (Ács et al., 2011, Calvo 1986). The result of the calculation based on the known temperature values at Mondsee is visible on the figure below (Fig. 2).

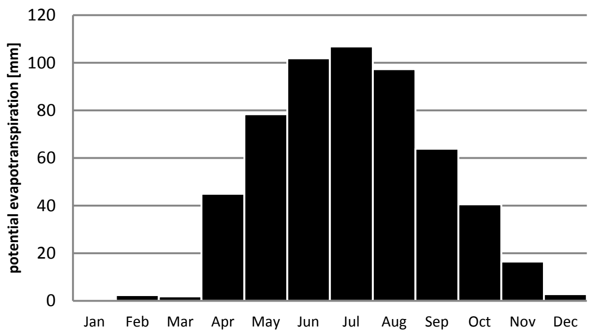

Figure 2. Potential evapotranspiration calculated with Thornthwaite method at Mondsee

2.4. Snowmelt

Snow accumulation and snow melting is incorporated in the NAM model by an integrated optional component called the snow module (DHI 2014). The accumulation and melting of snow is based on the degree-day approach, confirmed by several investigations (e.g. U.S. Army Corps of Engineers 1956), calculated by equation 3:

$$QS = \begin{cases} C_{snow}(T - T_0) for\ T > T_0 \\ 0\ for\ T \leq T_0 \end{cases} , \qquad (3)$$

where QS is the snowmelt, C_{snow} = degree-day coefficient, T is temperature and T_0 is the base temperature. The details of the calculation are explained in chapter 3.2.3.

The melt water is retained in the snow storage until the total amount exceeds the water retention capacity of the snow storage. The excess melt water is than routed to the surface storage of the NAM model.

Sublimation from snow is neglected. Altitude based distribution of the snowmelt model is also incorporated, which allows the elevation zoning of temperatures and precipitations and introduces individual snow storages separately for each altitude zone. The simple degree-day approach can be extended by using a seasonal variation of the degree-day coefficient, the melting effect of absorbed short wave radiation and the heat contribution from rainfall.

In case of unmonitored catchments, the above described approach could be sufficient for a general approximation of snowmelt contribution to the overall runoff, but if more detailed data is available (e.g. snow covered area, snow depth) there are more sophisticated models to simulate this process, as case studies confirm for example on Tamor and Aksu river basins (Rulin 2008, Panday 2013).

2.5. Model calibration procedure

A bare model is unable to provide the right answer using input data unless its free variables are calibrated. The calibration process is generally a trial and error task, but a great number of hydrological and hydraulic models (Dung et al., 2011) incorporate some kind of automatic calibration method with both disadvantages and advantages that have to be realized.

Since most of the values in NAM are not based on the physiographic, climatic and soil physical characteristics of the catchment, but are of empirical and conceptual nature, the calibration must be performed using time series of hydrological observations (DHI 2014). Thus, the numerical performance can be measured with the coefficient of determination or the Nash-Sutcliffe coefficient (NSE) (Nash & Sutcliffe 1970). We used the coefficient of determination as it is a default output of the NAM model. It is indicated with R^2 and calculated with equation 4:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left[Q_{obs,i} - Q_{sim,i}\right]^2}{\sum_{i=1}^{N}\left[Q_{obs,i} - \bar{Q}_{obs}\right]^2}, \qquad (4)$$

where $Q_{sim,i}$ is the simulated discharge at time i, $Q_{obs,i}$ is the corresponding observed discharge, and $\bar{Q}_{obs}$ is the average observed discharge. A perfect match corresponds R^2 = 1 (DHI 2014). The coefficient of determination can also be interpreted as an explained variance in percentiles.

The automatic calibration of the NAM model is based on multiple objectives. Using the symbols of equation (4) and by identifying the set of model parameters to be calibrated with θ, and the number of time steps in the calibration period with N, these are based on equation 5:

Overall volume error is:

$$F_1(\theta) = \left|\frac{1}{N}\sum_{i=1}^{N}\left[Q_{obs,i} - Q_{sim,i}(\theta)\right]\right| \qquad (5)$$

Overall RMSE is:

$$F_2(\theta) = \left[\frac{1}{N}\sum_{i=1}^{N}\left[Q_{obs,i} - Q_{sim,i}(\theta)\right]^2\right]^{1/2} \qquad (6)$$

The coefficient of determination in equation (4) is a transformed and normalised measure of the overall RMSE (normalised with respect to the variance of the observed hydrograph). Thus, minimisation of Eq. (6) corresponds to maximising R^2 (DHI 2014).

Average RMSE of peak flow events:

$$F_3(\theta) = \frac{1}{M_p}\sum_{j=1}^{M_p}\left[\frac{1}{n_j}\sum_{i=1}^{n_j}\left[Q_{obs,i} - Q_{sim,i}(\theta)\right]^2\right]^{1/2} \qquad (7)$$

where M_p is the number of peak flow events in the calibration period, and n_j is the number of time steps in event j. Peak flow events are defined as periods where the observed discharge is above a given (user-specified) threshold level.

Average RMSE of low flow events:

$$F_4(\theta) = \frac{1}{M_l}\sum_{j=1}^{M_l}\left[\frac{1}{n_j}\sum_{i=1}^{n_j}\left[Q_{obs,i} - Q_{sim,i}(\theta)\right]^2\right]^{1/2} \qquad (8)$$

where M_l is the number of low flow events, as M_p is in Eq. (7).

A general form of the multi-objective optimization challenge can be formalised as of equation 9:

$$min\{F_1(\theta), F_2(\theta), F_3(\theta), F_4(\theta)\}, \theta \in \Theta \qquad (9)$$

where Θ is the feasible parameter space for θ. This parameter space is a hypercube given by the physically and mathematically defined lower and upper limits of parameters. The detailed solution of Eq. (9) can be found in model's references manual (DHI 2014) and the implementation of this method is demonstrated in Madsen (2000).

Generally, the automatic calibration module of the NAM model requires a more systematic approach than a simple multi-objective process, and can be adjusted with manual calibration (Giang & Phuong 2010), although there are stronger algorithms reported with superior results (Zakermoshfegh et al., 2008).

3. RESULTS

3.1. Uncalibrated model on daily data

The model was run on the entire watershed for the simulation period from 1977 to 2011. During the first simulation, we did not define any other values than the input time series of precipitation and potential evapotranspiration, so we let the model calculate the following default parameters:

– U_{max}**:** maximum capacity of surface storage
– L_{max}: maximum capacity of root-zone storage
– *CQOF***:** overland flow coefficient
– *CKIF*: interflow coefficient
– *TOF***:** root-zone threshold for overland flow
– *TIF:* root-zone threshold for interflow
– *TG:* root-zone threshold for groundwater interception
– *CKBF:* base flow time coefficient
– *CK1,2:* overland flow time coefficient

In this first step two types of results were obtained. The first group of results include the main outputs including total outflow and runoff, the second group comprises partial results showing the current level of storages and exchange among them for each time step visible on the NAM model schematics figure (Fig. 1). The first group of results were then compared with the measured data, as they serve as the basis of calibration (Fig. 3 and Fig. 4).

Figure 3 shows a representative period of 2 years (1994-1995) from the simulation period (1972-2006), while Figure 4 shows the entire simulation period. The explained variance of the runoff is 42.7% in the uncalibrated case, and the total error of the water balance (difference of the observed and simulated accumulated runoff values at end of the simulation period) is 14.8%. We resume from Figure 3 that the low flow discharges are well approximated by the model, but the high flow events are incorrect.

3.2. Autocalibrated model on daily data

NAM provides an autocalibration algorithm besides manual calibration (see chapter 2.5.); therefore, the parameters can be adjusted based on target functions.

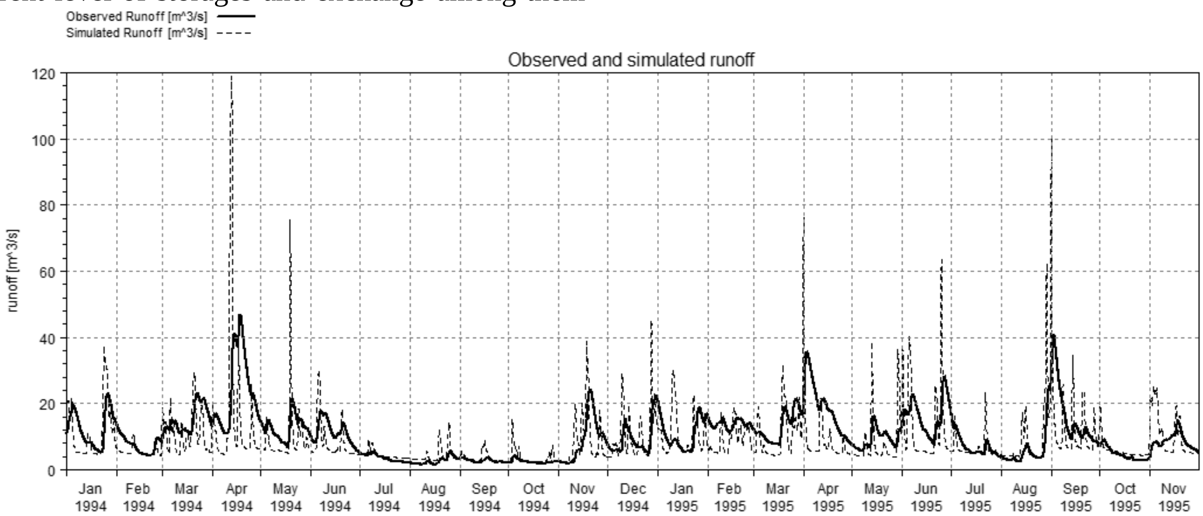

Figure 3. Observed and simulated runoff (uncalibrated)

Figure 4. Measured and calculated accumulated runoff (uncalibrated)

Such a target function could be the minimal error of water balance or the RMSE of runoff (Madsen et al., 2001). Our experience during the modelling was that the best method of autocalibration is to do it systematically, defining only one or two target functions simultaneously. For this simulation, we used the results of the previous simulation as initial condition.

We selected the water balance error minimization as the first target function. As a result of the autocalibration water balance error decreased from 14.8% to 6.7%, as can be observed in Figure 5. Both the observed and the simulated cumulative runoff series are increasing in parallel except two events, in the first third of years 2005 and 2006. The reason is probably inconsistency between the calibration discharges and the input precipitation data. The fitting of the observed and calculated runoff values is worse compared to the initial state, the explained variance of the runoff is 5.8%. This behaviour of the autocalibration routines of the NAM model has already been documented by Madsen (2000).

The target function of the next calibration step was the minimization of the RMSE of runoff values, aiming to achieve a better fitting of the observed and simulated runoff series (Fig. 7).

The highest value of explained variance was 55.2% and the water balance error was 15.9% after a series of autocalibration attempts. The simulations were made systematically focusing firstly on the RMSE, then the fitting of discharges below 5 and 10 m^3/s, finally above 30, 20 and 10 m^3/s.

3.3. Introduction of snow calculations to the calibrated model

Some early spring floods in 2005 and 2006 remained invisible in the model runs (Fig. 7). The model did not accumulate the precipitation of the winter season in snow to release it during the snowmelt of the spring season as surplus runoff, but provided immediate flood response to each rainfall events. In order to overcome this challenge, the snow module of the NAM model was applied (see chapter 2.4).

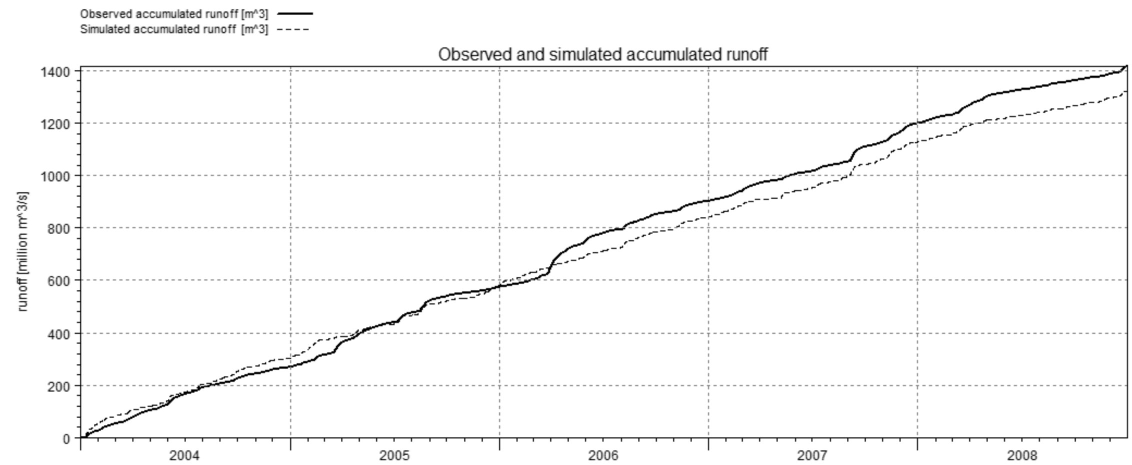

Figure 5. Measured and calculated runoff (after autocalibration with the target function of water balance error minimisation)

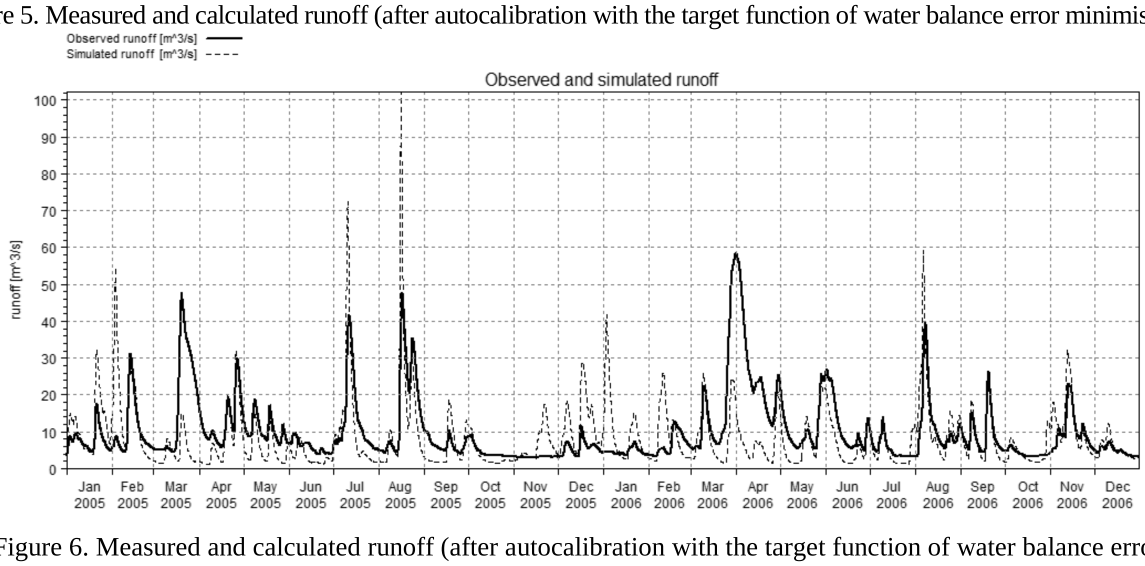

Figure 6. Measured and calculated runoff (after autocalibration with the target function of water balance error minimisation).

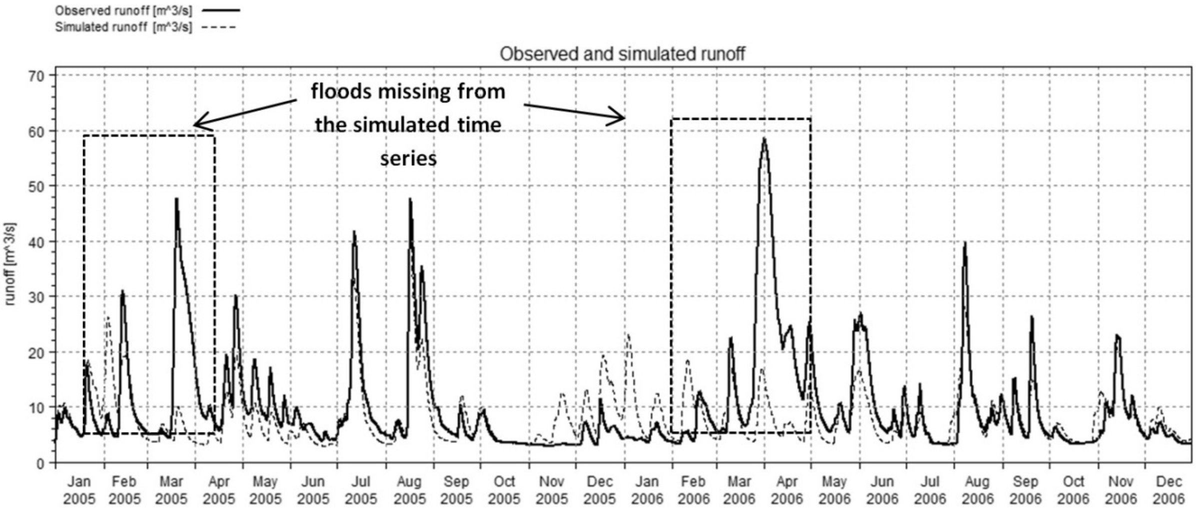

Figure 7. Measured and calculated runoff (after systematic autocalibration with the target function of higher variance).

To introduce the contribution of the snow in the model, it requires additional temperature time series as input data. Since the temperature has an obvious role in the formation of floods from snowmelt, we could not use the mean monthly temperatures as we used for the evaporation estimation, thus the daily mean temperatures were applied. We selected the period of 2004 to 2008 for further calibration. Based on manual calibration we defined the base temperature that separates rainfall from solid precipitation (snow). The degree-day coefficient defines decreasing snow depth based on the one-degree Celsius increment above the base temperature in a day. The seasonal variation of this parameter increased the model performance significantly (Fig. 8).

Having incorporated the snow module and recalibrated the model, the explained variance of the simulation period is of 81% accuracy. Thus, the model is not capable of simulating the remaining variability of 19% with the current structure and set of parameters.

The overall water balance error as shown in Figure 9 is 2.8%, indicating a 3.9% of improvement compared to the simulation results without the snow module but using the target function of water balance error with the minimization procedure. The snow module significantly increased the accuracy of the output results and their correspondence with the observed data.

The model during low flow periods is accurate, but has a slightly varying performance during floods. In case of shorter (app. below 10 days) flood events, caused by intense rainfalls, the input time series of daily precipitation data is not descriptive enough to allow the model to catch such fast flood events and thus provides much longer floods in time with a lower peak discharge, resulting in a significant phase error.

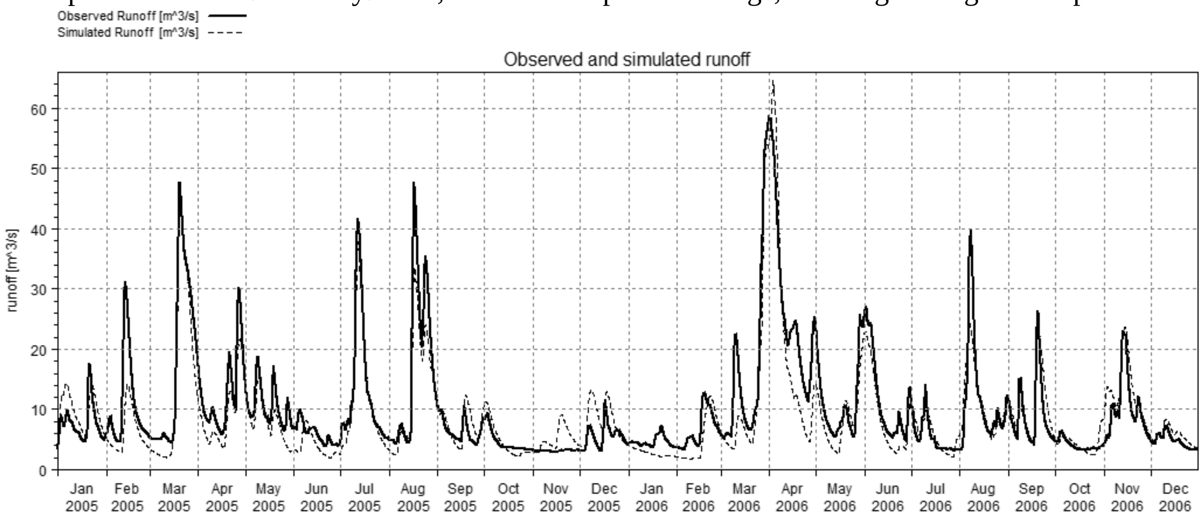

Figure 8. Measured and calculated runoff (after snow module introduction and calibration)

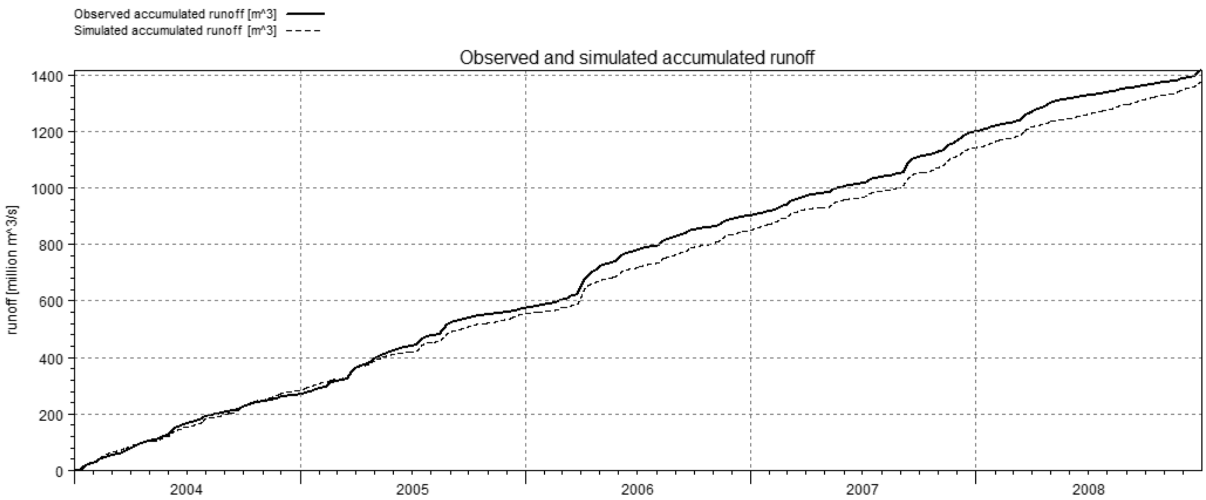

Figure 9. Measured and calculated accumulated runoff (after snow module introduction and calibration)

In case of longer floods caused by a continuously wetting catchment and longer rainfall events, the model is able to estimate a more accurate overall runoff. Any additional calibration attempt targeting these errors results in significant water balance error.

3.4. Recalibration on 6-hour step data

A serious limit of better fitting of the observed and simulated runoffs is the temporal resolution of the input data, especially of precipitation. Long and low-intensity rainfall results in continuous infiltration and slow downward propagation of the wetting front in the soil, while a short intense rainfall may cause immediate flooding triggered by significant overland runoff, and partitioning of rainfall into runoff rather than infiltration into the soil. As the rainfall data is available in 6-hour intervals, we changed the input of the model to assess its response to higher temporal resolutions. As the temporal resolution of precipitation has effect mainly on short-term water dynamics, the refinement of the model was focused mainly on surface related components such as overland flow and interflow routing, snow calculations, etc. Starting with the snow module the seasonal variation of the degree-day coefficient had to be modified to have a much stronger snow accumulation during winter period, and the melting effect of rain was introduced into the model to obtain a better match between the measured and simulated flood waves.

To assess the performance of the model with 6-hour precipitation totals as input parameters, new model simulations were developed for the period of May 2004 to September 2005, when the new precipitation time series was continuous enough for comparison. The variance increased from 81% to 86.3%, improving model accuracy about 5%. However, the simulation shows a worse performance for low flow periods, resulting in a significant change in water balance, therefore a manual correction of the groundwater parameters was required.

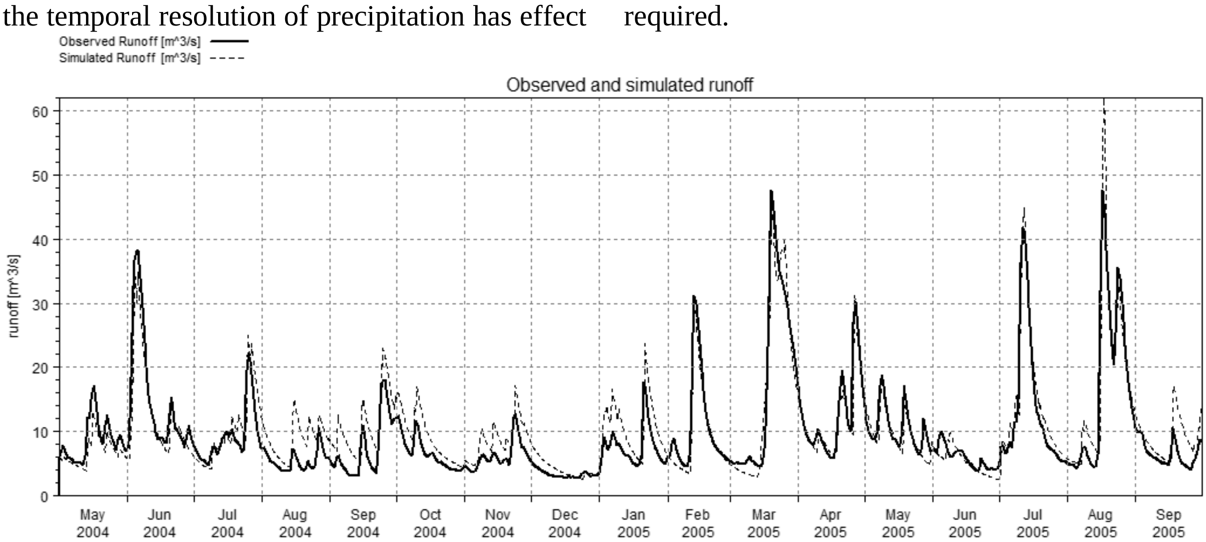

Figure 10. Measured and calculated runoff (after recalibration based on 6-hour precipitation data).

Table 1. Overview of surface and groundwater model parameters

	U_{max}	L_{max}	CQOF	CKIF	$CK_{1,2}$	TOF	TIF	TG	CKBF	C_{area}
v1	10	300	0.92	200	100	3.42E-04	8.33E-05	1.26E-04	4000	1
v2	10	298	0.84	200	100	1.04E-05	8.81E-05	1.27E-05	1101	2

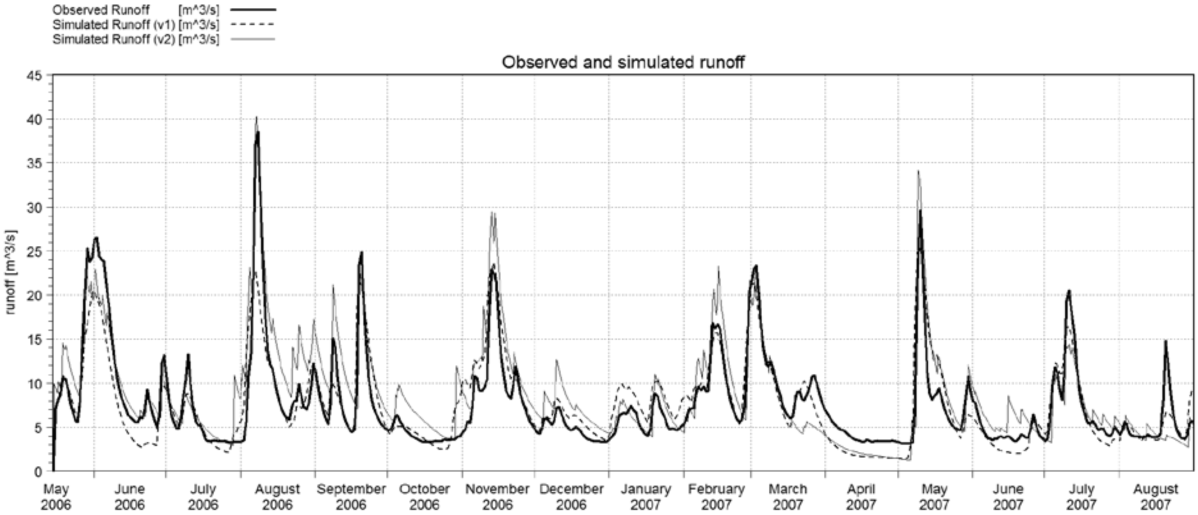

Figure 11. Comparison between measured and calculated runoff

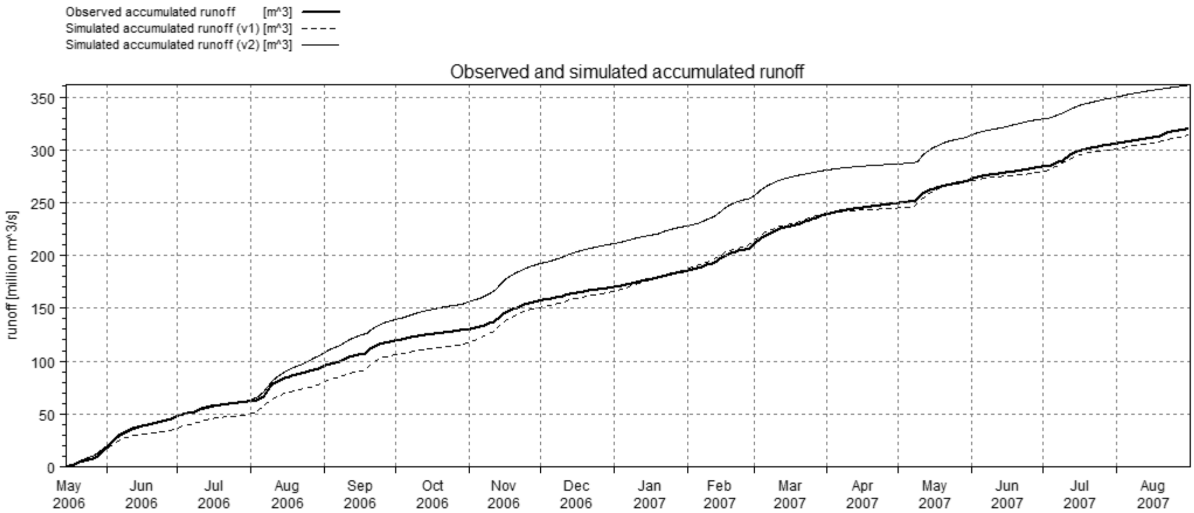

Figure 12. Verification: measured and calculated accumulated runoff.

The final water balance error was 7.8%, resulting in a decreasing performance from the previous model output based on daily rainfall. With further manual adjustments of the long-term parameters targeting the water balance, better results were obtained, but only besides disadvantageous changes of the variance (see also chapter 3.2).

3.5 Model verification

Verification on an independent set of input data is the justification of the model performance. The first scenario for verification (v1) was the full model setup including the extended snow module ran on a daily precipitation input. The second scenario (v2) was the same setup but recalibrated based on 6-hour step input precipitation data. The model parameters are listed in Table 1.

Recalibration slightly effected the surface runoff parameters and heavily effected the groundwater part. The reason is most probably the different nature of the input time series used for the simulations, especially their result during low-flow periods where such a slow runoff component as base flow has a major part.

The results of verification are shown in Figure 11 and Figure 12. By analysing the statistics, the explained variance of v1 was 76.1% (81% on calibration period) while 70% was observed for v2 (86.3% on calibration period). It means 4.9% drop in case v1 and 16.3% drop for v2. The water balance error is 1.8% for v1 and -13% for v2, which confirms the tendency shown by the explained variance values. However, v2 proved to be better calibrated against the RMSE and showed close fitting of the observed and simulated runoff series on the calibration period, but the performance on the verification time series is worse compared to v1. V1 resulted in slightly worse explained variance compared to the calibration process, but achieved a slightly better result on the water balance.

4. DISCUSSION AND CONCLUSION

To increase model performance, further calibration attempts were made, but none of them resulted in a generally acceptable outcome. When the model was optimized for distinct floods or high-flow periods that provides reasonable results locally, but we observed negative effect on the flow of the entire watershed. A significant flood event was observed in March 2005, generated by snowmelt and 30 to 40 mm of precipitation in a 24-hour period, while the daily average temperature was gradually increasing (Fig. 13). The flood wave peaked around 47.7 m^3/s and lasted for approximately 20 days. The solid line on Figure 13 represents the observed runoff, the dashed line the simulated runoff of the globally accepted calibration, while the dotted line shows the results of the targeted calibration of this flood event. Prior to recalibration, the RMSE of the simulation, calculated for this event was 7.1 m^3/s, while it decreased to 4.2 m^3/s after the recalibration. This means a better simulation of the flood wave, which is also visible on the graph below (Fig. 13). Nonetheless, this calibration resulted in a much worse model performance for floods in April, May and June of 2005. This instance is a typical case of an overlearning model, which indicates better local model performance that leads to poorer model performance globally.

By achieving NSE values higher than 86%, our results are considered satisfactory, therefore the hypothesis of the study is considered to be justified. Moreover, the secondary objective of autocalibration strategy is also fulfilled. Makungo et al., (2010) reached NSE=0.74 on South African catchments slightly under 100 km^2 with parameter regionalization, however the underestimation of peak discharges was a major issue in that case. Keskin et al., (2007) applied the model to a catchment of similar size (257.8 km^2) in north-eastern Turkey where snow accumulation and melt also have a major importance similarly to Alpine catchments and reached NSE=0.7 for high flow events and slightly lower values for low flow. Ostojski (2013) simulated multiple catchments in Poland ranging from 1500 km^2 to 15000 km^2 in area and obtained NSE values between 0.5 and 0.8. Hafezparast et al., (2013) reached NSE=0.74 while modelling a catchment in Iran of 2470 km^2. Reading through these previously published cases no Alpine case study about NAM model could be found, however some of the analysed catchments had similar characteristics to the Mondsee watershed. Comparing our results with these case studies, superior model performance was achieved even under the validation scenario, which is a result of targeted auto calibration strategy and simplified, goal oriented model structure.

Based on the results of the current study we believe that the MIKE 11 NAM model is applicable for the reconstruction of long-period flow time series with autocalibration and manual adjustment of calibration parameters and their sensitivity analysis.

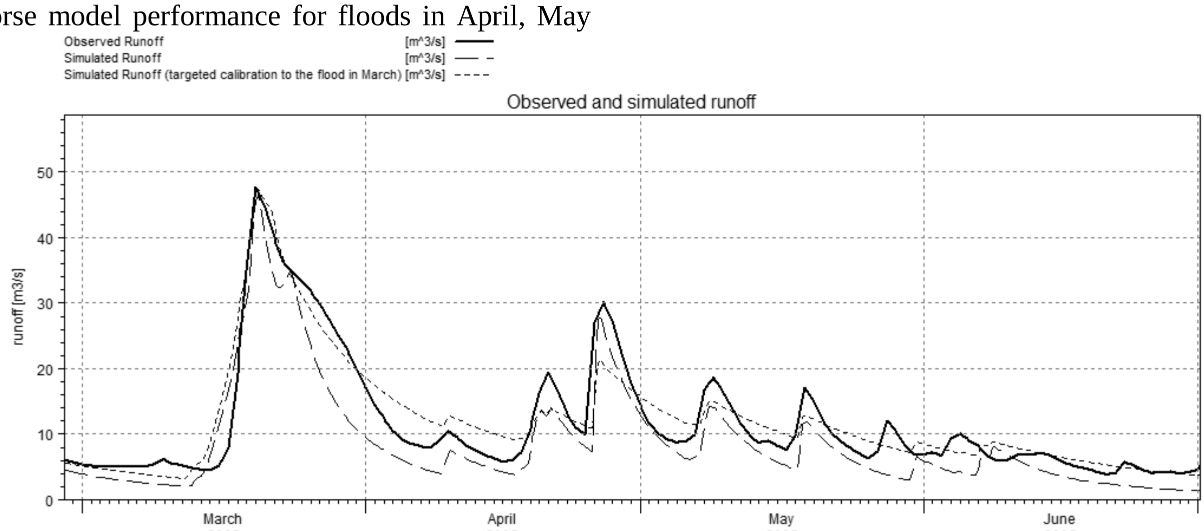

Figure 13. Measured and calculated runoff (targeted calibration to the flood in March 2005).

Table 2. Summary of the performance of the different model scenarios

	Uncalibrated	Autocalibration (water balance)	Systematic autocalibration	Snow module introduction	6h precipitation input
WBE*	14.8%	6.7%	15.9%	2.8%	7.8%
R^2	42.7%	5.8%	55.2%	81%	86.3%

* water balance error at the end of the simulated period

This conceptual model requires relatively little input data; however, the calibration is time demanding and the number of calibration parameters is high. In conclusion, the NAM model is applicable for Alpine/pre-Alpine, watersheds between rugger (south) and smoother (north) topography to estimate total runoff. Such modelling is particularly important on poorly monitored catchments where data have limited availability. The model can be further refined with specific calibration on distinct type of events, and detailed sensitivity analysis of the free variables in correlation with physical values. The operative application of this model as a numerical formulation in an ensemble forecasting system with changing initial conditions could be useful in flash flood hazard prevention and protection.

The MIKE 11 NAM model is robust, well-constructed system, with a clear and transparent background of relations. The MIKE by DHI software package is strong in both input data preparation and output management. Moreover, NAM is an integrated part of MIKE 11 model with advanced hydrodynamic, water quality, sediment transport capabilities. After the studies presented in this scientific paper and by reading through corresponding papers NAM proves to be a well-structured, regionally independent model. There are of course superior overall models or superior algorithms for distinct tasks such as the multi-objective automatic calibration, or the extension of snow module with additional measured data.

When snow accumulation was involved, the long-term model performance significantly improved for the estimation of runoff conditions for the Mondsee Catchment. However only a moderate model performance increase was found when input precipitation was decreased from daily precipitation totals to a 6-hour temporal resolution. Consequently, larger computational efforts, required to handle a four times larger database of input data, were essential to run the model. The accuracy of the output data, however, did not increase significantly with larger input data, thus we confirm that in the presented study case decreasing rainfall temporal resolution from 24-hor to 6-hour did not provide significant model performance increment, and disadvantages (e.g. processing time and data handling) outperform the benefits gained from the 6-hour model runs (Table 2).

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