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Analysing the Sub-processes of a Conceptual Rainfall-Runoff Model Using Information About the Parameter Sensitivity and Variance

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Abstract Sensitivity analyses are often carried out for the main model output and using a predefined evaluation period. It is possible, however, to get much more knowledge about how the system works when estimating the sensitivity for the output of individual modules for each time step (time-varying sensitivity analysis). This is shown here using a variance-based sensitivity analysis for a conceptual rainfall-runoff model applied to a mountainous catchment. The first-order and total sensitivities were computed using Sobol's method. Since the parameter ranges used in the sensitivity analysis were obtained through a Markov chain Monte Carlo (MCMC) sampling, the sensitivity indices reflect the parameter uncertainty and make a good use of the previous available information. As a first step, the variance of each flow component was calculated. The flow component with the highest variance at each time step can be regarded as the 'dominant physical control', which has been defined as the parameter to which the model output reacts in a highly sensitive way when the parameter varies within realistic ranges. This information about the dominant processes can be used for facilitating model calibration by identifying the periods on which to focus when calibrating different parameters. It also can be useful for estimating the amount of data available for calibrating each process. The second part presents the total sensitivity indices and interactions for individual flow components considering a 2-year period. The results show large differences in the time-varying sensitivity patterns of the flow components. It is concluded that such a high-resolution sensitivity analysis for each flow component is a good complement to a sensitivity analysis of the total discharge, increasing our understanding about the internal functioning of individual modules which can be helpful when comparing different model formulations.

Keywords Global sensitivity analysis · Model evaluation · Dominant model controls · Sobol · Time-varying sensitivity analysis · Parameter interactions

1 Introduction

Using environmental models correctly involves much more than knowledge about the required inputs and resulting outputs. It is important to follow good modelling practices and to have realistic expectations about what can be achieved [1]. Further, it is necessary to know the assumptions embodied in the model, which can give first indications about the limitations, omissions and uncertainties modellers are confronted with [2]. While the assumptions can usually be inferred from the mathematical descriptions used, a comprehensive understanding of model limitations and omissions requires additionally an examination of the implementation of the mathematical descriptions as well as the linkages and interplay between different model components.

Various approaches are available for analysing the internal functioning of a model. One of them uses sensitivity analyses, which provide information about the impact that changes in the model input have on the modelled outputs. Model input refers here to any factor that can cause changes in the model output, such as model parameters and inputs, initial and boundary conditions, model structure or numerical schemes. This study will, however, consider only the impact of model parameters on the model output; more specifically, it will be shown how sensitivity analyses can help in understanding how models work by (a) analysing the sensitivities of individual processes and (b) identifying the model controls.

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With respect to the first point, there are some examples of sensitivity analyses carried out for different model processes. Hartebrodt et al. [3], for instance, modelled the net income for large German forest enterprises using a data-based model. They estimated the sensitivity for individual components and considered this to be a useful approach for identifying casual chains. Judd et al. [4] and Sumner [5] show examples of sensitivity analysis for sub-modules in physically based models. Sumner [5] differentiates the effect that parameters have on the modules which they describe (intra-sensitivity) from the effect that parameters have on subsequent modules (inter-sensitivity). In hydrology, we found a study analysing different model processes (evapotranspiration and bottom fluxes) and one state variable (soil moisture) for the SWAP model by looking at the combined effect of three parameter groups (crop, weather and soil parameters) [6]. Since the parameters were analysed as a group, it was not possible to make inferences about individual parameters or module functioning, which requires an analysis at a more detailed level. One common characteristic of all these studies is that they estimate average sensitivities for a given period. While this informs about the average impact that parameters have on the model output, it is possible to obtain much more detailed information with time-varying sensitivity analyses [7–12] which estimate the sensitivity at each time step. Since the processes taking place in a catchment vary depending on the state of the catchment and the prevailing climatic conditions, an analysis of high-temporal resolution is much better for seeing what happens during the simulation period. Therefore, we decided to carry out a high-resolution sensitivity analysis (daily steps) for each process considered in our model.

Besides helping to see how individual model processes work, a sensitivity analysis for each time step and module provides information about the processes influencing the model results at individual points in time. This is done here by identifying the process with the highest variance at each time step and agrees well with the definition of 'dominant physical control' as 'a model parameter to which model predictions are extremely sensitive to when varied over a realistic range of values' [13]. Unlike the term dominant physical control, which refers exclusively to the results of a modelling process, the term 'dominant processes' has a more general connotation. It has been defined as the model components (and therefore processes) that are needed for a reliable simulation [14] or also as the process that 'controls hydrological response in different environments and at different scales' [15]. Since this is a very general definition, some attributes of the dominant processes concept will be briefly addressed here. It is noted in the first place that 'hydrological response' can be defined as the adaptation of the hydrologic states and fluxes to varying climatic boundary conditions. This hydrological response can be evaluated using different response variables, for instance soil moisture, groundwater table or runoff. This last variable was used by Scherrer and Naef [16] and Schmocker-Fackel et al. [17] in a decision tree for classifying areas according to their main runoff formation process. The next important issue when dealing with dominant processes is to determine which characteristic of the hydrologic state or flux defined as response variable is regarded as the criterion for labelling a specific process as dominant. Schmocker-Fackel et al. [17] defined, for instance, dominant process as the process which 'contributes most to runoff', while it could also be possible to define it as the process with the highest variance in the discharge. It must also be considered that the hydrological response can be analysed for long periods, which could provide a frequency distribution of dominant processes for a specific system, but that it is also possible to look at the dominant processes for specific conditions, like flood events or high-intensity rainfalls [18]. Casper [19] distinguished in this context explicitly between the actual dominant processes, which are the result of the specific conditions prevailing during a period, and the potentially dominant processes which depend on the characteristics of the catchment. The publication by van den Bos et al. [20] shows how such an identification of potential dominant processes can be carried out based on the analysis of the catchment lithology which allows some inferences about how certain meteorological conditions result in different runoff and soil moisture patterns.

Information about dominant processes can be of use in several practical instances. For instance, it might support model calibration by using the periods during which each process dominates for calibrating the parameters describing the respective process. The idea behind this is that these parameters have a large effect on the model results when the process is dominant, making it easier to evaluate the effect of different parameter values. This has the advantage that each parameter is calibrated so that it serves its principal goal, which is to describe a specific process, instead of being used to just increase the overall model fit [21].

Variance-based sensitivity analyses require Monte Carlo runs for estimating the sensitivity indices, and the results of such analyses depend on the parameter ranges between which each parameter is allowed to vary [22]. This is why it is important to select these limits carefully. A characteristic of this study is that it takes parameter uncertainty into account, since they are the result of a Markov chain Monte Carlo (MCMC) sampling of the posterior parameter distribution. An alternative to this would have been to optimise the model and consider, for instance, ±20 % for all parameters as limits for defining the parameter ranges. We think, however, that models should be analysed considering as much as possible the available data for the catchment being modelled. This can be achieved using the MCMC limits, which reflect our uncertainty about the parameter values.

Summarising, the main objective of this paper was carrying out a time-varying sensitivity analysis for the sub-processes of a conceptual rainfall-runoff model applied to a mountainous catchment for increasing our understanding about how the model works. We first identified the model controls for each day in the considered period and then estimated the first-order sensitivities and the total interactions for each model process. The sensitivity indices were obtained using Sobol's method which has been used recently in water-related studies dealing with eutrophication models [23], life cycle salmon simulation models [24], models for micropollutants in storm runoff [25] and the analysis of the SWAT model [26, 27].

2 Description of the Field Site, Model and Methodology

2.1 Description of the Field Site

The analysis was done for the Jalovecky Creek located in the western Tatra Mountains in Slovakia. About half of the catchment area is located between 1,300 and 1,700 m.a.s.l., and the remaining area lies above 816 and below 2,178 m. The average slope in the catchment is 30°. With respect to the geological characteristics, it is estimated that 50 % of the catchment consists of crystalline rocks and that about 7 % of the surface is underlain by carbonate rocks, a situation which could result in karstic features [28]. The soils are in general shallow with an average depth of 60 to 90 mm [29] and have a high skeleton content, sometimes up to 50 % [30]. The most important land cover classes are forests (44 %) and shrubs (31 %). The rest are grasslands and bare rock surfaces [28].

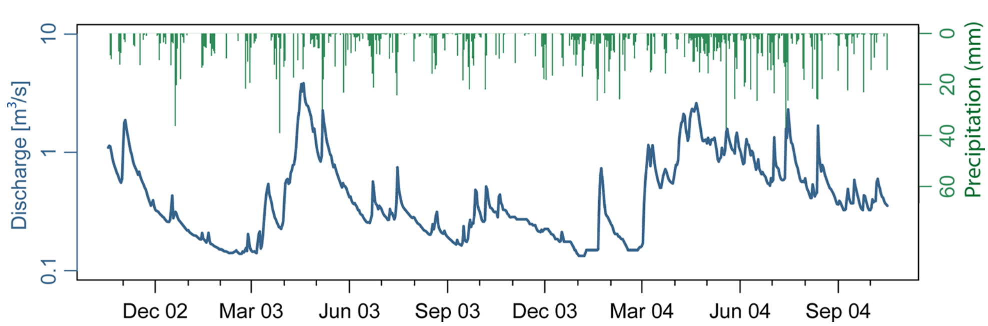
There were data available for the daily average temperature and precipitation from meteorological stations inside the catchment covering the period between November 2001 and October 2007 (Figs. 1 and 2). In addition, there were data for two stations located in the vicinity. Effective values for the precipitation were obtained by weighting the values of the stations using the Thiessen method [31]. The highest precipitation was observed in summer, between May and August, when all months had values higher than 150 mm. The months with lowest precipitation were April and December, both with about 76 mm/month. This pattern is reflected in the discharge, which was measured at a point draining a surface of 22.2 km^2, since there is a clear maximum of the monthly depth of runoff in May (206 mm) and the values are below 40 mm in winter.

The average monthly temperature for the reference station at 1,500 m was 1.5 °C. Between November and March, the monthly average was below zero and it reached a maximum of 12 °C in July. The potential evapotranspiration was estimated using the Thornthwaite method [32], which has the advantage of requiring only the monthly mean temperature as input. The results showed that the maximum potential evapotranspiration reached about 100 mm in July.

2.2 Description of the Hydrological Model Used

The model used is a lumped bucket-type conceptual model (Fig. 3). It is based on the model presented in Holzmann and Nachtnebel [33]. This former model was coded as one single program, but for increasing its flexibility, it was recoded assigning one subroutine to each process. This allows adapting the model structure according to the characteristics of the catchment and to the objective of the modelling. New modules and process descriptions not available in the former model were also added, but they are not used in this study. The model inputs are the daily potential evapotranspiration, precipitation and temperature time series. Snow accumulation and melt are dependent on temperature and therefore modelled in a semi-distributed way for 100-m elevation bands. Snow accumulates if the temperature during rainfall is below a predefined threshold, and snowmelt is modelled using a day-degree approach. The parameters *hypgrad* and *fak* represent the hypsometric lapse rate and the melt factor, respectively. The Hortonian flow process is observed when the infiltration capacity of the soil is lower than the rainfall intensity. It is modelled using three parameters. The parameter *inf_cap* stands for the infiltration capacity of the soil, while *surf_prop* represents the proportion of the catchment in which this process is observed. The water exceeding the infiltration capacity of the soil is routed to a storage unit from where it is released as a function of the recession constant *akval*. The

Fig. 1 Daily discharge and areal rainfall for the Jalovecky Creek between November 2002 and October 2004



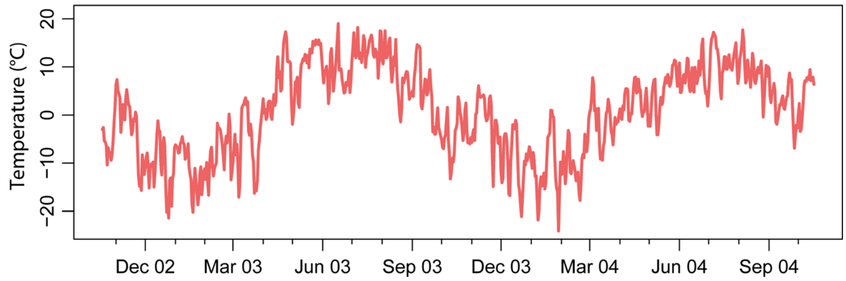


Fig. 2 Daily temperature for the Jalovecky Creek between November 2002 and October 2004

water outflow from the storage is modelled using the relationship:

$$Q = Sk^{-1} \tag{1}$$

where Q [LT^{-1}] represents the specific discharge and S [L] stands for the water level in the storage. K [T] is the recession constant, which is called *akval* for the Hortonian flow storage. The water infiltrating into the soil reaches the soil storage from where it can be released as saturation flow (only active when the water level in the soil storage is above *adepms*), interflow or percolation. This water release is modelled using the same principle as for Hortonian flow (Eq. 1). The recession constants are named $k1$, $k2$ and $k3$ for saturation flow, interflow and percolation flow, respectively. The percolated water reaches the groundwater storage and is released as baseflow as function of the parameter $k4$.

2.3 Sensitivity Analysis

Sensitivity analyses can be separated into local and global methods with local methods quantifying the impact that input changes have on the output at given locations of the corresponding input and output surfaces [34]. Global sensitivity methods, on the other hand, consider the whole input range and also may allow taking the interactions between different parameters into account. One important group of global sensitivity analyses is variance-based decomposition methods, which disaggregate the total variance of the model output into different components. These components can then be used for constructing sensitivity indices. The variance of the model can be calculated based on the results of a Monte Carlo approach (i.e. many model runs carried out with different parameter sets). Since each of these model runs will result in a different model output, it is possible to describe this spread of the output using the variance as a measure. This total variance (Var) is calculated as the sum of the variance explained by the different parameters on its own and the variance explained by parameter interactions [35]:

$$\mathrm{Var} = \sum_{i}^{n} \mathrm{Var}_i + \sum_{i}^{n} \sum_{j=i+1}^{n} \mathrm{Var}_{ij} + \sum_{i}^{n} \sum_{j=i+1}^{n} \sum_{k=j+1}^{n} \mathrm{Var}_{ijk} + \ldots + \mathrm{Var}_{12\ldots n} \tag{2}$$

where the indices i, j and k represent the considered model parameters and n equals the number of parameters. The terms Var_i and Var_{ij} stand respectively for the variance explained by the parameter i on its own and in combination with the parameter j. The proportion of the variance explained by the parameter i on its own is described by the first-order sensitivity index S_i [36]:

$$S_\mathrm{i} = \frac{\mathrm{Var}_i}{\mathrm{Var}} \tag{3}$$

Similarly, the total sensitivity index S_Ti describes the proportion of the variance explained by the parameter i considering its first-order effect and all interactions with the other parameters:

$$S_\mathrm{Ti} = 1 - \frac{\mathrm{Var}_{\sim i}}{\mathrm{Var}} \tag{4}$$

The term $\mathrm{Var}_{\sim i}$ describes the variance not explained by parameter i. It is calculated by adding up all the terms of Eq. 2 which do not have i as an index. The difference between the total sensitivity and the first-order indices represents the proportion of the variance explained by the interactions involving the considered parameter [37].

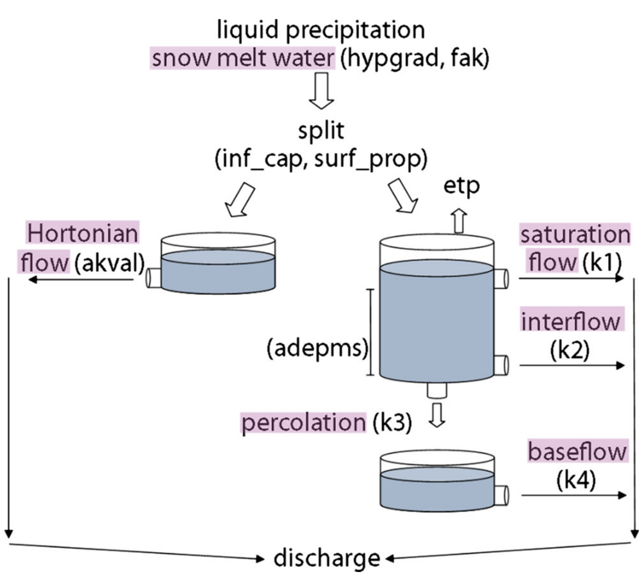


Fig. 3 Scheme of the conceptual model used. The analysed outputs (flow components) are in a *violet rectangle* and the considered parameters are in *parentheses*

The work presented here uses Sobol's method for calculating the sensitivity indices. This method was selected since it allows the estimation of the total sensitivities besides the first-order sensitivities. The disadvantage of this method is that it requires a high number of model runs, specifically $n(k+1)$ with k standing for the number of parameters and n for the size of the parameter sample [38]. The variance of the model is calculated based on the model results obtained with the Monte Carlo runs. The parameter sets are stored in one matrix which is then split into two matrices with the same number of parameter sets. For estimating the effect that a specific parameter has on the variance, the columns containing the parameter values for the variable of interest are exchanged between both matrices after which the model is run again with these modified matrices. The substitution of the first matrix aims at calculating the effect of the individual parameters, while the other matrix allows assessing the impact of the remaining parameters when not interacting with the analysed parameter. Saltelli [39] provided more background information about the method, and detailed examples of its implementation are presented in Cibin et al. [40] and Massmann and Holzmann [41].

2.4 Implementation of the Sensitivity Analysis

This study used a sample of 160.000 parameter sets. For obtaining the parameter ranges, we first defined some broad ranges based on literature information (for the snowmelt process) and previous experience (for the remaining processes). Using a MCMC approach, the ranges were further adapted. For avoiding the effect of outliers, the parameter ranges for the sensitivity analysis were set at the limits containing 99 % of the sampled MCMC parameter values (Table 1).

The used MCMC algorithm was Delayed Rejection Adaptive Metropolis (DRAM) [42], and it was assumed that the errors were normally distributed. DRAM is a modification of the Metropolis-Hastings algorithm which is well described in Chib and Greenberg [43]. The main differences are the inclusion of delayed rejection and adaptive Metropolis. Delayed rejection means that when a proposal is not accepted, the chain does not go further in time keeping its current position in the parameter space, but that a second proposal is tested instead, resulting in a chain with better asymptotic characteristics. Adaptive Metropolis adapts the covariance matrix after a certain number of time steps based on the values of the current chain. Since the covariance matrix is used for drawing the proposals, adapting the covariance matrix allows a better tuning of the matrix to the proposal distribution, increasing the efficiency of the algorithm. Four chains of 300.000 runs initiated at different points in the input space were generated. The chain convergence was tested visually and with the Gelman-Rubin statistic [44]. They were thinned afterwards by keeping only every fourth value in order to reduce the autocorrelation of consecutive samples. Although thinning was not necessary for this application, it is not expected that it resulted in a modification of the results [45]. The last 43.000 of each thinned chain were then used for further analysis, discarding the first part as a burning-in period.

Table 1 Considered ranges for each parameter

Parameter	Process	Unit	Minimum	Maximum
hypgrad	Snowmelt	°C m^{-1}	−0.0081	−0.0055
fak	Snowmelt	mm°C day^{-1}	3.75	6.3
inf_cap	Hortonian flow	mm day^{-1}	15	65
surf_prop	Hortonian flow	–	0.014	0.25
akval	Hortonian flow	day	0.23	10
adepms	Saturation flow	mm	23	90
$k1$	Saturation flow	day	6.1	15
$k2$	Interflow	day	20	200
$k3$	Percolation	day	15	176
$k4$	Groundwater flow	day	35	494

The daily variances and sensitivity indices were computed for the total discharge as well as for the discharge of the following flow components: Hortonian flow, saturation flow, interflow, percolation flow, groundwater flow and snowmelt flow. The period considered in this analysis started in November 2001 and went on until October 2004, but the first year was left out because it was taken as a warm-up period.

3 Results and Discussion

The results are split into two parts. The first part focuses on the variance of the total discharge and the outflow from the different sub-processes and identifies the model controls at each time step. The second part shows the first-order sensitivities and total interactions for the outflow of different sub-processes (i.e. the flow components Hortonian flow, saturation flow, interflow, percolation flow, groundwater flow and snowmelt) for a 2-year period.

3.1 Analysis of the Variances of Sub-processes

The variance of the discharge is required for calculating the sensitivity indices (see denominator of Eqs. 3 and 4). This section analyses the variances of the sub-processes in more detail (Fig. 4). The variance reflects the sensitivity of the output of the sub-processes to changes in the parameter values. For instance, if a given output has a high variance at a time step, it indicates that the selection of a value for the parameters describing this process is important, since the output varies significantly depending on the value the

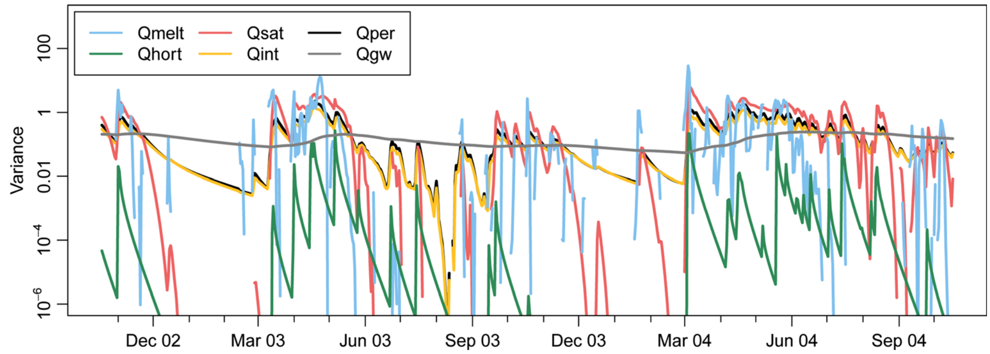


Fig. 4 Variances for the total discharge and each flow component between November 2002 and October 2004

parameter takes. When the variance is low, on the other hand, it is less important to know the value of the parameters, since all parameter values result in similar model outputs. While it is clear that a sub-process with a low variance for all time steps does not need to be parameterised (e.g. we could fix the corresponding parameters), it is often the case that sub-processes are active during certain periods (e.g. peaks), when they can have a large impact in the model output. This is something that can be identified using time-varying sensitivity analyses.

The variances of the flow components show large differences, and it is possible to distinguish between the more dynamic processes (Hortonian flow, snowmelt, saturation flow, interflow and percolation) and groundwater flow. This last process has a much smaller variability in the variance, and it reflects almost only patterns at a seasonal scale. The different behaviour of the processes is explained by the structure of the model, which 'filters' the groundwater signal by the addition of the groundwater storage, while the other processes are influenced in a more direct way by the model inputs, reflecting the large influence that meteorological and soil conditions have on these more dynamic processes. Unfavourable circumstances for the activation of specific processes (e.g. snowmelt in the absence of a snow cover or without a sufficient energy input for melting) result in a very small or zero variance during these periods. When the meteorological conditions change, these processes might get activated in a short period. This activation and deactivation of processes result in a higher variability of the variance when considering individual time steps in comparison to groundwater flow, which is active during most of the time.

It is further seen that the variances for interflow and percolation almost overlap. The reason for this is that both processes are modelled in the same way: as an outflow from the soil storage depending on the water content in this storage and as a function of a recession constant. As seen in Table 1, both recession constants (*k*2 and *k*3) were assigned similar parameter values and ranges, which results in similar variances.

In a next step, only the variance of the flow component with the highest variance at each time step was plotted (Fig. 5). This corresponds to the dominant model control as defined by Atkinson et al. [13], and it is the process for which we would like to know the parameter values with more certainty, since their uncertainty (reflected in the width of the parameter ranges used for the sensitivity analysis) results in large differences in the amount of water released by the process in question, depending on the specific values taken by the parameter.

It can also be seen that higher discharges are usually related to higher variances (e.g. compare Figs. 1 and 4). It is, therefore, possible that the processes or controls identified as dominant based on the highest variance (as done here) bear some similarity with the dominant processes/controls identified using the highest discharges.

The information about the dominant process at each day can be aggregated and taken as an indicator of the amount of data available for the calibration of each process. This can be used as one criterion for deciding if there is enough information in the time series for calibrating all the parameters. It is seen, for instance, that groundwater and saturation flow are dominant on 56 and 33 % of the days, respectively, while Hortonian flow does not dominate on any day (Table 2). If it is additionally taken into account that groundwater and saturation flow are described together by four parameters (*adepms*, *k*1, *k*2 and *k*3), while Hortonian flow requires three parameters on its own (*inf_cap*, *surf_prop* and *akval*), it is expected that Hortonian flow will be a process more difficult to calibrate, at least if the calibration is done manually.

Nevertheless, it must be taken into account that the length of a time series is only one factor influencing the decision about the processes and parameter to calibrate. Other criteria are the representativeness and informativeness of these observations, both of which are difficult to assess. The representativeness for short periods can be estimated if there are long-term records [46]. In these cases, it is possible to compare graphically the mean values and cumulative distributions for the long- and short-term records. If there is a good agreement, the short time series can be considered as representative of the long-term characteristics of the catchment. Another alternative is to use statistical tests. These approaches have however the disadvantage of requiring long observational periods, and when they are lacking, it is only possible to estimate

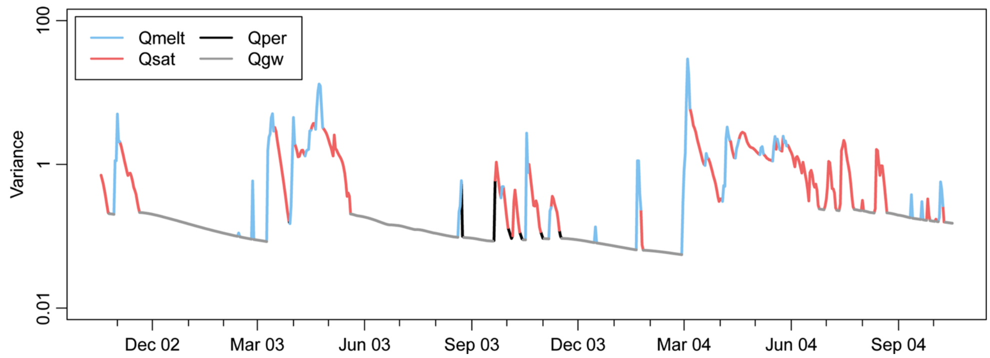


Fig. 5 Dominant process (defined as the process with the highest variance) for each time step

qualitatively and based on the experience of the modeller, if the time series cover the whole range of possible situations. Further, it must be taken into account that representativeness does depend on the objective of the modelling [47]. For instance, a model focusing on extreme conditions should be calibrated using data representative of such extreme events. Singh and Bárdossy [48] showed that a calibration carried out using a small number of unusual events gave as good results as a calibration using the whole period. This indicates that representativeness can be achieved by a limited number of informative events, where informativeness refers to the information content that the observations have [49]. Limited informativeness of data can be observed when the conditions during which they were measured show little variability. Additional measurements for similar periods will be then much less informative than data for periods with different conditions. Another source of uninformative data is errors and uncertainties in the data measurement and manipulation processes, resulting in observations with values that do not agree well with the 'real' value [49]. It is, however, difficult to identify these observations unless they are clearly wrong. Since the criteria representativeness and informativeness are not easy to evaluate, they are often neglected. This means that information about the number of days in which each process dominates becomes an important factor for deciding if there is enough information for calibrating specific processes.

Finally, it must be considered that the results obtained from an analysis of the variance as shown above do depend on the ranges defined for the parameters [22]. In this case, they were specified based on a MCMC sampling for a 4-year period. If data for another period would have been used or if there would be additional information about the values of some parameters, these parameter ranges would change. Since these changes would not necessarily be proportional for all parameters and also because the model might react differently to changes in the parameter ranges depending on the parameter in question, the identified dominant physical process might vary depending on the available information.

Table 2 Number of days each process dominates and the percentage of the considered period this represents

Process	Number of days it dominates	Percentage
Saturation flow	244	33
Percolation	17	2
Groundwater flow	411	56
Hortonian flow	0	0
Snowmelt	59	9

3.2 Analysis of the Sensitivities for Individual Flow Components

The first-order sensitivities and the total interactions of all parameters were calculated for each flow component. The plots only show the parameters which have at least at 1-day sensitivity indices above 0.05.

3.2.1 Snowmelt

The first-order indices and total interactions for the parameters *fak* and *hypgrad* which describe snowmelt (snowmelt water in Fig. 3) are shown in Fig. 6. The black lines on the upper part of the first-order indices plot indicate the periods during which this process dominates (see Fig. 5). The first-order indices indicate that snowmelt has the potential for having some effect during most of the year. However, it is most sensitive to the parameters describing it in April, when the snow cover accumulated during the winter melts. There is not a clear pattern about the importance of the parameters: sometimes, the hypsometric gradient (*hypgrad*) is most important, while the snowmelt factor (*fak*) shows a high importance during other periods. An analysis of the input and output files showed that the hypsometric gradient is more important when the snow cover is rather thin. For instance, on July 03 and July 04, *hypgrad* is much more important than *fak*, because *hypgrad* does affect the amount of water stored in the snow cover which is released shortly after and also because in the summer the temperature is anyway high enough for melting the snow, independently of the value of *fak*.

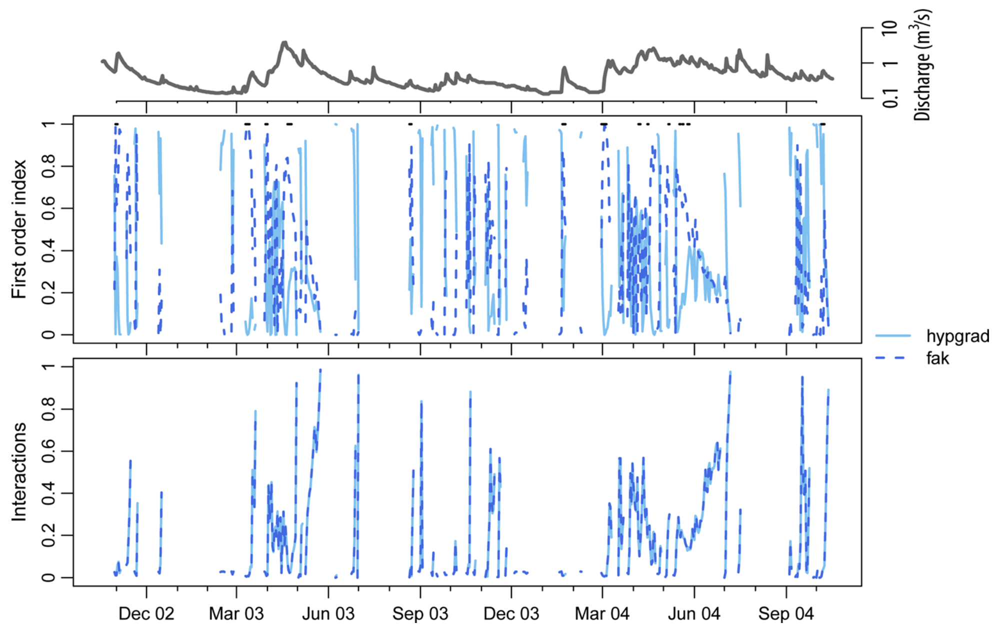


Fig. 6 Total discharge, first-order indices and total interactions for snowmelt. The *black lines on the upper part of the first-order indices* highlight the periods during which this process dominates

The fact that there is sensitivity to snowmelt parameters in July indicates that there are large differences in the output (snowmelt), depending on the value the parameters take. As mentioned in Section 2.4, the parameter ranges used in the sensitivity analyses were obtained through an MCMC sampling which considered the whole period. As a result of the sampling, we got a probability distribution for each parameter. Table 1 shows, for instance, that the hypsometric gradient *hypgrad* varied between −0.0081 and −0.0055 °C/m. If a value close to −0.0055 was used for modelling the catchment, there would be a less frequent and less important accumulation of snow (and consequently also snowmelt, i.e. the process is not activated), while a value close to −0.0081 would result in a more frequent activation of this process. The sensitivity to *hypgrad* in July means only that some parameter sets obtained with the MCMC sampling result in an accumulation of snow at the highest altitudes at this time. Another explanation for the sensitivity to snowmelt parameters in summer could be that by using the MCMC approach, we got values for the set of parameters (i.e. one value for each parameter), which means that the values for different parameters are not necessarily independent. It is therefore possible that certain combinations between both snowmelt parameters were not observed in the MCMC sample, but that they are considered in the sensitivity analysis, since Sobol's method assumes that the parameters are independent.

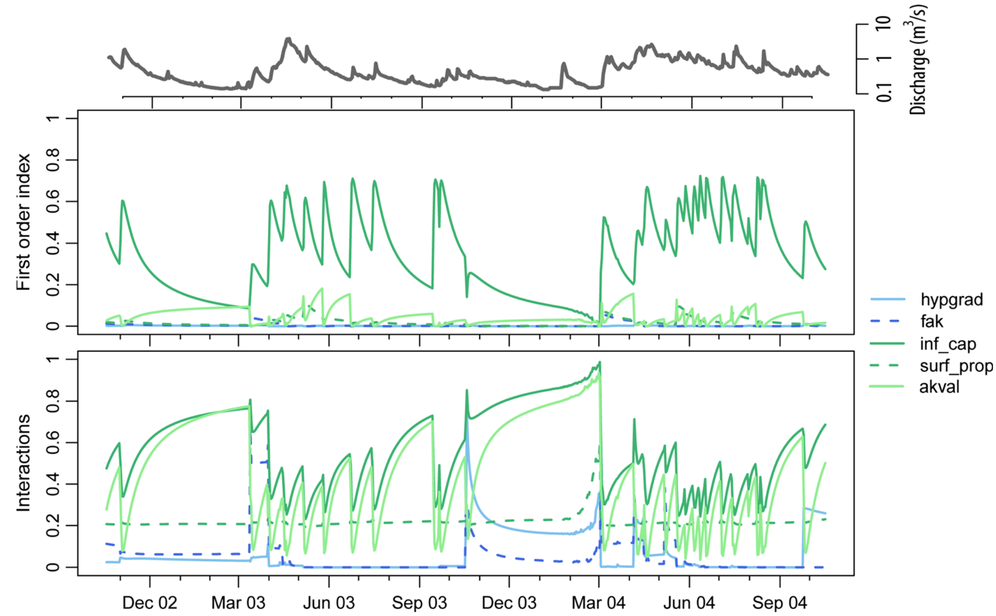
With respect to the interactions, it is seen that they do overlap for both parameters, showing that no other parameters influence the output of this process. This is not surprising since it is the process first coming into contact with the precipitation and there is no way that the parameters describing processes coming afterwards could affect snowmelt. A detailed analysis of the sensitivity files also showed that the maximum interactions are observed 1–2 days after the first-order indices peak, which indicates that the parameters are important on its own when snowmelt takes place and that after that, the interactions between parameters gain importance. What can also be seen is that the sum of the total interactions is larger than one, which is explained because each interaction of order r is counted r times [50]. In this case, since the interactions of both parameters overlap, we know that they are second-order interactions and, therefore, counted twice.

3.2.2 Hortonian Flow

As mentioned before, Hortonian flow does not dominate at any time during the considered 2-year period. It is however observed that the process might have potentially some effect (although small) during the whole period (Fig. 7). This is, on one hand, a result of the small lower value for the parameter *inf_cap* which means that already small precipitation intensities might activate this process. But, it also reflects the way this process is modelled, as a storage from which water which does not infiltrate is released gradually over a longer time period. It must also be mentioned here that this analysis was carried out at a daily scale and that Hortonian flow is a process which needs to be considered at much smaller temporal scales. This is because a high daily precipitation distributed evenly over the day may not result in Hortonian flow, but concentrated over a short period, it could well surpass the infiltration capacity of the soil. The process was nevertheless considered, since the main objective of this study was to understand and see how different modules react which still can be assessed at a daily scale.

When considering the first-order indices, the most important parameter is the infiltration capacity of the soil, which

Fig. 7 Total discharge, first-order indices and total interactions for Hortonian flow



defines when the process gets activated and, by this, how much water infiltrates into the soil and how much is routed to the Hortonian flow storage. This parameter is important on its own (first-order indices) when the high-intensity rainfall takes place. After the event, its importance decreases rapidly and the Hortonian flow recession constant starts increasing its importance.

It is seen that the interactions are low when the first-order indices are important but that their importance increases after the rainfall event. This indicates that it might be good to calibrate the parameter *inf_cap* first, since it has a high effect on its own, and only after that to go on calibrating the other two Hortonian flow parameters, which have mostly an effect through interactions. In this way, once the value for *inf_cap*, is fixed it is easier to find adequate values for the other two parameters. The interactions involve mostly the parameters *akval* and *inf_cap*, but also *surf_prop* has interactions of about 20 %. It is further seen that the interactions involving the snowmelt parameters are important, reaching a few times values above 50 %. These are probably Hortonian flow events caused primarily by snowmelt instead of by direct rainfall and are a good example of inter-sensitivity, where parameters describing other processes do have an effect on the sensitivity of other processes.

3.2.3 Saturation Flow

The parameters with important first-order indices for saturation flow are the size of the soil storage (*adepms*) and the recession constants for interflow (*k*2) and percolation (*k*3) which determine how fast the water level drops in the storage (Fig. 8). In general, it is seen that the curves for both parameters have the same shape but that *k*3 is more important than *k*2. This is explained by the lower minimum and maximum values that the percolation recession was allowed to take (Table 1), meaning that on average, this outlet is responsible for a higher proportion of water leaving the soil storage. What can be also seen is a seasonal pattern in the importance of the parameters: between March and July, the recession constants tend to have a higher influence on the variance than the size of the soil storage, while this last parameter tends to predominate during winter. At this time, the catchment is dry and the size of the soil storage is critical since it determines how much water is required for activating saturation flow. In contrast to this, the most important parameters during wetter periods are the recession constants, since they define the rate by which the storage is emptied.

The interactions involve additionally the parameters describing snowmelt and Hortonian flow. It is seen that the interactions of *adepms* have the inverse shape of the first-order indices of this parameter, indicating again that the interactions gain importance when the first-order indices decrease its importance. The parameters *k*2 and *k*3 have interactions with a similar shape than adepms, suggesting that the interactions between these parameters might be important. For this process, it can also be clearly observed that the first-order indices are high when the process dominates, while the interactions are more important during the remaining time.

3.2.4 Interflow and Percolation

This section shows only the plot for percolation (Fig. 9), since the only difference between this process and interflow is that the curves for parameters *k*2 and *k*3 are interchanged. With respect to the first-order sensitivities, the percolation recession

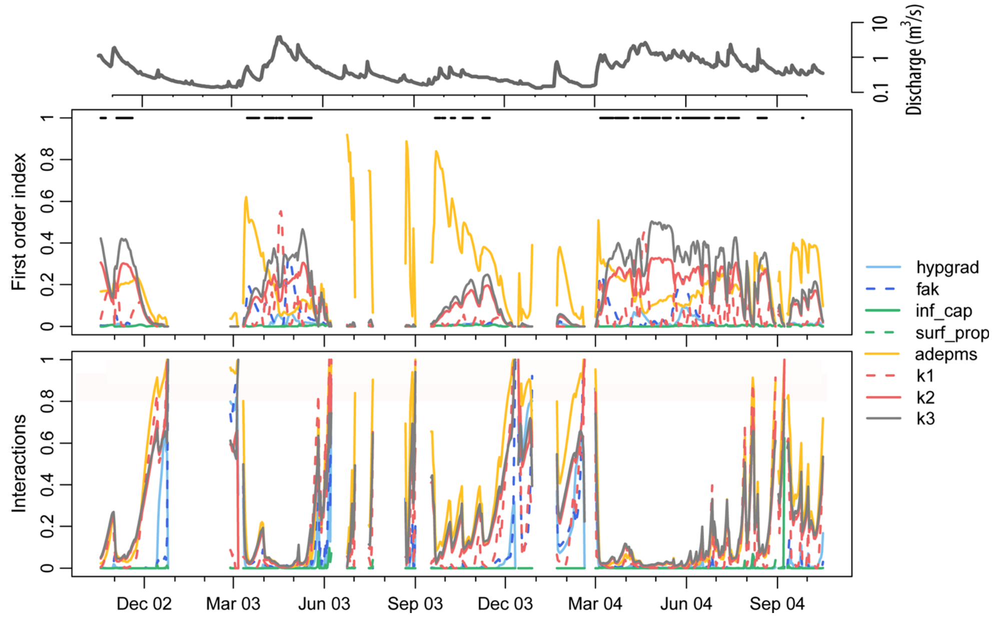


Fig. 8 Total discharge, first-order indices and total interactions for saturation flow. The *black lines on top* indicate the periods during which this process dominates

constant $k3$ is in general the most important parameter. Nevertheless, the parameter $k2$ is also important during some periods. A look at the recessions shows that they follow a general pattern and that they can be divided into three periods. At the beginning, there is plenty of water in the soil storage, which is why the percolation outflow depends mostly on the percolation recession. As the storage empties, its importance decreases, leading to a point where the sensitivity index of $k3$ intersects the sensitivity index of $k2$. It is also during this period that the sensitivity index for *adepms* peaks. This period characterises therefore the time when the soil storage empties, which explains that the percolation output depends on the size of the soil storage. The last period shows a decline of the sensitivities of *adepms*, indicating that the storage is almost empty regardless of the size of the storage. It is also seen that the sensitivity of $k2$ exceeds the sensitivity of $k3$.

The interactions for this process are, with two exceptions, smaller than 15 % and in this way smaller than the interactions observed up to now for the other sub-processes.

3.2.5 Groundwater Flow

The plot for groundwater is less dynamic than the plots for the other components (Fig. 10). The percolation recession is the most important parameter during the whole period, and none

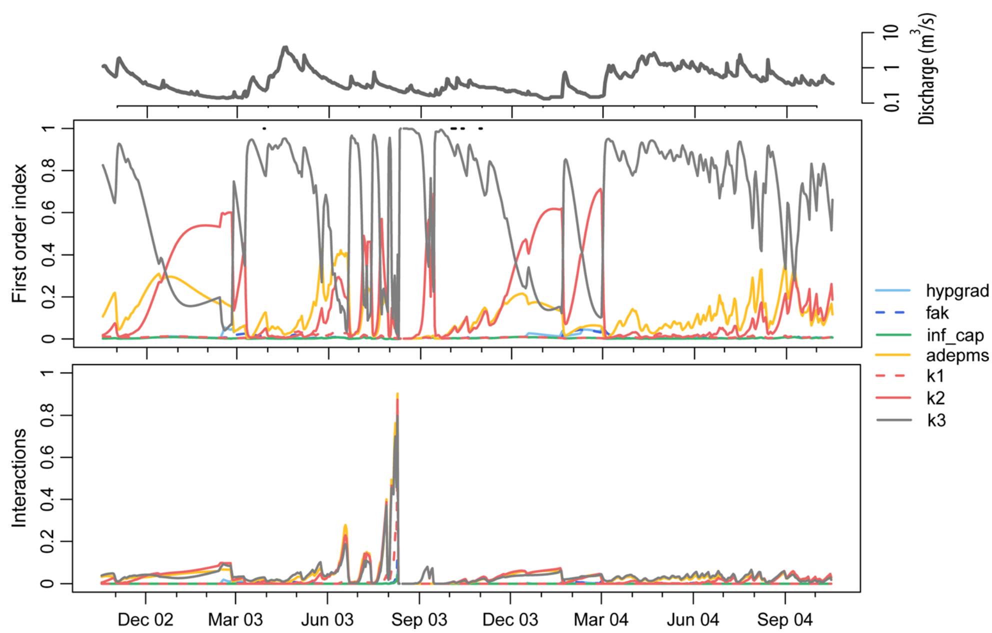


Fig. 9 Total discharge, first-order indices and total interactions for percolation. The *black lines on top* indicate the periods during which this process dominates

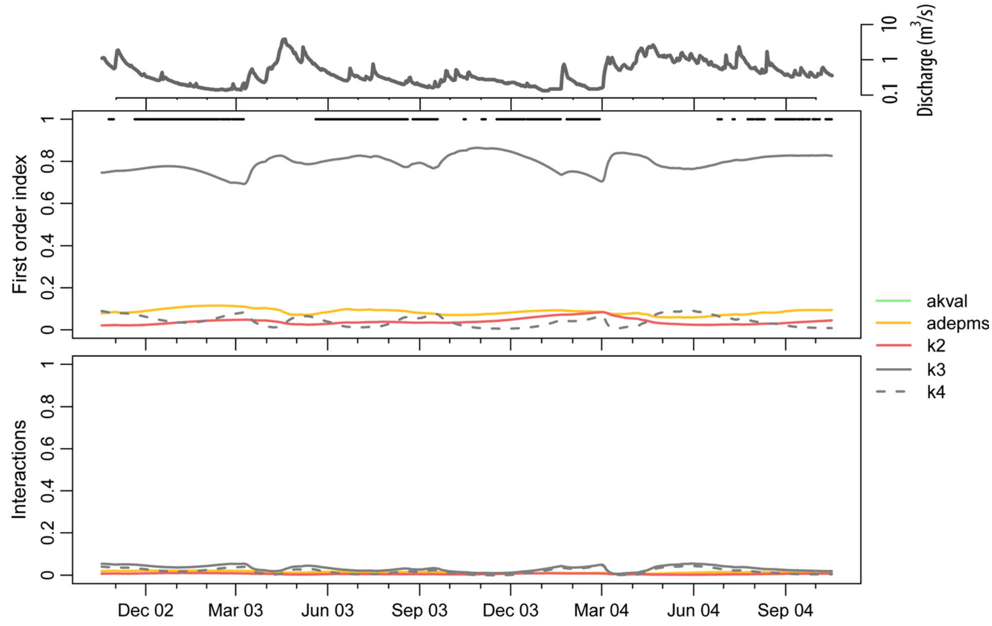


Fig. 10 Total discharge, first-order indices and total interactions for groundwater flow. The *black lines on top* indicate the periods during which this process dominates

of the other parameters reaches sensitivity indices above 20 % at any day. The shape of the first-order index curve for *k*3 shows some correlation with the measured discharge: the first-order indices tend to be smaller when the total discharge is low. This process has the smallest interactions which do not show any clear pattern.

4 Summary and Conclusions

For increasing the understanding about the internal functioning of the sub-processes of a hydrological model, a time-varying global sensitivity analysis was carried out for the flow components of a conceptual rainfall-runoff model applied to a mountainous catchment. The sub-processes taken into account were the following: snowmelt, Hortonian flow, saturation flow, interflow percolation and groundwater flow. The sensitivity analysis was carried out using Sobol's method, a variance decomposition approach. This method requires the definition of parameter ranges based on which Monte Carlo simulations are carried out. Since the parameter ranges for the Monte Carlo runs were selected by means of a MCMC sampling of the posterior parameter distribution, the obtained sensitivity values reflect the uncertainty of the parameters.

The first step consisted in an analysis of the variance of the outflow from each sub-component. It was seen that the groundwater variance shows only some seasonal patterns, while the other flow components had a much higher variability of the variance, spanning more than six orders of magnitude. After that, the process with the highest variance was identified at each time step. This process is the one for which we would really like to narrow down the parameter uncertainty, because this uncertainty results in a large variance of the flow component depending on the values assigned to the parameters. This process with the highest variance can be referred to as the dominant physical control which has been previously defined by Atkinson et al. [13] as the model parameter to which the model output is very sensitive, when the parameter is varied within realistic ranges.

This information can be useful, on one hand, to help in the planning of future measuring campaigns, which should try to reduce the uncertainty of the most critical parameters. It is also possible to use this information in model calibration by focusing on the periods each parameter is dominant when calibrating the respective parameters. This is a way for making sure that each parameter focuses on the module it describes instead of being used for increasing the overall agreement between the measured and observed values. Further, it can be useful to look at the number of time steps each process dominates. For processes that are dominant only for short periods, it might be better to fix the parameter values instead of trying to calibrate them.

The second part of the study looked at the sensitivity of individual flow components. It was seen that snowmelt is affected sometimes primarily by the hypsometric lapse rate but that the day-degree factor was the most important parameter at other times. Which of both parameters predominates depends mostly on the amount of snow stored on the snow cover and also on the temperature. The first-order indices of Hortonian flow involve mostly the infiltration capacity, but the interactions are additionally strongly affected by the proportion of the catchment in which Hortonian flow is active and by the Hortonian flow recession constant. In this case, the information gained can be used for determining the order in which the parameters should be calibrated, since it should be attempted to calibrate first the parameters which have an effect on its own, and only after that the parameters having mostly an effect through interactions. The Hortonian flow process, together with saturation flow, have high interaction peaks with snowmelt parameters, highlighting melt events releasing a high amount of water which might activate the Hortonian and saturation flow processes. Saturation flow depends mostly on the size of the soil storage during drier periods. During wetter periods, it is not as important how much water is required for activating the process (this could happen frequently) but how fast the water level decreases, something that depends on the percolation and interflow recession constants, since they compete for the water in this storage affecting its depletion rate.

The processes of interflow and percolation evidence the same sensitivity pattern, since they are based on the same mathematical description and both were assigned similar parameter ranges and values. The only difference between both processes is that the sensitivities for the interflow and percolation recession coefficients are interchanged. Groundwater flow had the least dynamic sensitivities and also the smallest amount of interactions, and it depends mostly on the percolation recession constant.

Carrying sensitivity analysis for individual flow components at high temporal resolutions might be useful for understanding how processes work in more detail, when the uncertainty of the parameters affects the model results and which parameters influence the flow components mainly through interactions. This information helps in confirming if the model works as expected by our understanding of the system, which is one aspect of quality assurance of hydrological models.

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References

1. Refsgaard, J. C., & Hansen, J. R. (2010). A good-looking catchment can turn into a modeller's nightmare. *Hydrological Sciences Journal, 55*(6), 899–912. doi:10.1080/02626667.2010.505571.
2. Jakeman, A. J., Letcher, R. A., & Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. *Environmental Modelling & Software, 21*, 602–614. doi:10.1016/j.envsoft.2006.01.004.
3. Hartebrodt, C. H., Aichholz, R., & Braasch, M. (2011). Analyzing and predicting forestry accountancy network variables with Bayesian Belief Networks as compared to traditional analyzing methods. *Small-Scale Forestry, 10*, 163–183. doi:10.1007/s11842-010-9124-0.
4. Judd, B.R., North, D.W., & Pezier, J.P. (1974). Assessment of the probability of contaminating Mars. *Final Report of the Stanford Research Institute for the NASA Planetary Programs Division, Grant NASW-2535*, 161p.
5. Sumner T. (2010). *Sensitivity analysis in systems biology modelling and its application to a multi-scale model of blood glucose homeostasis*. PhD thesis, Centre for Mathematics and Physics in the Life Sciences and Experimental Biology, University College London, 162p.
6. Baroni, G., & Tarantola, S. (2014). A General Probabilistic Framework for uncertainty and global sensitivity analysis of deterministic models: A hydrological case study. *Environmental Modelling & Software, 51*, 26–34. doi:10.1016/j.envsoft.2013.09.022.
7. Cloke, H. L., Pappenberger, F., & Renaud, J.-P. (2008). Multi-method global sensitivity analysis (MMGSA) for modelling floodplain hydrological processes. *Hydrological Processes, 22*, 1660–1674. doi:10.1002/hyp.6734.
8. Guse, B., Reusser, D., & Fohrer, N. (2014). How to improve the representation of hydrological processes in SWAT for a lowland catchment—temporal analysis of parameter sensitivity and model performance. *Hydrological Processes, 28*, 2651–2670. doi:10.1002/hyp.9777.
9. Herman, J. D., Kollat, J. B., Reed, P. M., & Wagener, T. (2013). From maps to movies: High-resolution time-varying sensitivity analysis for spatially distributed watershed models. *Hydrology and Earth System Sciences, 17*, 5109–5125. doi:10.5194/hess-17-5109-2013.
10. Herman, J. D., Reed, P. M., & Wagener, T. (2013). Time-varying sensitivity analysis clarifies the effects of watershed model formulation on model behavior. *Water Resources Research, 49*, 1400–1414. doi:10.1002/wrcr.20124.
11. Massmann, C., Wagener, T., & Holzmann, H. (2014). A new approach to visualizing time-varying sensitivity indices for environmental model diagnostics across evaluation time-scales. *Environmental Modelling & Software, 51*, 190–194. doi:10.1016/j.envsoft.2013.09.033.
12. Reusser, D. E., Buytaert, W., & Zehe, E. (2011). Temporal dynamics of model parameter sensitivity for computationally expensive models with the Fourier amplitude sensitivity test. *Water Resources Research, 47*, W07551. doi:10.1029/2010WR009947.
13. Atkinson, S. E., Woods, R. A., & Sivapalan, M. (2002). Climate and landscape controls on water balance model complexity over changing timescales. *Water Resources Research, 38*(12), 1314. doi:10.1029/2002WR001487.
14. Montanari, L., Sivapalan, M., & Montanari, A. (2006). Investigation of dominant hydrological processes in a tropical catchment in a monsoonal climate via the downward approach. *Hydrology and Earth System Sciences, 10*(5), 769–782. doi:10.5194/hess-10-769-2006.
15. Grayson, R., & Blöschl, G. (2000). Summary of pattern comparison and concluding remarks. In R. Grayson & G. Blöschl (Eds.), *Spatial patterns in catchment hydrology: Observations and modelling* (pp. 355–367p). Cambridge: Cambridge University Press.
16. Scherrer, S., & Naef, F. (2003). A decision scheme to indicate dominant hydrological flow processes on temperate grassland. *Hydrological Processes, 17*, 391–401. doi:10.1002/hyp.1131.
17. Schmocker-Fackel, P., Naef, F., & Scherrer, S. (2007). Identifying runoff processes on the plot and catchment scale. *Hydrology and Earth System Sciences, 11*, 891–906. doi:10.5194/hess-11-891-2007.
18. Reszler, C., Komma, J., Blöschl, G., & Gutknecht, D. (2008). Dominante Prozesse und Ereignistypen zur Plausibilisierung flächendetaillierter Niederschlag-Abflussmodelle [Dominant processes and event types for checking the plausibility of spatially distributed runoff models]. *Hydrologie und Wasserbewirtschaftung, 52*(3), 120–131.
19. Casper M. (2002). Die Identifikation hydrologischer Prozesse im Einzugsgebiet des Dürreychbaches (Nordschwarzwald) [The identification of hydrological processes in the Dürreychbach catchment

(northern Black Forest)]. *Mitteilungen des Institutes für Wasserwirtschaft und Kulturtechnik, Universität Karlsruhe (TH) Nr*, 210
20. van den Bos, R., Hoffmann, L., Juilleret, J., Matgen, P., & Pfister, L. (2006). Regional runoff prediction through aggregation of first-order hydrological process knowledge: A case study. *Hydrological Sciences Journal, 51*(6), 1021–1038. doi:10.1623/hysj.51.6.1021.
21. Wagener, T., McIntyre, N., Lees, M. J., Wheater, H. S., & Gupta, H. V. (2003). Towards reduced uncertainty in conceptual rainfall-runoff modelling: Dynamic identifiability analysis. *Hydrological Processes, 17*, 455–476. doi:10.1002/hyp.1135.
22. Shin, M.-J., Guillaume, J. H. A., Croke, B. F. W., & Jakeman, A. J. (2013). Addressing ten questions about conceptual rainfall-runoff models with global sensitivity analyses in R. *Journal of Hydrology, 503*, 135–152. doi:10.1016/j.jhydrol.2013.08.047.
23. Estrada, V., & Diaz, M. S. (2010). Global sensitivity analysis in the development of first principle-based eutrophication models. *Environmental Modelling & Software, 25*, 1539–1551. doi:10.1016/j.envsoft.2010.06.009.
24. Zeug, S. C., Bergman, P. S., Cavallo, B. J., & Jones, K. S. (2012). Application of a life cycle simulation model to evaluate impacts of water management and conservation actions on an endangered population of Chinook salmon. *Environmental Modeling and Assessment, 17*(5), 455–467. doi:10.1007/s10666-012-9306-6.
25. Vezzaro, L., & Mikkelsen, P. S. (2012). Application of global sensitivity analysis and uncertainty quantification in dynamic modeling of micropollutants in stormwater runoff. *Environmental Modelling & Software, 27–28*, 40–91. doi:10.1016/j.envsoft.2011.09.012.
26. Nossent, J., Elsen, P., & Bauwens, W. (2012). Sobol' sensitivity analysis of a complex environmental model. *Environmental Modelling & Software, 26*, 1515–1525. doi:10.1016/j.envsoft.2011.08.010.
27. Zhang, C., Chu, J., & Fu, G. (2013). Sobol's sensitivity analysis for a distributed hydrological model of Yichun River Basin, China. *Journal of Hydrology, 480*, 58–68. doi:10.1016/j.jhydrol.2012.12.005.
28. Kostka, Z., & Holko, L. (2000). Vplyv klimatickej zmeny na priebeh odtoku v malom horskom povodí [Impact of climate change on runoff in a small mountain catchment]. *National Climate Program of the Slovak Republic, 8*, 91–109.
29. Holko, L., & Kostka, Z. (2006). Hydrologický výskum vo vysokohorskom povodí Jaloveckého potoka [Hydrological research a high-mountain catchment of the Jalovecky creek catchment]. *Journal of Hydrology and Hydromechanics, 54*(2), 192–206.
30. Holko, L., & Kostka Z. (2010). Hydrological processes in mountains—knowledge gained in the Jalovecky Creek catchment, Slovakia. In: Status and perspectives of hydrology in small basins, *IAHS Publ*, 336
31. Han, D., & Bray, M. (2006). Automated Thiessen polygon generation. *Water Resources Research, 42*, W11502. doi:10.1029/2005WR004365.
32. Thornthwaite, C. W. (1948). An approach toward a rational classification of climate. *Geographical Review, 38*(1), 55–94.
33. Holzmann, H., & Nachtnebel, H. P. (2002). Abflussprognose für mittelgroße Einzugsgebiete – Methodik und Anwendungen [Runoff forecast for medium sized basins—methods and applications]. *Österreichische Wasser- und Abfallwirtschaft, 54*(9–10), 142–153.
34. Matott, L. S., Babendreier, J. E., & Purucker, S. T. (2009). Evaluating uncertainty in integrated environmental models: A review of concepts and tools. *Water Resources Research, 45*, W06421. doi:10.1029/2008WR007301.
35. Lilburne, L., & Tarantola, S. (2009). Sensitivity analysis of spatial models. *International Journal of Geographical Information Science, 23*(2), 151–168. doi:10.1080/13658810802094995.
36. Tang, Y., Reed, P., van Werkhoven, K., & Wagener, T. (2007). Advancing the identification and evaluation of distributed rainfall-runoff models using global sensitivity analysis. *Water Resources Research, 43*, W06415. doi:10.1029/2006WR005813.
37. Ratto, M., Young, P. C., Romanowicz, R., Pappenberger, F., Saltelli, A., & Pagano, A. (2007). Uncertainty, sensitivity analysis and the role of data based mechanistic modeling in hydrology. *Hydrology and Earth System Sciences, 11*, 1249–1266. doi:10.5194/hess-11-1249-2007.
38. Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., & Tarantola S. (2008). *Global sensitivity analysis. The primer*. Wiley & Sons, 292p.
39. Saltelli, A. (2002). Making best use of model evaluations to compute sensitivity indices. *Computer Physics Communications, 145*(2), 280–297. doi:10.1016/S0010-4655(02)00280-1.
40. Cibin, R., Sudheer, K. P., & Chaubey, I. (2010). Sensitivity and identifiability of stream flow generation parameters of the SWAT model. *Hydrological Processes, 24*, 1133–1148. doi:10.1002/hyp.7568.
41. Massmann, C., & Holzmann, H. (2012). Analysis of the behavior of a rainfall-runoff model using three global sensitivity analysis methods evaluated at different temporal scales. *Journal of Hydrology, 475*, 97–110. doi:10.1016/j.jhydrol.2012.09.026.
42. Hario, H., Laine, M., Mira, A., & Saksman, E. (2006). DRAM: Efficient adaptive MCMC. *Statistics and Computing, 16*, 339–354. doi:10.1007/s11222-006-9438-0.
43. Chib, S., & Greenberg, E. (1995). Understanding the Metropolis-Hastings algorithm. *The American Statistician, 49*(4), 327–335. doi:10.2307/2684568.
44. Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science, 7*(4), 457–511. doi:10.1214/ss/1177011136.
45. Link, W. A., & Eaton, M. J. (2012). Forum: On thinning of chains in MCMC. *Methods in Ecology and Evolution, 3*, 112–115. doi:10.1111/j.2041-210X.2011.00131.x.
46. Shein, K. A. (2006). Assessing the long-term representativeness of short wind records. *Proceedings 18th Conference of Probability and Statistics in the atmospheric Sciences 2006*, Atlanta.
47. Bennett, N. D., Croke, B. F. W., Guariso, G., Guillaume, J. H. A., Hamilton, S. H., Jakeman, A. J., et al. (2013). Characterising performance of environmental models. *Environmental Modelling & Software, 40*, 1–20. doi:10.1016/j.envsoft.2012.09.011.
48. Singh, S. K., & Bárdossy, A. (2012). Calibration of hydrological models on hydrologically unusual events. *Advances in Water Resources, 38*, 81–91. doi:10.1016/j.advwatres.2011.12.006.
49. Beven, K., & Westerberg, I. (2011). On red herrings and real herrings: Disinformation and information in hydrological inference. *Hydrological Processes, 25*, 1676–1680. doi:10.1002/hyp.7963.
50. Saltelli, A., Tarantola, S., & Campolongo, F. (2000). Sensitivity analysis as an ingredient of modeling. *Statistical Science, 15*(4), 377–395. doi:10.1214/ss/1009213004.