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Effect of watershed delineation and areal rainfall distribution on runoff prediction using the SWAT model

Hamed Rouhani, Patrick Willems and Jan Feyen

ABSTRACT

The effect of the division in number of subcatchments and the spatial distribution of areal rainfall on the prediction of streamflow was evaluated using the SWAT model and data from the Grote Nete River catchment (Flanders, Belgium). A multi-automatic calibration scheme (MACS), using the Shuffled Complex Evolution (SCE) optimization algorithm, was applied. A total of 6 delineations were examined. The performance of each model set-up was assessed with respect to the outlet measured daily total, quick and slow flow component. The highest Nash–Sutcliffe Efficiency (EF) value for daily total flow was obtained by a delineation of 21 subcatchments. The EF of daily slow flows are high (>0.7) and comparatively stable for all analyzed delineations. Although quick flows are systematically underestimated, for larger number of subcatchments a relative good agreement exists between observed and simulated extreme flows with medium to high return period, expect for the 65 subdivision. The effect of the spatial density of rainfall input was evaluated running the model with uniform and non-uniform areal distribution of rainfall. A modified definition of Nash–Sutcliffe Efficiency (NSE_{ref}) was introduced to measure the performance of the simulated runoff versus the reference flow, derived with the Thiessen-based areal rainfall as input. The analysis revealed that: (a) the NSE_{ref} decreases with the number of subcatchments in which the basin is divided, and (b) simulations using a uniform rainfall distribution equal to the rainfall recorded in a rainfall station situated centrally in the catchment underperform as input.

Key words | aerial rainfall, automatic calibration, hydrologic modelling, model performance, subbasin delineation, watershed

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INTRODUCTION

More than a decade ago, Sorooshian & Gupta (1995) highlighted that parameter specification and estimation are among the two most important activities in modelling. The challenge of catchment modelling lies in identifying, through a sensitivity analysis, which inputs and model parameters strongly affect system relevant outputs, and trying to define those inputs and model parameters in the most accurate way. Inputs and parameter values ought to be representative of the scale to which the mathematical descriptions in the model are formulated. It is to be expected that the larger the subunit, the less the inputs and parameter values correspond to the inherent *in situ* spatial variability of the subunit. As such, the number of subcatchments which a catchment is divided into definitively affects the values of the parameters derived in the calibration. Therefore, the search for the best parameter set has to consider the partitioning level of the catchment (Vázquez *et al.* 2002). Jha *et al.* (2004) studied the effect of the number of subcatchments of four catchments in Iowa (USA), each 2,000–18,000 km^2 in size, in order to define the level of subcatchment division that best simulated flow, sediment and nutrient transport. Bingner *et al.* (1997)

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showed that annual fine sediment yield is highly sensitive to the number of subbasins used to represent the watershed, but seemingly the annual streamflow is not significantly affected by the watershed partitioning. The effect of spatial aggregation using the Soil Water Assessment Tool (SWAT) model was examined by FitzHugh & Mackay (2000).

Analogous to examining the effect of the delineation of the watershed in subcatchments, there have been many attempts to define the most optimal number of point rainfall values to achieve the best match between observed and simulated river flows (Wilson *et al.* 1979; Troutman 1983). A comprehensive review of the literature addressing the relation between the density of point rainfall observations and the accuracy with which the river flows are predicted can be found in Chaubey *et al.* (1999), Booji (2002) and Bárdossy & Das (2008), among others. Bárdossy & Das (2008) used different spatial resolutions of the rainfall input in the model calibration and application of the semi-distributed Hydrologiska Byråns Vattenbalansavdelning (HBV) model. They found that the model performance radically worsens with an excessive reduction of raingauges. However, the overall performance did not improve significantly by increasing the number of raingauges above a certain threshold number. Chaubey *et al.* (1999) provide examples of variability solely due to the spatial rainfall variability in estimated hydrologic/water quality model parameters.

In this research the Shuffled Complex Evolution (SCE) algorithm for finding the global optimum set of model parameters was applied in a manner analogous to many authors (e.g. Duan *et al.* 1992, 1993; Sorooshian *et al.* 1993; Kuczera 1997; Thyer *et al.* 1999; Madsen 2003; Vrugt *et al.* 2003; Brath *et al.* 2004; Butts *et al.* 2004).

The research had three objectives, namely:

1. to identify the most sensitive model parameters;
2. to define the optimal parameters for different levels of subcatchment delineation using an automatic calibration scheme based on the SCE method; and
3. to examine the effect of areal rainfall input, uniform and non-uniform spatial distribution, on the model performance.

For the research, use was made of the SWAT (Arnold *et al.* 1994; Neitsch *et al.* 2002) code and daily data of the highly vegetated and sandy-loam flat Grote Nete River catchment, 384 km^2 in size, situated in Flanders, Belgium.

MATERIAL AND METHODS

SWAT model description

The model developed by the Agricultural Research Service of the United Stated Department of Agriculture (ARS-USDA) simulates eight components of the environment system, i.e. hydrology, generation of weather data, sedimentation process, soil energy balance, crop growth, nutrient and pesticide leaching and agricultural management (Neitsch *et al.* 2002). SWAT is a semi-distributed model using process descriptions that are either empirically or physically limited in its process basis, operating on a daily time step. SWAT uses hydrologic response units (HRUs) to describe the spatial heterogeneity in terms of land cover and soil type. The model simulates the hydrologic processes at four levels: (i) the soil surface, (ii) the intermediate unsaturated zone, (iii) the shallow and deep aquifers, and (iv) the open channels. Relevant hydrologic components such as evapotranspiration, surface runoff, groundwater flow and soil moisture change are estimated at the level of each HRUs. Streamflow in the main channel is the sum of the surface runoff, the lateral flow and baseflow. For predicting the runoff volumes, SWAT use a modified computational efficient version of the Soil Conservation Service Curve Number (SCS CN) method (SCS-USDA 1972), relating runoff to soil type, landuse and management practices. In addition, SWAT uses an empirical procedure for channel routing. The baseflow recession constant is calculated using an equation suggested by Smedema & Rycroft (1983), a function of the overall basin topography, drainage pattern, soils and geology composition of the watershed. For more information about the SWAT model, the reader is referred to Neitsch *et al.* (2002).

Study area and model input

Hydrological data of the Grote Nete River catchment in Belgium, 384 km^2 large, were used for the period 1 January

1994–31 December 2002. The elevation of the basin is 12–68 m, slopes generally smaller than 1%. Sandy loam soils (44.96%) are the dominant soil type, followed by sandy (37.77%) and clay (17.27%) soils. Sandy soils occupy the northern part of the catchment, while the sandy loam soils are dominant in the south of the catchment. The clay soils are patched along the river branches. Five land-use classes can be distinguished with forest (37.17%) most widespread followed by pasture (21%). Wetlands and water bodies occupy 1.35% of the area. The region has a temperate climate, with an average annual precipitation of 790.3 mm, a mean July temperature of 16°C and a mean January temperature of 2°C. No dry and wet seasons can be distinguished as the intensity, duration and frequency of rainfall events are uniformly distributed throughout the year.

The model was set up using the following datasets.

- Daily maximum and minimum air temperature, relative humidity and daily precipitation were gathered from the Royal Meteorological Institute (Belgium) and the Flemish Water Administration for Land and Water.
- Daily streamflow data were available from the Varendonk limnigraphic station on the Grote Nete River, and made available by the Flemish Water Administration for Land and Water.
- The soil map was available at a scale of 1:25,000 and the soil physical data derived from the Aardewerk-SIBIS Soil Information System (Van Orshoven *et al.* 1993) using the pedotransfer functions of Vereecken *et al.* (1990).
- Land-use was determined using the multitemporal LANDSAT 5 TM images of 18 July 2001.
- Digital elevation data were derived by digitizing the iso-elevation lines of the national topographic map, scale 1:50,000, followed by the creation of a rectangular 40 × 40 m grid in the UTM reference system. By re-projecting the data to the Belgian reference system, a point geo-dataset, in which the points are distributed in almost rectangular grids, is obtained. This point dataset was converted to a 50 m grid using the Interpolate Grid (Van Orshoven 2005).

The study catchment was partitioned into 6 catchment delineations, which were divided into 1, 4, 9, 21, 40 and 65 subcatchments. Catchment delineations were further divided into a different numbers of HRUs by setting the land cover and soil thresholds. This resulted in the following number of HRUs per subcatchment delineation: 1, 42, 71, 169, 280 and 392. The maximum and average CN2 (Table 1) from coarser to finer delineation were 73, 85, 83, 85, 85, 92 and 73, 76.6, 75.27, 75.87, 76.82, 76.87, respectively. The minimum CN2 in the lumped scenario was 73 and in the other scenarios 60.

Simulations were run on a daily basis; weather and discharge data were available from 1 January 1994 to 31 December 2002. The discharge data for the periods 1 January–31 December 1996 and 5 January–13 August 2002 were not used due to river calibration works near the limnigraphic station. The years 1999–2002 were selected for model calibration. Data from the years 1994–1998, with a more normal rainfall distribution, were used for model validation. The areal rainfall was generated using the daily rainfall data of 4 weather stations (Kleine Brogel, Westerlo, Geel EA25 and Kwaadmechelen), weighted by the Thiessen area. The station of Kleine Brogel is situated east of the catchment, the Westerlo station is situated in the catchment close to the basin outlet, the station of Geel EA25 is situated north of the Westerlo station and located at the water divide and the station of Kwaadmechelen is located centrally in the study basin.

The annual rainfall for the period 1994–2002 varied from a minimum of 641.8 mm to a maximum of 1,037.7 mm, with an average annual rainfall of 852.3 mm or 7.85% above the regional average annual rainfall of 790.3 mm, indicating that the period of analysis with the exception of 3 years (1995, 1996 and 1997) was wetter than normal. The average annual rainfall during the calibration period (1999–2002) was 927.5 mm or 17.36% higher than the regional average annual rainfall. During the validation period (1994–1998), the average annual rainfall was close to that of the regional average annual rainfall, equal to 792.1 mm. The average monthly rainfall for the observation period varied between 56.6 and 91.9 mm, illustrating that rainfall is fairly uniformly distributed throughout the year. The lowest recorded monthly rainfall in the period 1994–2002 is 3.3 mm (January 1997) and the highest 173.1 mm (August 1996).

Table 1 | Ranking of the initially selected 18 most sensitive model parameters

Parameter	Mean deviation of the parameter estimate in the sensitivity analysis	Definition
CN2	0.547	SCS runoff curve number for Soil Moisture Condition II
RCHRG_DP	0.309	Groundwater recharge to deep aquifer (fraction)
SOL_AWC	0.134	Available water capacity of the soil layer (mm mm^{-1} soil)
ESCO	0.129	Soil evaporation compensation factor
GW_REVAP	0.093	Groundwater 'revap' coefficient
CANMX	0.072	Maximum canopy storage (mm)
ALPHA_BF	0.069	Baseflow alpha factor (days)
GWQMN	0.068	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)
GW_DELAY	0.046	Groundwater delay (days)
REVAPMN	0.010	Threshold depth of water in the shallow aquifer for 'revap' to occur (mm)
CH-K2	0.006	Effective hydraulic conductivity in main channel alluvium (mm hr^{-1})
SLSUBBSN	0.0023	Average slope length (m)
SURLAG	0.0022	Surface runoff lag coefficient
SOL_K	0.0020	Saturated hydraulic conductivity (mm hr^{-1})
SLOP	0.0016	Average slope steepness (m m^{-1})
BIOMAX	0.0006	Biological mixing efficiency
BLAI	0.0000	Leaf area index for crop
EPCO	0.0000	Plant uptake compensation factor

Separation of flow components

The flow separation program of Arnold & Allen (1999) was used to determine the relative contribution of surface runoff and groundwater to total streamflow. A flow-component hydrograph is obtained by subtracting a time series of filtering flow from the total hydrograph. The filtering time series is generated by applying Equation (1):

$$q_F(t) = \beta \times q_F(t-1) + \frac{1+\beta}{2} \times (Q(t) - Q(t-1)) \quad (1)$$

where $q_F(t)$ is the quick flow component at a given time-step, separated from the total flow (Q). β is a filter parameter set at 0.925 (Heuvelmans 2005). The filter parameter affects the degree or attenuation, and the number of passes determines the amount of smoothing. The filter can be passed over the data as many times as the user chooses, typically alternating forward and backward passes. In Heuvelmans (2005) the filter was passed 2 times. During each iteration, more flow is removed from the hydrograph and q_F is recalculated.

Given the characteristics of the study basin, the daily total flow is assumed to consist of a quick and slow water flow component. The slow flow component is considered as the sum of the intermittent and baseflow. The applied splitting of the daily total flow is based on the fact that the basin is relatively flat, primarily composed of sandy soils with high hydraulic conductivity, intensively drained by a network of ditches and pipe drainage systems. If the land in the basin were not properly drained, the water table in the wet season would imply that the surface was constraining the agricultural exploitation. Physically, given the local conditions, it is very difficult to discern the intermittent flow from the baseflow. Both are therefore summed and considered as the slow water flow component in this study, whereas the difference between the total and slow flow component is defined as the quick flow component (Rouhani *et al.* 2007).

The number of days for the calculation of the coefficient regulating the decrease of the runoff hydrograph down to the base flow ALPHA_BF in the recession was set at 10 (minimum number of days) and 10,000 (maximum number of days to calculate the value for alpha in the groundwater recession equation), respectively.

When the baseflow days are known, ALPHA_BF can be calculated:

$$\alpha_{gw} = \frac{1}{N}\cdot\ln\left[\frac{Q_{gw,N}}{Q_{gw,O}}\right] = \frac{1}{\mathrm{BFD}}\cdot\ln[10] = \frac{2.3}{\mathrm{BFD}} \tag{2}$$

where α_{gw} is the baseflow recession constant, N is the time lapsed since the start of the recession (days) and BFD is the number of baseflow days for the catchment. A value of 0.008 was found for ALPHA_BF and 125 for the number of days for the baseflow recession to fall through one log cycle. The ALPHA_BF of 0.008 days was very small compared to commonly used values (typically 0.3–1.0 days), suggesting slow drainage and huge storage in the shallow aquifer of the study basin. To further validate the separation model, the determined hydrographs were confirmed with another flow separation model: the Water Engineering Time Series Processing tool (WETSPRO) (Willems 2003). The results of the two models were mostly consistent. Approximately 18% of streamflow is contributed by direct runoff and 82% of streamflow by slow flow.

Extreme value analysis

An extreme value analysis was applied for the statistical description of extremes and their frequency in time. In general, this consists of modelling an observed dataset of extreme values by an appropriate probability distribution function for which the Generalized Extreme Value, Pareto or Weibull distributions are typical examples. The discharge series was split for this purpose in nearly independent quick flow events. Quick flow maxima were selected as the highest discharge values during the quick flow periods (Willems 2000).

If the calibrated distribution of independent flow extremes x is denoted $F(x)$, the return period T (years) is defined by:

$$T = \frac{1}{1-\exp\left(-\frac{t(1-F(x))}{n}\right)} \tag{3}$$

The most efficient way to analyze the type of distribution is by means of the so-called quantile-quantile plots. The empirical quantiles match the observed extremes x_i, $i = 1, m$ $(x_1 \geq \cdots \geq x_m)$ (the order statistics), with $p_i = i/(m+c)$ as their corresponding empirical probabilities of exceedance. The scores $c(0 \leq c \leq 1)$ are given a value of 1, corresponding to the so-called Weibull plotting position of a quantile plot. For each empirical quantile x_i, the theoretical quantile is defined as $F^{-1}(1-p_i)$. The function $F(x)$ is the cumulative distribution that is tested in the Q–Q plot, named according to this distribution. If the observations agree with the considered distribution $F(x)$, the points in the Q–Q plot approach the bisector (Willems 2000). In this study the Q–Q plots and the so-called quantile function $U(p)$ are plotted instead of the inverse distribution $F^{-1}(1-p)$. For exponential Q–Q plots, the distribution and inverse distribution are defined:

$$F(x) = 1 - \exp\left(-\frac{x-x_m}{\beta}\right) \quad \text{or} \qquad F^{-1}(1-p) = x_m - \beta\ln(p) \tag{4}$$

where x_m is the threshold level above which the distribution is considered, and β the scale parameter. The quantile function is then defined:

$$U(p) = -\ln(p) \tag{5}$$

Identification of most sensitive model parameters

The one-factor-at-a-time (OAT) method has been applied in combination with Latin Hypercube (LH) sampling, as proposed by van Griensven *et al.* (2006) to determine the most sensitive model parameters. The advantage of the LH-OAT approach is that (a) it combines the strength of a global and local sensitivity analysis; (b) it allows the incremental investigation of the sensitivity of each parameter over the parameter range; and (c) it allows the nonlinearity effect of each single parameter to be examined. In summary, the LH-OAT performs the LH sampling followed by the OAT sampling. It combines the robustness of the LH sampling, and ensures that the full range of all parameters has been sampled with the precision of an OAT design and that the changes in the output in each model run can be unambiguously attributed to a specific model parameter (Huisman *et al.* 2004). The sample points are chosen randomly, taking n Latin Hypercube sample points for n intervals, and then varying each LH sample point k times by changing each parameter one at a time, as is done in the OAT method (van Griensven *et al.* 2006). The final effect is calculated by averaging partial effects of each loop for all Latin Hypercube points (thus for n loops). The method is efficient, as for m intervals in the LH sampling a total of $n \times (k+1)$ model runs is required. The final effects can be ranked with the largest effect being given rank 1 and the smallest effect being given a rank equal to the total number of parameters analyzed. A detailed description of the algorithms is beyond the scope of this paper. Interested readers are referred to van Griensven *et al.* (2006).

Over 40 parameters can be distinguished in the SWAT model for modelling rainfall-runoff, should all modules be used. It is important to have an understanding of catchment characteristics and the hydrological processes involved before blindly applying automatic calibration to the available data. Based on a critical analysis of the SWAT, the parameters related to the hydrological description of the study area were reduced to 18. To further reduce the number of parameters in the calibration process, a sensitivity analysis was conducted to define the most sensitive parameters controlling the streamflow generating process. The sensitivity analysis was performed for a predefined set of 18 parameters with 10 intervals in the LH sampling. This means that the model was run 190 times to complete the sensitivity analysis. The values of parameters used were within the range suggested by previous research (Heuvelmans 2005; Rouhani *et al.* 2007) and the SWAT user's manual (Neitsch *et al.* 2002). Table 1 depicts the sensitivity ranking of the 18 predefined parameters of the streamflow module, whereby it is observed that the last 2 parameters (BLAI, EPCO) (see Table 1) do not really affect the model output.

Model calibration and validation

In this study, the different model structures were calibrated using the SCE algorithm (Duan *et al.* 1993), simultaneously minimizing the error of the simulated total and slow flow. van Griensven & Bauwens (2003) succeeded in implementing two objective functions in the SWAT optimization manager, i.e. the sum of the squares of the residuals (SSQ) and the sum of the squares of the difference of the measured and simulated values after ranking (SSQR). The SSQ is very similar to the Mean Square Error function (MSE) and aims to estimate the matching of a simulated series to a measured time series. The SSQR method, on the other hand, aims to fit the frequency distribution of the observed and the simulated series. Equations (6) and (7) represent the computation of the SSQ and SSQR, respectively:

$$\mathrm{SSQ} = \sum_{t=1,n} [\mathrm{TF}(Y_{\mathrm{measured}}(t)) - \mathrm{TF}(Y_{\mathrm{simulated}}(t))]^2 \tag{6}$$

$$\mathrm{SSQR} = \sum_{r=1,n} [y_{\mathrm{measured}}(r) - y_{\mathrm{simulated}}(r)]^2 \tag{7}$$

where n is the number of pairs of measured and simulated variables, TF is a user-defined transformation function and r is the rank (van Griensven & Bauwens 2003).

Several SSQs or SSQRs can be combined to a Global Optimization Criterion (GOC) using (van Griensven *et al.* 2006):

$$\mathrm{GOC} = \sum_{m=1}^{M} \frac{n\mathrm{SSQ}_m}{\mathrm{SSQ}_{\min}} \tag{8}$$

where $\mathrm{SSQ}_{\min}$ is the lowest of all SSQs considered. In this study, SSQs and SSQRs were considered for both total and slow flow. Initially, $\mathrm{SSQ}_{\min}$ is not known. Therefore after each loop in the SCE optimization, an update is performed for $\mathrm{SSQ}_{\min}$ using the newly gathered information within the loop, after which the GOC value is recalculated.

In parallel with the GOC, model performance was also assessed on the basis of the EF coefficient (Nash & Sutcliffe 1970):

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n} (y_{\mathrm{simulated}}(i) - y_{\mathrm{observed}}(i))^2}{\sum_{i=1}^{n} (y_{\mathrm{observed}}(i) - \overline{y}_{\mathrm{observed}})^2} \tag{9}$$

Automatic calibration was undertaken varying the most sensitive parameters in different catchment discretization to achieve a close match between the observed and simulated daily total and slow flows. The maximum number of trials allowed was 4,000 before optimization was terminated with the complex shuffling set at 97.5% probability for each model structure.

RESULT AND DISCUSSION

Sensitivity analysis and calibration results

Based on previous experience acquired during manual model calibration (Rouhani *et al.* 2007) and from a global-search, fine tuning of the 7 parameters listed in Table 2 (RCHRG_DP, CN2, SOL_AWC, ESCO, GW_REVAP, GWQMN and REVAPMN) gave the best model performance. In addition, the ALPHA_BF parameter was increased in order to reproduce steeper hydrograph recession. The remaining parameters were not calibrated because of their reduced impact on the model output and to keep the calibration parsimonious, recognizing concerns regarding over-parameterization.

The analysis revealed that the components of the water balance (see Table 2) are most sensitive to the parameters CN2 and RCHRG_DP. RCHRG_DP values of 0.18–0.20 were determined during the model calibration process, permitting 18–20% of the percolated water to bypass the shallow aquifer and enter the deep, regional system; thereby reducing baseflow to match measured values. In this study the original CN2 values were decreased by 2.41 to 5.28% for delineations larger than 1 and increased by 5.66% for the lumped delineation scenario, leading to a better simulation of peak values.

SOL_AWC (available water capacity for all soils) was decreased by 32.88 to 50% in order to increase the water release of the soil profile. The soil evaporation compensation coefficient (ESCO) was increased with the size of the subcatchment, allowing more evaporation from the lower soil layers. The GWQMN value, except for the delineation of the study basin in 21 subcatchments, was increased in order to restrict baseflow. The value of the REVAPMN parameter was decreased but kept larger than the GWQMN parameter in order to ensure that groundwater return flow occurs before 'revap' (transfer of groundwater to upper soil layers). The value of the GW-REVAP parameter was increased from 0.01 to 0.20 for all delineation scenarios.

Effect of the number of subcatchments on model predictions

Figure 1 depicts the annual averaged observed and simulated daily total and slow flow as a function of the number of subcatchments and for the calibration (left panel) and validation period (right panel). The daily average total flow is fairly well simulated during the calibration and validation period, independent of the subcatchment delineation, whereas the daily average slow flow is overestimated for all delineations. The overestimation is largest for the smallest number of subcatchments. Agreement between simulated and observed total and slow flows is generally better during the validation period, which most probably is due to a rainfall distribution close to normal. The overestimation of the slow flow component, according to Watson *et al.* (2005), is most likely explained by a delay in routing. SWAT routes channel flow but do not route overland flow. Instead, a simple surface runoff storage feature is used to lag a portion of the surface runoff released to the main channel. This simple approach may be affecting

Table 2 | Values of the 7 most sensitive parameters after calibration for each of the catchment delineations studied

		Number of the subcatchments					
Parameter	**Default value**	**60**	**40**	**21**	**9**	**4**	**1**
GWQMN*	0.02	0.16	0.06	0.02	0.06	0.28	0.44
GW-REVAP*	0.01	0.20	0.20	0.20	0.20	0.20	0.20
REVAPMN*	1	0.75	0.75	0.50	0.61	0.88	0.93
ESCO*	0	0.00	0.00	0.53	0.87	0.80	0.77
SOIL_AWC†		−44.08%	−50.0%	−33.00%	−49.87%	−50.0%	−50.0%
RCHRG_DP*	0.05	0.20	0.20	0.20	0.19	0.20	0.20
CN2†		−4.92%	−5.28%	−4.81%	−2.41%	−5.06%	5.66%

*Replacing the initial parameter by the value listed in the table.
†Multiplying initial parameter by the value (%) listed in the table.

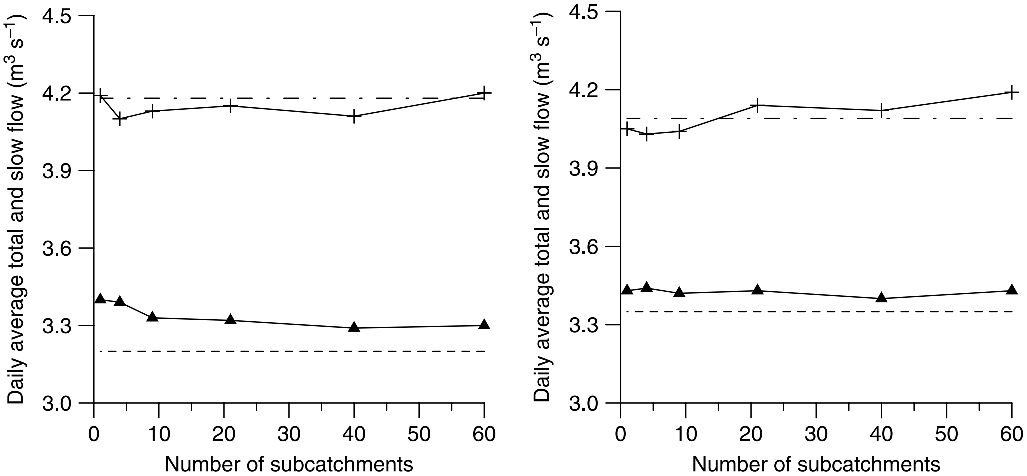

Figure 1 | Average daily total (full line, +) and slow (full line, ▲) flow ($m^3 s^{-1}$) and corresponding observed total (dash point line) and slow (dash line) flow during model calibration (left panel) and validation (right panel) as a function of the number of subcatchments in which the catchment is divided.

recession rates. FitzHugh & Mackay (2000) found that streamflow increased by 12% between the coarsest and finest watershed delineation in annual and monthly model output. Results of this study indicate that streamflow and its components are moderately to slightly affected by changing the subcatchment delineation.

Figure 2 depicts the EF for daily total (left panel) and slow (right panel) flow, calculated for the calibration (full line) and validation (dotted line) period. Whereas the EF for the daily slow flow is fairly constant, fluctuating around 0.7 for all delineations scenarios, the EF for the daily total flow fluctuates strongly as a function of the number of subcatchments during the calibration and validation period.

In the calibration period the EF is significantly highest for a delineation of 21 subcatchments, decreasing for respectively smaller and larger delineations. During the validation period, EF for the daily total flow is smaller than 0.7 for the delineations 1 and 4 and fairly constant for finer delineations, fluctuating around 0.7.

Overall, the results using mid-resolution discretization scales varying between 9 and 40 subcatchments are fairly acceptable, with a delineation of 21 subcatchments yielding the best result. Also, the water balance estimation using mid-resolution discretization scales were simulated better. Increasing the number of delineations results in lower efficiencies for the daily total flow, particularly during the

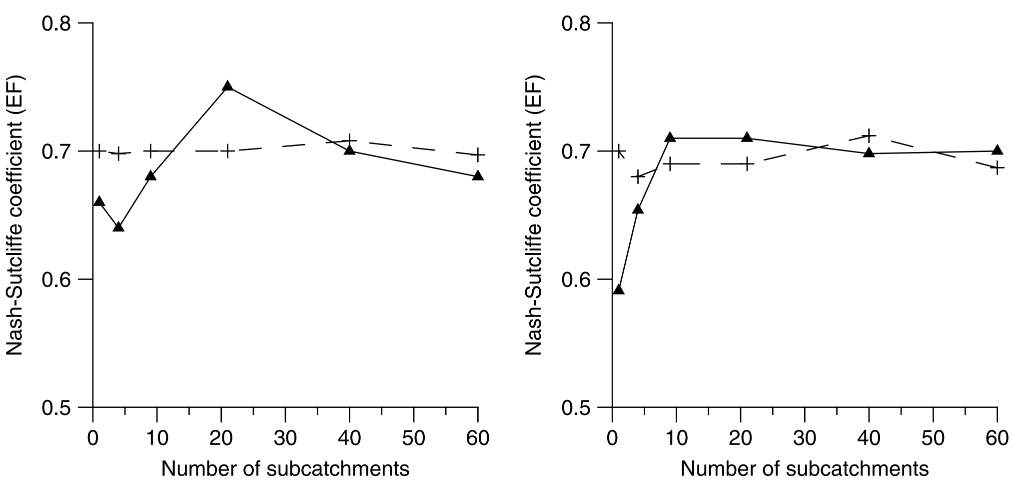

Figure 2 | Nash–Sutcliffe Efficiency (NCE) coefficient for daily total (▲, full line) and slow (+, dash line) flow ($m^3 s^{-1}$) during model calibration (left panel) and validation (right panel) as a function of the partitioning in subcatchment.

calibration phase. This can be explained by problems with the parameter optimization as we used a fix number of parameters and iterations for different catchment subdivisions. The large number of subcatchments may require more parameters to be optimized and iterations.

These findings are in line with the general findings of Reed *et al.* (2004), who showed that the higher spatial and temporal resolution of data does not always lead to a better model performance. Recent work by Das *et al.* (2008) confirmed that the highest value of model performance was obtained using the semi-distributed and semi-lumped model structure, and the least level of model performance using the distributed model structure. Ogden & Julien (1994) and Smith *et al.* (2004) came to the same conclusion that distributed modelling approaches may not always provide improved outlet simulations compared to lumped conceptual models. A similar analysis was carried out by Boyle *et al.* (2001). In their study, they found that 8 subdivisions of a basin provided no gain in simulation accuracy compared to a three sub-basin representation. They reasoned that the more coarse representation of the basin better captured the essential variability of the rainfall and basin features. On the other hand, Jha *et al.* (2004) showed that SWAT's streamflow components are relatively insensitive to changes in the number of subcatchments in which the watershed is divided. Those findings are somehow in contrast with our findings and the observation of Mamillapalli *et al.* (1996), who stated that the accuracy of SWAT streamflow predictions were affected by the number of subcatchments and HRUs used to present the watershed. Decline in accuracy at coarser levels of aggregation were apparently due to changes in the distribution of the CN2 runoff parameter.

In general, there may be an inherent tradeoff between modelling accuracy, the complexity of the model descriptions necessary to represent the catchment processes and the accuracy required to achieve reliable simulation results (Butts *et al.* 2004).

In addition, the effect of subcatchment delineation on extreme flows was examined using the method described by Willems *et al.* (2007). The frequency distributions of observed and simulated extreme events in different catchment discretization during the calibration (left panel) and validation (right panel) period are shown in Figure 3. As depicted in the left panel of Figure 3, the frequency distribution of extreme flows are systematically underestimated in the calibration period, and the deviation with respect to the frequency distribution of observed extreme flows increases with increasing number of subcachtments. This could be due to the automatic updating of the CN value based on the soil moisture condition, which with more subdivisions is more variable leading to more fluctuating lower peak flows. Another contributing factor can be that more subdivisions cause higher variability of runoff values and consequently more variance and a heavier tail of the

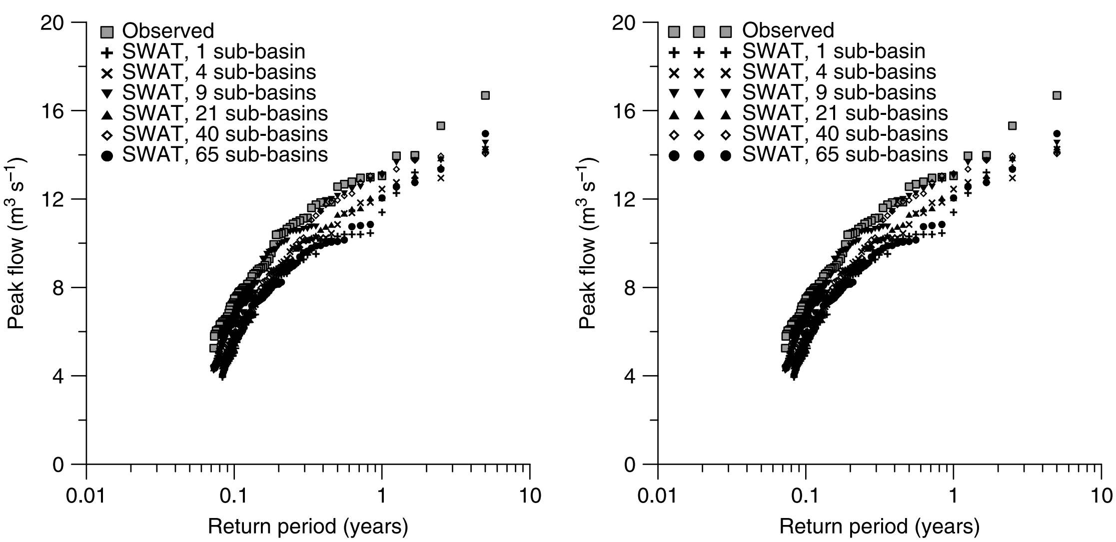

Figure 3 | Empirical frequency distribution of observed and simulated peak discharges as a function of the subcatchment delineation during model calibration (left panel) and validation (right panel).

extreme value distribution. Also, the travel time will increase with increasing number of subcatchment delineations. If the time delay is significant, as it would be in large subcatchments, than the runoff travelling from the upper portions of the subcatchment will arrive at the outlet after the runoff from the lower portions of the subcatchment has been discharged, with a lowering of the magnitude of the peak flow as a consequence.

The validation results are displayed in the right panel of Figure 3. The results for the validation period are similar to the observations for the calibration period. However, the frequency distribution for the different delineations, although slightly underestimated, deviate less from the frequency distribution of observed extreme flows. The general trend of the underestimation of peak flows, as observed in this study, is in line with the findings of several previous studies which addressed the underestimation of the peak flows generated with the SWAT model (e.g. Bosch *et al.* 2004; Chu & Shirmohammadi 2004). In SWAT, runoff is derived using the daily rainfall, of which the intensity in most cases is lower than the intensity of short storms. Lowering the real intensity of the storm automatically results in a lowering of the runoff intensity (Wischmeier & Smith 1978). Limitations of the CN method also include no explicit account of the effect of the antecedent moisture conditions in runoff computation, the difficulties in separating storm runoff from the total discharge hydrograph and runoff processes not considered by the empirical formula (Garen & Moore 2005). Consequently, estimates of runoff and infiltration derived with the CN method may not represent reality. In addition, in SWAT the CN value is updated based on the available water content of the entire soil profile. However, it is probably more appropriate to update the CN value in accordance with the soil water content of the top soil layer, which would more closely reflect the process of surface saturation during heavy rainfall events (Laura *et al.* 2006).

Effect of the spatial density of rainfall input on the prediction accuracy

In this section the effect of spatial resolution of the rainfall on simulated runoff, for different scales of catchment discretization, are presented. Similar to the work published by Segond *et al.* (2007), in the simulation experiment for each delineation use was made of the calibrated and validated values of the most sensitive parameters presented in Table 2. Only the rainfall input varied from uniform to non-uniform spatial distribution (Chaplot *et al.* 2005; Bárdossy & Das 2008). Doing so allowed the verification of the validity and transferability of the parameter values derived in the calibration, with rainfall input the Thiessen-based areal rainfall, also called the non-uniform spatial rainfall distribution scenario (Scenario 3); considered as the reference in the comparative analysis.

For the generation of the rainfall scenarios the daily rainfall collected in 4 stations was used, as described in 'Study area and model input'. The rainfall scenarios analyzed are two areal uniform distributions, equal to the rainfall measured at the Kwaadmechelen station (Scenario 1) situated inside the catchment and the average daily rainfall calculated as the weighted average of the daily rainfall measured in the 4 stations. The Thiessen polygons defined the area as weighting factor (Scenario 2).

Figure 4 shows the frequency distribution of the daily rainfall (histogram) of the 4 stations for the period 1994–2002 versus the Thiessen defined areal daily rainfall (+, full line). Differences between the observed rainfall distributions of the 4 stations and the reference rainfall distribution are rather small. The average difference in annual areal rainfall was 7%, ranging between 4 and 12%. Figure 5 depicts the average daily total flow as a function of subcatchment delineation using the three areal rainfall scenarios as model input. The non-uniform rainfall distribution (Scenario 3; + with full line) yields a higher daily average total flow in all scenarios. With the uniform rainfall scenarios, the average daily total simulated flow is smallest using the rainfall of the Kwaadmechelen station representative for the entire study basin (Scenario 1) as model input. The average daily total simulated flow using the average rainfall calculated with the Thiessen polygons derived areal weighting factor as model input (Scenario 2) is situated between the two other scenarios. The lower simulated daily average total flow for Scenario 1 is logic and most likely due to the systematic lower rainfall volume measured in the Kwaadmechelen station; average annual rainfall of 827 mm versus 886 mm for the non-uniform areal distribution.

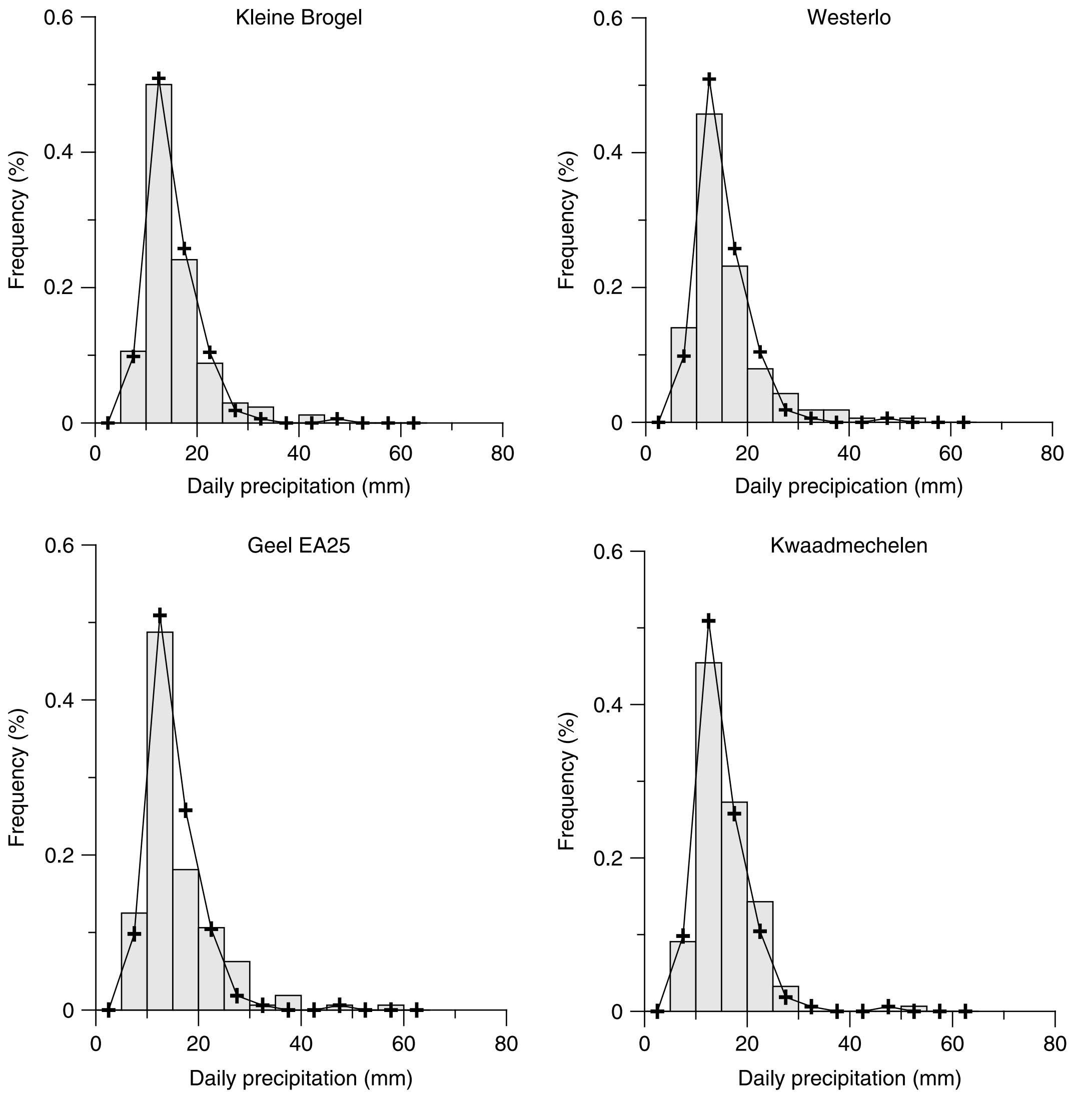

Figure 4 | Frequency distribution of daily precipitation measured in the rainfall stations Kleine Brogel, Westerlo, Geel EA25 and Kwaadmechelen for the period 1994–2002 versus the basin daily rainfall defined using the Thiessen polygon method (+ , full line).

The results presented are in line with the findings of analogous studies, which also conclude that using too coarse a raingauge network can give rise to remarkably poor hydrological simulation results (e.g. Brath *et al.* 2004; Chaplot *et al.* 2005; Schuurmans & Bierkens 2006; Bárdossy & Das 2008). A modified definition of EF introduced by Segond *et al.* (2007) (here called NSE_{ref}) was applied to quantify the performance of the simulated runoff using a uniform rainfall distribution (Scenarios 1 and 2) versus the reference flow simulated using a non-uniform rainfall distribution (Scenario 3) as model input. The NSE_{ref} for the rainfall Scenarios 1 and 2 as a function of the subcatchment delineation are presented in Figure 6. As shown in Figure 6, the NSE_{ref} derived for the rainfall Scenarios 1 and 2 decreases with increasing number of subcatchments, and the observed decline in NSE_{ref} is largest for Scenario 1. Notwithstanding the minor differences in the considered rainfall scenarios, results clearly show the importance of the way rainfall is input on the SWAT simulated flows. Our findings are in line with the results reported in Michaud & Sorooshian (1994) and Vischel & Lebel (2007).

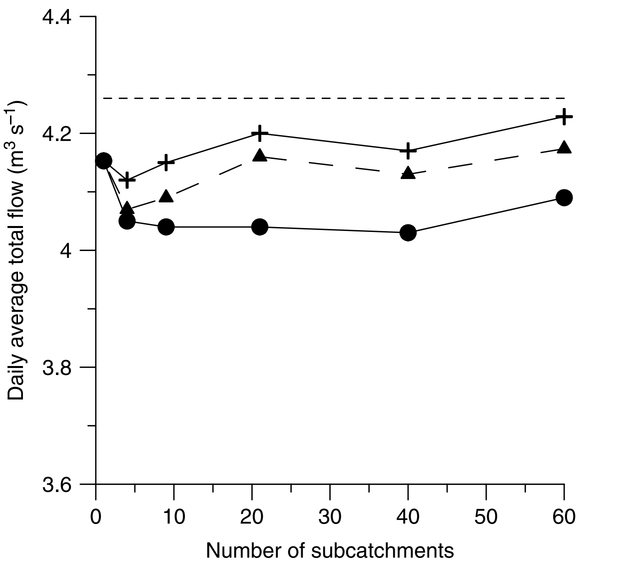

Figure 5 | Average daily total flow ($m^3 s^{-1}$) as a function of the subcatchment delineation for (a) Scenario 1: uniform areal rainfall using the daily rainfall of the Kwaadmechelen station (●, full line), (b) Scenario 2: uniform areal rainfall defined by weighted average daily rainfall using the the Thiessen polygon method for defining the weights of each of the 4 stations (▲, dash dash line), and (c) Scenario 3: non-uniform areal rainfall based on the Thiessen method (+, full line) and the average observed total flow (point line).

Figure 7 depicts the frequency distributions of observed and simulated extreme flows for the division of the basin in 21 subcatchments and the three rainfall scenarios. This figure shows that the extreme flow distribution of Scenario 3 is very similar to the distribution of observed extreme flows. Using Scenario 2 as rainfall input, the areal weighted average rainfall defined on the basis of the rainfall measured in 4 stations in and around the catchment, yields lower simulated extreme flows. When taking the rainfall of the Kwaadmechelen station, situated inside the catchment as representative for the entire catchment, the lowest simulated extreme flow distribution results. This could be expected given the slightly higher magnitude of the extreme rainfall distribution of the non-uniform rainfall scenario. Arnaud *et al.* (2002) concluded from the calibration of the MERCEDES rainfall-runoff model, with application to a relatively large basin in Mexico City, that the simulated runoff is severely affected when using a spatial average rainfall instead of the areal rainfall distribution. Faures *et al.* (1995) and Andreassian *et al.* (2001) also showed that a single raingauge can lead to large uncertainties in runoff predictions due to the reduction of knowledge on the areal rainfall variability. Arnaud *et al.* (2002) indicated that, as is generally the case in this type of study, conclusions may be very case-specific i.e. dependent upon the scale of the basin, rainfall variability, event frequency and rainfall-runoff mechanism.

Based on the visual and statistical comparisons of the simulated hydrographs, multi-gauge rainfall information produces more accurate predictions of the daily total flow

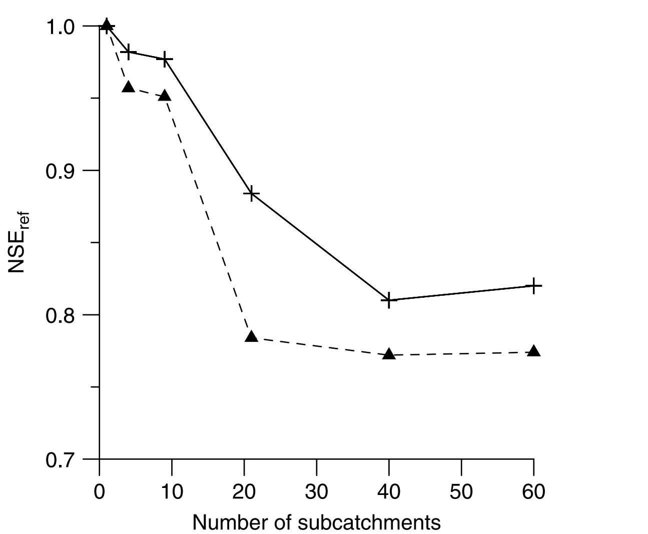

Figure 6 | NSE_{ref} for the daily total flow using respectively the daily rainfall of Scenario 1 (data of the Kwaadmechelen station) (▲, dash line) and Scenario 2 (areal rainfall based on the weighted average rainfall of 4 stations, with the weighting factor being defined by the Thiessen method (+, full line), as a function of the number of subcatchments in which the catchment is divided.

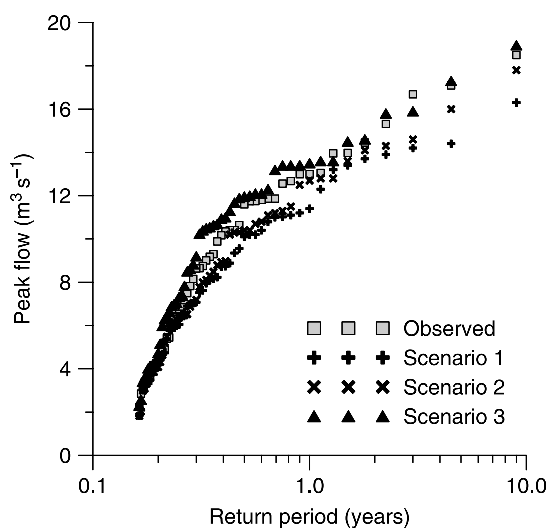

Figure 7 | Frequency distribution of observed (grey square) and simulated peak discharge for a subcatchment delineation of 21 and the 3 areal rainfall scenarios (Scenario 1: uniform rainfall distribution equal to the rainfall measured in Kwaadmechelen station, +; Scenario 2: uniform rainfall distribution equal to the weighted average rainfall measured in 4 stations, x; Scenario 3: non-uniform rainfall distribution as defined with the Thiessen polygon method, ▲).

for the study catchment. Differences, however, are not that large as a consequence of the limited difference in the rainfall distribution of the 4 rainfall stations of which information was used. The data presented in Figures 5–7 reveal the following.

- Incorporating rainfall distribution in the model input significantly amplified the predicted runoff in total flow but hardly seems to affect the slow flow.
- Increasing the number of subcatchments into which the catchment is divided affects the predicted total flow strongly. The impact is considerably less when the slow flow is simulated.

CONCLUSIONS

The authors used the SWAT model to analyze the hydrologic response of the Grote Nete River basin in Flanders (Belgium), using catchment data from the period 1 January 1994 to 31 December 2002. A LH-OAT sensitivity analysis yielded the 7 most sensitive parameters, which were optimized in the calibration process using a multi-automatic calibration scheme based on the SCE algorithm. The parameters that were identified as the most sensitive correspond very well to the parameters mentioned in literature as having the largest effect on streamflow. The values of the parameters are within the range of published parameter values. The parameter values defined in the calibration phase performed well in the validation phase, notwithstanding that the annual areal rainfall in the calibration phase was on average 17.36% larger than the normal annual rainfall depth, whereas the annual areal rainfall in the validation phase was close to the regional average rainfall.

Of the different catchment discretizations analyzed, a delineation of 21 subcatchments yielded the highest EF value. The model performance decreased by increasing the number of subdivisions. This could be explained by the fixed number of parameters and iterations applied for the different catchment subdivisions, whereas it might be justified to make the number of parameters in the optimization and the number of iterations as a function of the number of subdivisions.

Research into the impact of the division of the catchment in subcatchments and accompanying HRUs revealed that varying the number of subcatchments hardly affects the daily slow flow, but affects the daily total flow component. The EF coefficient for the daily slow flow component is less affected by the variation in subcatchment division. The latter is most likely due to the fact that the catchment is very flat, consisting of sandy-loam soils with high hydraulic conductivity, intensively drained by ditches and subsurface drains. By increasing the size of the subcatchment, the model seems to be less able to mimick the extreme flows. The numerical analysis revealed that when the number of subcatchments decreases and the spatial rainfall pattern is assumed uniform, the SWAT model is less accurate in predicting the peak flows. Furthermore, it was found that the larger the subdivision of the study basin into subcatchments, the better the agreement between observed and simulated extreme flows for the 3 areal rainfall scenarios.

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