Incremental model breakdown to assess the multi-hypotheses problem

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Abstract. The ambiguous representation of hydrological processes have led to the formulation of the multiple hypotheses approach in hydrological modelling, which requires new ways of model construction. However, most recent studies focus only on the comparison of predefined model structures or building a model step-by-step. This study tackles the problem the other way around: We start with one complex model structure, which includes all processes deemed to be important for the catchment. Next, we create 13 additional simplified models, where some of the processes from the starting structure are disabled. The performance of those models is evaluated using three objective functions (logarithmic Nash-Sutcliffe, percentage bias and the ratio between root mean square error to the standard deviation of the measured data). Through this incremental breakdown, we identify the most important processes and detect the restraining ones. This procedure allows constructing a more streamlined, subsequent 15th model with improved model performance, less uncertainty and higher model efficiency. We benchmark the original Model 1 with the final Model 15 and find that the incremental model breakdown leads to a structure with good model performance, fewer but more relevant processes and less model parameters.

1 Introduction

In the world of hydrological modelling, scientists construct models and apply them for a specific research question. Sometimes, these models are modified or extended afterwards, but the core components stay the same. This approach has existed from the earliest days of simple equations until the models of connected, conceptual elements used today (Todini, 2007).

During the development of hydrological models, the issues of parameter and input data uncertainty were often in the center of the scientific debate and numerous methods for assessing this uncertainty have been proposed. Structural uncertainty has been investigated in the past decade (Breuer et al., 2009; Son and Sivapalan, 2007) and gained more momentum in the last few years (e.g Clark et al., 2015; Fenicia et al., 2011; Hublart et al., 2015). It was noted that problems often arose from the focus on trying to build one model that was meant to work equally well for all catchments (Fenicia et al., 2011).

In order to better scrutinize problems associated with the model structure, the theory of the multiple hypotheses was introduced, first by Beven (2001, 2002), and more recently picked up by Clark et al. (2011). This theory enables a more structured approach to model building, as it identifies a given model not as a single hypothesis, but as an assemblage of coupled hypotheses. Hence, Clark et al. (2011) proposed that a model should be constructed in a way that allows the testing of every single hypothesis of every process separately. In addition, the interactions of single elements within such a model should also be considered to better understand why a certain model works or fails (Clark et al., 2016).

When the idea of multiple hypotheses emerged, there was no easy way to construct models with interchangeable components (Buytaert et al., 2008) except for some comparison inside the TOPMODEL model family (Beven and Kirkby, 1979). We now have model frameworks at hand that facilitate such a design, e.g. SUPERFLEX (Fenicia et al., 2011), Structure for Unifying Multiple Modelling Alternatives (SUMMA) (Clark et al., 2015b, 2015a), or the Catchment Modelling Framework (CMF) (Kraft et al., 2011). SUPERFLEX targets the construction of lumped conceptual models (van Esse et al., 2013; Gharari et al., 2014). SUMMA and CMF support the generation of multi scale approaches from plot over hillslope to basins and from lumped to fully distributed models. SUMMA focusses on the comparison of process-based models with predefined parameters sets and is up to now mainly tested for surface-atmosphere interactions (Clark et al., 2015b, 2015a). CMF is a programming library to build hydrological models from building blocks with both, process-based and conceptual models. It can be used for subsurface and surface water fluxes, surface-atmosphere exchange and solute transport. So far, it has been applied in studies to better understand hydrological processes (Holländer et al., 2009; Maier et al., 2017; Orlowski et al., 2016; Windhorst et al., 2014), to simulate solute transport (Djabelkhir et al., 2017; Kraft et al., 2010) and to capture hydrological lateral and vertical transport processes in coupled complex ecosystem models (Haas et al., 2013; Houska et al., 2014, 2017; Kellner et al., 2017).

All toolboxes enable a stepwise modification of the model structure. Additionally, they allow an easier comparability of different models, as they are all constructed from the same parts and a more straightforwardly handled through interfaces (Buytaert et al., 2008). Recently, some studies tried to tackle the multi-hypotheses problem within a model framework (e.g. van Esse et al., 2013; Fenicia et al., 2008; Gharari et al., 2014; Hublart et al., 2015; Kavetski and Fenicia, 2011). Most of these studies built their models incremental from bottom up to find out, if small modifications allow a better simulation (Bai et al., 2009; Westerberg and Birkel, 2015). Others compared predefined model structures (van Esse et al., 2013; Kavetski and Fenicia, 2011). In all cases, researchers stopped improving the models once a sufficient performance was reached. However, there is a chance that they have missed an even better model performance by including further modifications.

Despite having the potential to create a wide range of models with such toolboxes, only a minor quantity in the vast space of possible model structures is currently explored. However, this thorough exploration is needed to find appropriate model structures for any catchment, as it seems that current hydrological knowledge does not allow to construct a model that works equally well for all environmental conditions, especially when using lumped models (Beven, 2000, 2007, 2016; Buytaert et al., 2008; Fenicia et al., 2014).

To better use the existing understanding of a given catchment and to test more complex models, this study turns the incremental approach of adding more process-understanding to a model upside down. First, we develop a conceptual model from current hydrological understanding that contains all structures that might be important for the functioning of a catchment. Then, parts of this model are disabled through incremental model breakdown, and the reduced model structures

5 are tested for their simulation performance. On this base, a subsequent model is constructed which uses the insights gained from those previous models with disabled processes.

The objective of this study is to demonstrate that incremental model breakdown allows a detailed examination of model structures, an easier identification of the most important hydrological processes, and thus the construction of an improved model. Ultimately, this approach also enables a better hydrological understanding of the catchment, as different structures,

10 flaws and errors of a first modelling approach become obvious.

2 Material and Methods

2.1 Study area

The study area is an upper section (AEO 2.977 km^2, gauging station Grebenau) of the Fulda catchment, a catchment with

15 Mid-European temperate climatic conditions. Relevant processes and catchment characteristics to be considered included the contribution of snowfall to precipitation, a mix of land uses with open and closed vegetation cover, and urban regions that impact hydrology through non-gradient driven fluxes (e.g. water abstraction for drinking water supply, sewage treatment works, reservoirs or sealed areas).

Precipitation input is influenced by the surrounding low mountain ridges of the Vogelsberg, the Wasserkuppe, the Knüll-

20 Mountains and the Melsunger Uplands, leading to a significant contribution of snowfall in winter. The elevation ranges from about 150 m a.s.l. at Grebenau to 950 m a.s.l. at the Wasserkuppe. Wittmann (2002) used tritium as a tracer and found that the Fulda catchment has two distinct groundwater reservoirs: A large one reacting slowly and a smaller one with faster reaction. Land use is dominated by agriculture (37%) and forests (41%).

2.2 Model input and validation data

25 Discharge data for the gauging station Grebenau, temperature and precipitation data were obtained from the Hessisches Landesamt für Naturschutz, Umwelt und Geologie (HLNUG). The point measurements for precipitation and temperature of the 108 measurement stations were extrapolated over the whole catchment, using kriging with altitude as an external drift (Hudson and Wackernagel, 1994). Finally, the extrapolated values were averaged over the whole catchment to get a single, lumped value per day.

30 The Fulda catchment has a humid, temperate climate. The climatic conditions during the calibration (1980-1985) and validation period (1986-1988) were rather similar with an annual precipitation of 838 mm. The annual runoff coefficient

ranges between 0.3 to 0.6 (average 0.39), which is in the range for comparable catchments (e.g. Rawlins et al., 2006). The discharge and groundwater of the catchment are influenced by drinking water abstraction for 80,000 inhabitants (Rhönenergie Fulda GmbH, 2017).

2.3 Model development using Catchment Modelling Framework

For the construction of all models and all numerical calculations, we used CMF. CMF is a modular framework for hydrological modelling developed by Kraft et al. (2011) (see also (CMF, 2017)). For solving the differential equations of models constructed with CMF, several numerical solvers are embedded in the toolbox. To avoid numerical problems (Clark and Kavetski, 2010; Kavetski et al., 2011; Kavetski and Clark, 2011) we selected the CVode Integrator (Hindmarsh et al., 2005) for all models. The CMF version used for this study was 0.1380.

In a first model set up (Model 1, Figure 1) all processes are reliant on different flow connections. The incoming precipitation is saved in a snow storage in case the air temperature is below freezing point and rereleased to the surface storage after snowmelt. All other precipitation is split between the canopy or reaches the surface directly, depending on canopy closure. From the surface, the water is either directly routed to the river or enters three serial soil/groundwater layers, which in turn route water to the river as well. In addition, a fixed amount of water is abstracted from the lower groundwater to simulate drinking water extraction, which in turn is routed to the river. The river then routes all water to the outlet. Thus, it contains the implementations of processes for evapotranspiration, a canopy, snow, surfaces, a river, upper- and lower groundwater body (Figure 1).

Following the findings of Singh (2002) all connections in the model with a flow curve (Figure 1) are described as kinematic waves (Equation 1) (Singh, 2002), except for the infiltration and the drinking water abstraction.

$$Q = \frac{1}{t_r} \left(\frac{V - V_{residual}}{V_0} \right)^{\beta} \tag{1}$$

where Q is the ratio of transferred water, $V_{residual}$ [m³] is the volume of water remaining in the storage, V_0 [m³ d^{-1}] is the reference volume to scale the exponent, and β is a parameter to shape the response curve [-]. The parameter t_r controls the reaction time of the storage, in case of $\beta = 1$, it is the mean residence time in days.

Water that reaches the surface, i.e. throughfall or snowmelt, is routed into the upper soil as infiltration, with the following limits applied:

- Infiltration excess expressed by a maximum surface permeability K_{sat}
- Saturation excess expressed by a limiting factor calculated from the water content of the first subsurface water storage using a sigmoidal function
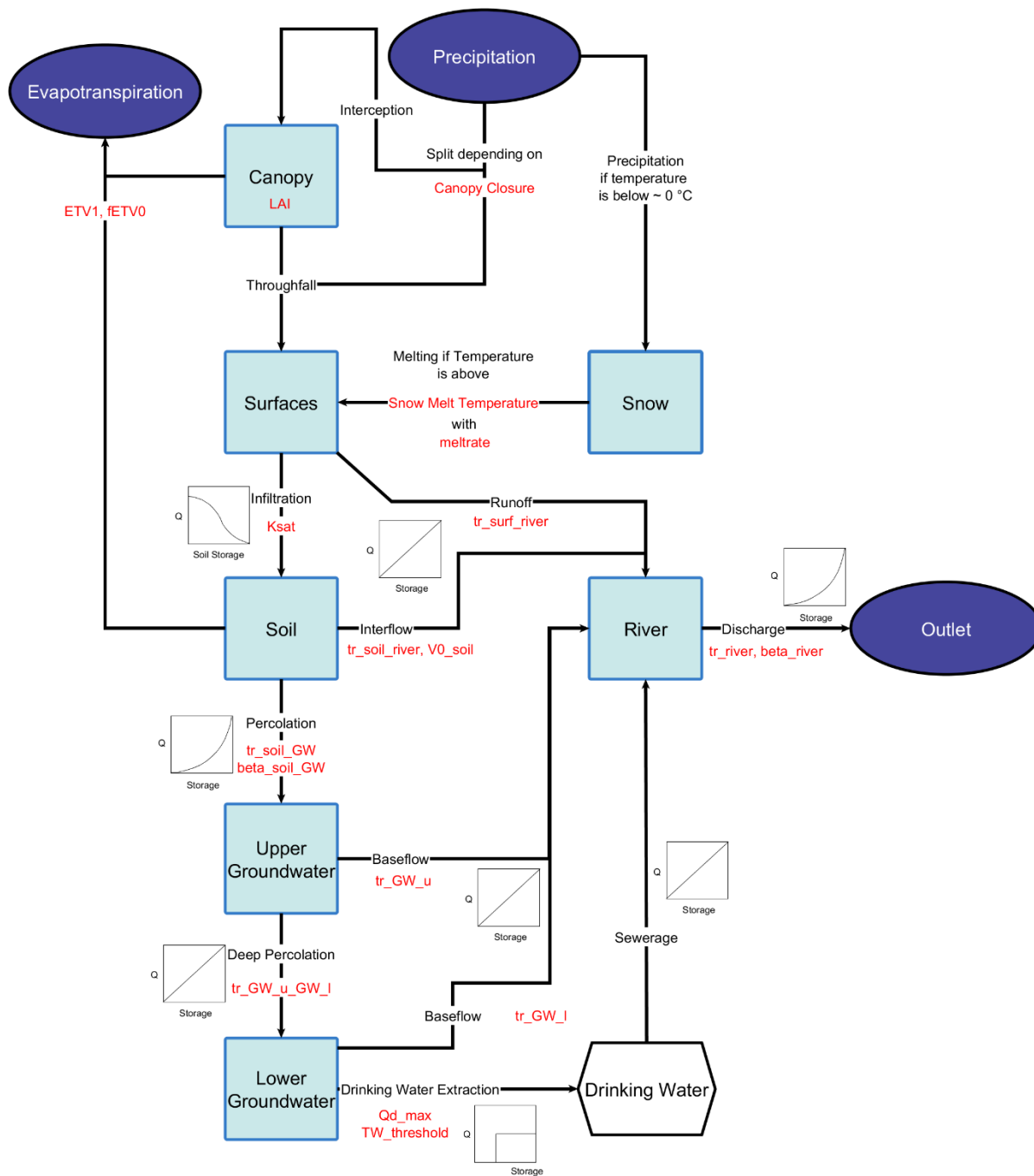
Figure 1: Structure of the Model 1 with water storages (light blue), boundaries (dark blue), temporary storages (white) calibrated parameters (red), fluxes (black arrows) and flow curves (for all applicable fluxes).

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Drinking water abstraction is implemented as a fixed amount of water. It is transferred to the drinking water storage as long as the amount of water in the groundwater storage is above a threshold. As this threshold is not exactly known, we included it as a parameter for calibration. From the drinking water storage, all water abstracted for a given day is routed to the river.

5 Snowmelt uses a simple degree-day method (see API in CMF (2017)). The snowmelt temperature parameter was calibrated. Interception from the canopy is realized as Rutter interception (Rutter and Morton, 1977). Potential evapotranspiration was calculated with the modified Hargreaves equation by Samani (2000).

The devised model was tested by using fluxogram graphs. Fluxograms allow creating animated graphs that resemble model structures with all their storages and fluxes and they were used to analyse the implemented model processes. The size of the

10 storages and fluxes change for each time step according to the amount of water stored/moved. For the fluxogram animations we used the model with the highest logarithmic Nash-Sutcliffe Efficiency (logNSE). A detailed explanation on the construction and source code of fluxograms (and CMF models in general) can be found in the tutorial section of CMF (2017), including a number of examples.

2.4 Incremental model breakdown

15 To test the influence of different structure elements in Model 1, we used the concept of a one-at-a-time sensitivity analysis, i.e. disabling one process after the other, to track changes. This resulted in 13 additional models with varying disabled processes (Table 1). In a second step, we disabled up to four processes, to scrutinize the interplay of processes, as proposed by Clark et al. (2011). For each simplified model, the model performance was evaluated. If the model performance was getting worse, the deleted process was valued essential for the model and vice versa. If the performance did not change, the

20 process was rated unimportant. This allowed us to separate influential processes from unnecessary ones and thereby assess if the chosen complexity was justifiable for the catchment (Table 2). The knowledge gained was then used to construct a final Model 15 containing only processes we found relevant to mimic the real world system.

5   **Table 1: Structural elements of the models and amount of parameters. GW = Groundwater, DW = Drinking Water. ET = Evapotranspiration. Light gray indicates active components. Dark grey indicates disabled components.**

| | Rain distribution | | | Soil | River | Groundwater (GW) | | | ET | Number |
						upper GW	lower GW	DW		Parameters
	Canopy	Surfaces	Snow							
Model 1 (start)	x	x	x	x	x	x	x	x	x	19
Model 2 (no GW)	x	x	x	x	x				x	13
Model 3 (no ET)	x	x	x	x	x	x	x	x		18
Model 4 (no river)	x	x	x	x		x	x	x	x	17
Model 5 (no rain distribution)				x	x	x	x	x	x	13
Model 6 (no surfaces)	x		x	x	x	x	x	x	x	17
Model 7 (no canopy)		x	x	x	x	x	x	x	x	17
Model 8 (no snow)	x	x		x	x	x	x	x	x	17
Model 9 (no DW)	x	x	x	x	x	x	x		x	17
Model 10 (no GW/river)	x	x	x	x					x	10
Model 11 (no canopy/surfaces)			x	x	x	x	x	x	x	15
Model 12 (no river/surfaces)	x		x	x		x	x	x	x	15
Model 13 (no lower GW)	x	x	x	x	x	x		x	x	17
Model 14 (no lower GW/DW)	x	x	x	x	x	x			x	15
Model 15 (final)	x		x	x		x		x	x	10

5 **Table 2: Number of behavioural runs, number of parameters, mean and standard deviation of the three objective functions for all behavioural runs for all models. logNSE = logarithmic Nash-Sutcliffe; PBIAS = percentage bias; RSR = ratio between root mean square error to the standard deviation of the measured data. Colours mark the performance in comparison to Model 1 (darker grey indicates better values).**

Model	Behavioural runs	Number parameters	Calibration						Validation					
			logNS [/]		PBIAS [%]		RSR [/]		logNS [/]		PBIAS [%]		RSR [/]	
1	9	19	0.53	± 0.04	3.97	± 5.55	0.68	± 0.01	0.61	± 0.05	1.13	± 5.95	0.69	± 0.03
2	-	13	-		-		-		-		-		-	
3	-	18	-		-		-		-		-		-	
4	6	17	0.55	± 0.03	1.28	± 5.60	0.68	± 0.02	0.63	± 0.04	0.13	± 7.27	0.67	± 0.04
5	-	13	-		-		-		-		-		-	
6	8	17	0.54	± 0.04	2.46	± 3.31	0.69	± 0.01	0.62	± 0.04	1.29	± 2.76	0.67	± 0.03
7	80	17	0.53	± 0.02	10.75	± 4.30	0.68	± 0.02	0.62	± 0.03	7.3	± 4.31	0.66	± 0.02
8	-	17	-		-		-		-		-		-	
9	6	17	0.55	± 0.03	3.29	± 4.12	0.68	± 0.01	0.62	± 0.05	4.13	± 5.61	0.68	± 0.03
10	-	10	-		-		-		-		-		-	
11	90	15	0.53	± 0.02	10.16	± 3.97	0.68	± 0.02	0.62	± 0.04	6.91	± 3.61	0.67	± 0.02
12	8	15	0.52	± 0.02	3.71	± 6.89	0.68	± 0.01	0.62	± 0.05	2.36	± 6.46	0.67	± 0.03
13	2	17	0.57	± 0.03	3.10	± 7.64	0.69	± 0.01	0.70	± 0.01	3.17	± 7.22	0.61	± 0.02
14	3	15	0.52	± 0.02	5.08	± 8.78	0.68	± 0.02	0.59	± 0.04	2.59	± 7.96	0.66	± 0.04
15	1731	10	0.57	± 0.05	4.86	± 8.03	0.66	± 0.04	0.65	± 0.06	5.56	± 7.94	0.65	± 0.05

2.5 Calibration and validation

A model run was separated into warm-up period of one year (1979), a calibration period of six years (1980-1985) and a validation period of three years (1986-1988). First CMF model runs showed that many simulated discharge peaks occurred one day ahead compared to observed data. This is caused by rainfall occurring in the later time of a day, that leads to a reaction in the hydrograph of the following day as water needs time to reach the gauging station (Ficchì et al., 2016). The model, however, reacts directly to this as its input data is resolved in a 24 h time step. Therefore, we shifted the simulated time series one day into the future as proposed by Bosch et al. (2004). This led to better calibration results.

We used the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven and Binley, 1992) to find behavioral parameters sets. As single-objective calibration lowers the identifiability of model parameters and structural elements (Efstratiadis and Koutsoyiannis, 2010) and often hide shortcomings of models (Ritter and Muñoz-Carpena, 2013), we pursued a multi-objective calibration procedure. Following the concept of Moriasi et al. (2007), a model run was deemed behavioural, if the logarithmic Nash-Sutcliffe-Efficiency (logNSE) was >0.5, the percentage bias (PBIAS) was below/above ±25% and the ratio between root mean square error to the standard deviation of the measured data (RSR) was <0.7. The logNSE focuses on low flows, the RSR depicts peak flows and the PBIAS considers the overall model deviation from observed data. It should be noted though, that this study does not aim on finding the optimal parameter sets for a single model, but to use the knowledge gained from calibration and validation to identify the most important processes in the model structure and use this to improve the model structure and reduce the number of parameters used.

The sampling of the parameter space for calibration was done by Latin Hypercube Sampling (McKay et al., 1979) implemented via SPOTPY (Houska et al., 2015). The CMF models were run 300,000 times each, using a High Performance Computing Cluster. See the tutorial section of CMF (2017) for more detailed information on the coupling of CMF with SPOTPY for model calibration. Implemented parameter boundaries for Model 1 are given in Table 3 and remained fixed for all further developed model structures to ensure comparability.

Table 3: Lower and upper parameters bounds of all models and their indented meaning. GW = Groundwater

Name	Intendent meaning	Min	Max
tr_soil_GW	Residence time from soil to upper GW	0.5	150
tr_soil_river	Residence time from soil to river	0.5	55
tr_surf_river	Residence time from surfaces to river	0	30
tr_GW_l	Residence time from upper GW to river/outlet	1	1000
tr_GW_u	Residence time from upper GW to river/outlet	1	750
tr_GW_u_GW_l	Residence time from upper to lower GW	10	750
tr_river	Residence time from river to outlet	0	3.5
V0_soil	Field capacity of the soil	15	350
beta_soil_GW	Exponent the changes the shape of the flow curve	0.5	3.2
beta_river	Exponent the changes the shape of the flow curve	0.3	4
ETV1	Volume under which the evapotranspiration is lowered	0	100
fETV0	Factor by what the evapotranspiration is lowered	0	0.25
meltrate	Meltrate of the snow	0.15	10
snow_melt_temp	Temperature of snow melt	-1	4.2
Qd_max	Maximal drinking water extraction	0	3
TW_threshold	Amount of water that cannot be extracted	0	100
LAI	Leaf area index	1	12
CanopyClosure	Canopy closure	0	0.5
Ksat	Saturated conductivity of the soil	0	1

3 Results

3.1 Behavioural runs of Model 1 to 14

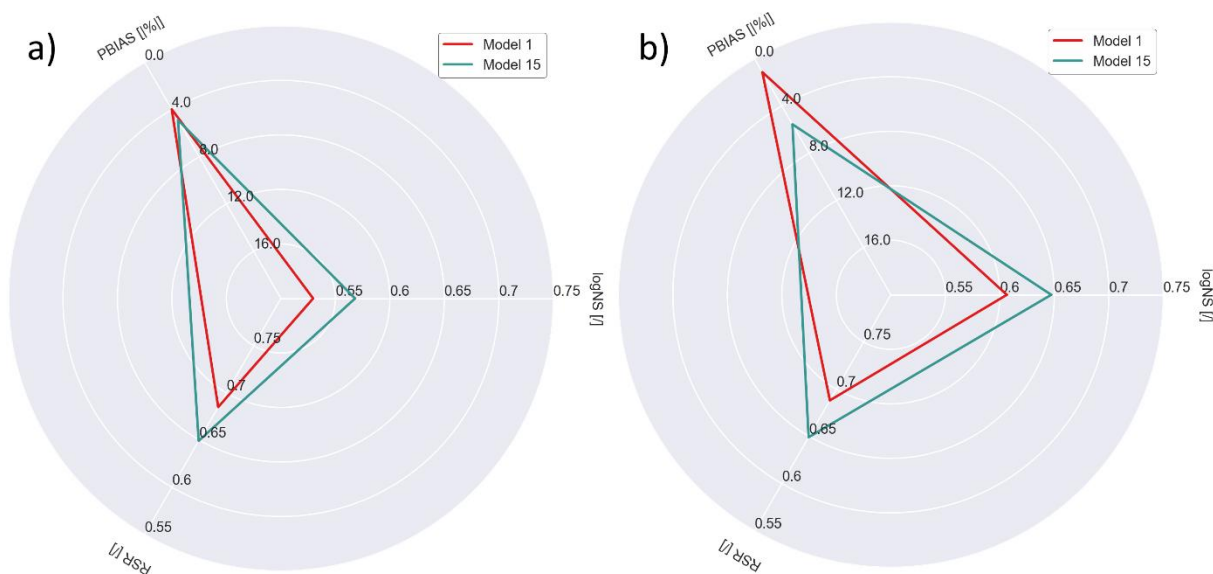
Model 1 was able to achieve nine behavioural runs. The model has a better performance in the validation period (Figure 2, Figure 3, Table 2). The simulated discharge is rather erratic (Figure 3), i.e. it reacts directly on small changes in precipitation. Those quick reactions are timed correctly. However, they overestimate the discharge from small precipitation events, while underestimating large ones. These differences are larger in summer than in winter. This behaviour leads to underestimated high flows and many overestimated small peaks, while the overall simulated amounts are unbiased. Investigation of storages and fluxes (fluxogram-graph: https://youtu.be/cP0PfDpfW88) show that most of the water is stored in the upper groundwater storage, while the lower groundwater storage is removed directly by the drinking water production, as soon as it is above the threshold. Only very small amounts of water are stored in the surface storage, the canopy storage and the soil storage. From the soil storage and the canopy storage large amounts of water evaporate, often exceeding the flow to the outlet. The river storage is mostly recharged from the groundwater and the drinking water storage. The soil storage

contributes significantly to the river storage only at large precipitation events or during snowmelt. Overall, Model 1 slightly overestimates base flow and the evapotranspiration, while largely underestimating the peaks.

Most of the deleted model processes from the most complex Model 1 led to more behavioural runs (Table 2). Model 1, 4 (no river storage), 6 (no surface storage), 9 (no drinking water simulation), 12 (no river and surface storages), 13 (no lower

5 groundwater storage) and 14 (no groundwater storages and drinking water simulation) have between two to nine behavioural runs. Model 7 (no canopy) and 11 (no canopy and surface storage) are able to produce 80 and 90 behavioural runs respectively (Table 2). The remaining models 2 (no groundwater storages), 3 (no evapotranspiration), 5 (no rain distribution), 8 (no snow) and 10 (no groundwater and river storages) were not able to produce behavioural runs.

The simplified models tend to show better performances for their mean values of the logNSE and the RSR (at least in the

10 validation period) than Model 1, while Model 1 has a PBIAS better than most of the other models. Especially model Model 13 (no lower groundwater storage) values for the logNSE outperform Model 1. Also all simplified models make use of less parameters than the first model.

15 **Figure 2: Radar plot for the calibration (a) and validation (b) period with all three objective functions of the models 1 and 15. The mean of all behavioural runs was used. PBIAS is used as an absolute value, so a larger area inside the triangle indicates higher values for the objective functions.**

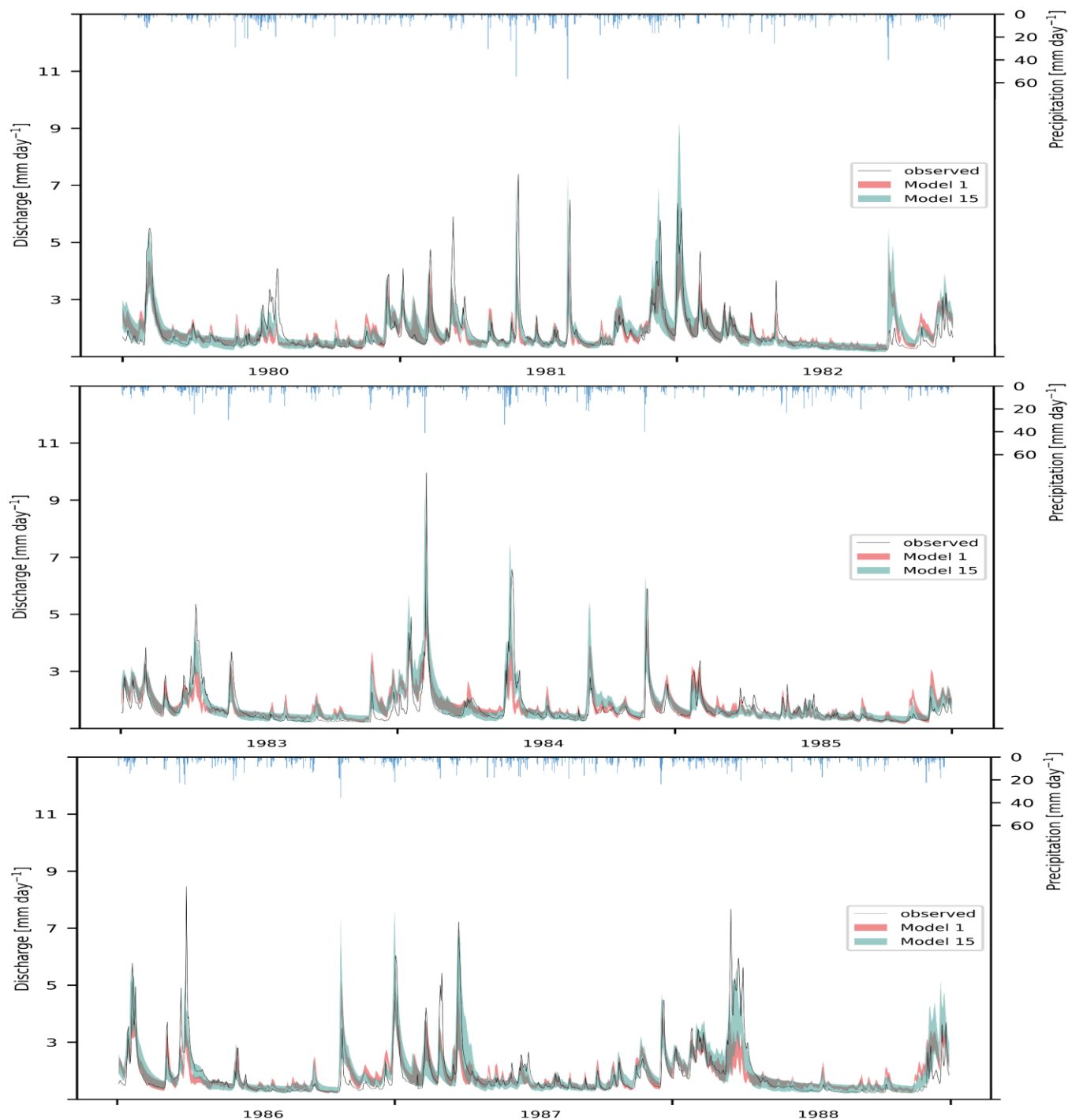



Figure 3: Hydrograph of the Fulda River for 1980-1988. Coloured areas depict the uncertainty of the behavioural model runs (5th to 95th percentile). Calibration time period is from 1980 till 1985 (first two subplots). Validation time period is from 1986 to 1988 (third subplot). Observed discharge is depicted as black line. Precipitation is drawn with an inverted y-axis.

3.2 Construction and behavioural runs of Model 15

We can report that representation of model processes for the upper groundwater body, evapotranspiration and snow have a positive impact on model performance in the Fulda catchment, given the increased number of behavioural runs and mean values of the objective functions (Table 2), as when those processes are excluded the models struggle to produce behavioural

5   runs. The exclusion of the canopy and drinking water have a more or less neutral impact on behavioural runs (Table 2). Whereas the chosen implementations of the river, the surfaces and the lower groundwater affect the model quality negatively (Table 2). The structure of Model 15 was created after all the other models had been evaluated. For this, we used the process knowledge gained from the reduced models (see discussion) and constructed Model 15 with only those processes, which had proven to have positive impact on the quality of the results. Therefore, Model 15 consists only of those processes most

10   important for the given Fulda catchment (Figure 4). In comparison with the model structure of Model 1, the processes surface water storage, lower groundwater storage, drinking water extraction, river storage and the simulation of the canopy were disabled.

Profiting from the insights of the models with disabled processes, Model 15 performs better than Model 1. The RSR and the logNSE depict better values, both in the validation and calibration period, while the PBIAS is slightly worse for both cases

15   (Table 2, Figure 2). Further, it has more behavioural runs than the best of the reduced models (Table 2). As for all other models, the performance increases from the calibration to the validation period for Model 15. The simulated hydrograph is a lot less erratic than the one from Model 1 (Figure 3). In addition, the peaks fit better than in Model 1. However, summer peaks are less likely to be predicted than those during the rest of the year (Figure 3). The overestimation of baseflow in Model 1 is only apparent on fewer days. In Addition, to this increase of the performance in comparison with Model 1, Model

20   15 uses nine parameters less (Table 2).

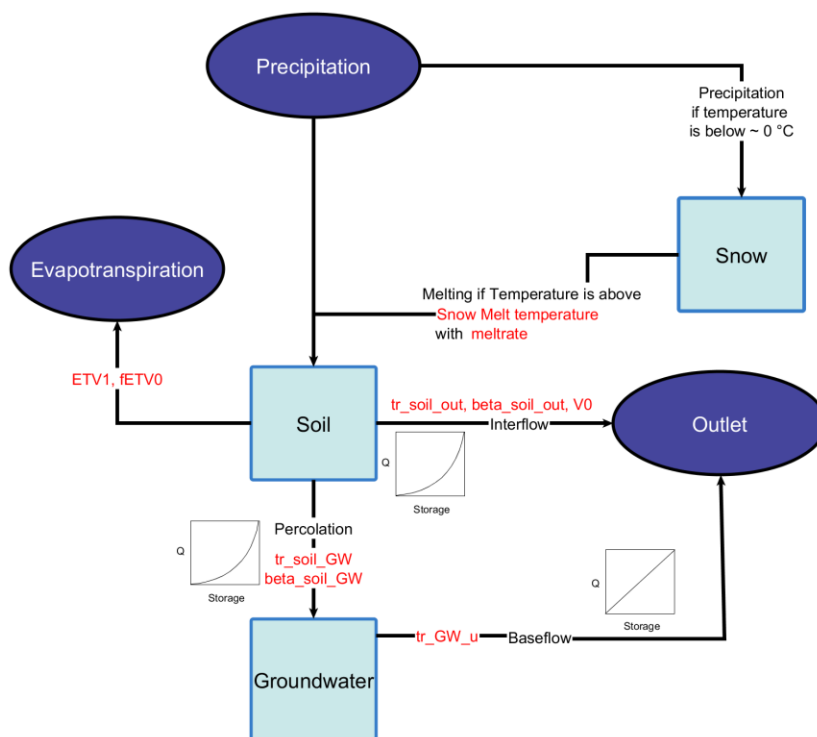



Figure 4: Structure of the final Model 15 with water storages (light blue), boundaries (dark blue), temporary storages (white) calibrated parameters (red), fluxes (black arrows) and flow curves (for all applicable fluxes.

4 Discussion

4.1 Overview

The results show that Model 1 fell short on simulating the catchment correctly. Mainly caused by a slow reaction to precipitation events, which reduced discharge peak prediction and caused the model to focus on evapotranspiration to handle the excess water. Still, it was a good basis to determine relevant processes by incremental model breakdown. Insights from this led to an improvement in the performance of Model 15, while at the same time allowed a reduction of the number of parameters (from n=19 to n=10)(Table 2). This suggests that the method of incremental model breakdown is a good way to improve model performance and reduce equifinality in the posterior parameter distribution, which improves the identifiability of the model structure (Ambroise, 2004). It enables insight to which processes are important for discharge simulations in a given catchment. It also allows revealing errors, using them "as a means of discovery" of false model assumptions (Elliott, 2004). It should be noted that this method does not necessarily lead to an improved model performance, but it allows creating a model, which relies on fewer processes, parameters and assumptions, thus being an application of "Occam's razor" (Clark et al., 2011).

4.2 Inspection of internal processes

Even though Model 1 did give sufficient but not excellent results, it was a good foundation for the construction of Model 15. Due to the implementation of many processes in Model 1, all those processes could be examined on their effect on the simulation. Upper groundwater, evapotranspiration and the simulation of the snow storage and snowmelt were identified as

5   the most important processes, as for example models 2, 5 or 10 could not achieve behavioural runs without those processes (Table 2). Model processes of drinking water and the canopy showed only minor impact on model discharge simulation performance (Table 2). Improved values for the objective function were found for models 4, 6 and 13 with no river, no surfaces and no lower groundwater, as those processes likely hindered the models from being better. Excluding these processes make the models react slower and with this, more accurate to precipitation inputs. The drinking water storage's

10   minor influence might simply be due to the rather low population of 159 persons per km² in the region, and neither water withdrawal for irrigation nor water-consuming industries are relevant players in the region's water cycle. The canopy, however, is commonly regarded as an important factor, as interception can cause 25 % and more of the rainfall not to reach the ground (Link et al., 2004). However, Model 15 was able to get better values for the objective functions than Model 1 even though the canopy was disabled (Table 2, Figure 2). Fenicia et al. (2008) showed that canopies have a large effect in

15   dry regions, which is underpinned by models developed for humid regions neglecting the canopy and still performing well, e.g. HBV-Light (Seibert and Vis, 2012). Also, the current implementation of the canopy in CMF assumes a fixed canopy storage for the whole year. A more realistic approach should be implemented for future applications, as was for example realized in plot scale CMF application coupled to plant growth models for winter wheat (Houska et al., 2014) and perennial grassland (Kellner et al., 2017).

20   The river storage is most likely too small to be an important reservoir in comparison to the catchment. The surface storages probably do not contribute to the runoff itself, because the catchment is mostly vegetated, which impedes overland flow. Lower groundwater was included because of the ability of the sand- and limestone in the catchment to store large quantities of water and because of the tritium based tracer experiments of Wittmann (2002). He found two distinct groundwater aquifers in the catchment. Their study comes to the results that the lower one of the aquifers must be very large. However,

25   our posterior parameter boundaries indicate a very slow response.

Model 15 falls short in predicting peak flow in summer (Figure 3). Due to that, the model has too much water and needs to compensate for this by overestimating baseflow and evapotranspiration (Figure 3). The problem of not predicting the peak flow in spring completely right is probably caused by the lumped and simple implementation of snowmelt. Most of the snow in the Fulda catchment is stored in a small area along the ridges, while the lumped model does not make such a spatial

30   distinction. A further, possibly influential, discrepancy between our lumped modelling assumptions and reality is that the snowmelt occurs evenly distributed over the whole catchment, so that the complete snowmelt in the model takes only a few days, often even in only one day. The fluxograms showed that Model 1 did not use the drinking water storage and used the canopy storage only rarely. These observations underline the demand of Clark et al. (2011) that the internal procedures of a

hydrological model should be inspected as well, to better understand its functioning. The fluxograms helped to detect that canopy and drinking water are not used by the model.

When examining the mean model performance of all reduced models and the resulting Model 15, one can see that the mean values of the objective functions of Model 15 are similar to those of Model 13 (Table 2). Model 15 is considered to be the better representation of the catchment than Model 13, as it has a more streamlined structure and seven parameters less. In addition, the good values for Model 13 are mainly caused by the low number of behavioural runs (n = 2), allowing one very good run to distort the mean.

Model 15 falls short in predicting peak flow in summer (Figure 3). Consequently, the model has too much water resulting in overestimated baseflow and evapotranspiration. The problem of not predicting the peak flow in spring completely right is probably caused by the lumped and simple implementation of snowmelt, which causes the snow to melt quicker than in reality. It might also be linked to the evapotranspiration. . In times of low evapotranspiration, the water is forced to leave the model as discharge. Therefore, large precipitation events are directly transferred to large peaks. During times of high evapotranspiration, much water can be released into the atmosphere, and as the water in the soil storage of Model 15 flows proportionately more if the storage is already high, this allows the water to stay longer in the soil, which in turn allows more evapotranspiration.

4.3 Does model incremental breakdown allow the construction of improved models?

The improved performance of Model 15 shows that a priori model selection is not useful, as the models with different process implementations deliver very different results. This is in line with the findings of Ley et al. (2016), who used predefined model structures on a large amount of different catchments and found that no model was able to simulate all catchments well. Similar results were also found by Kavetski and Fenicia (2011) and Fenicia et al. (2014), who showed that lumped models need to be tailored for single catchments as they are often over-simplified.

Lumped models have the advantage of an easy set-up and low data requirements, but this comes at the cost of not being able to address the spatial heterogeneity of the catchments (Ley et al., 2016) and that the parameters and structures have no direct equivalence in the real world (Bergström and Graham, 1998). Therefore, a lumped model structure might simply have been too simple for the upper section of the Fulda, calling for a semi-distributed or even distributed model set up. Overall, we think that the proposed method of incremental model breakdown led to an improvement in model performance. In addition, the model complexity and amount of parameters and with this equifinality were reduced. Both topics are often stated as the main goals of model development e.g. Efstratiadis and Koutsoyiannis (2010) and Gupta and Nearing (2014).

5 Conclusion

This study shows that the process-based incremental breakdown of a hydrological model using fluxograms and a multi-objective calibration allows the identification of important hydrological processes in a model and the reconstruction of the

starting model structure to a less uncertain and more efficient version. We conclude that the method provided offers a useful approach in the identification of relevant hydrological processes. Model frameworks such as CMF facilitate the development of such an approach.

The incremental model breakdown can be used best in two cases: (1) finding out why an existing good model does produce good results in the sense of a diagnostic tool to assess model structures; or, as in this study, (2) determining which processes are most relevant, to allow the streamlining of a model.

One goal of this study was to find another strategic way to test the multiple implementations of catchment functioning. We were able to distinguish between unnecessary and relevant model processes. Further, it became clearer what causes those problems, by examining the model piece by piece as proposed by Clark et al. (2016). Therefore, this method can be seen as a useful third way, in addition to step-wise model building (Bai et al., 2009; Westerberg and Birkel, 2015) and the comparison of predefined structures (van Esse et al., 2013; Kavetski and Fenicia, 2011), to explore the realm of multiple hypotheses. We propose future research should consider an automatic assemblage of model structures to test not only a manually manageable number of models but rather scan a larger variety of feasible combinations.

Data availability. Datasets are available by contacting the Hessian Agency for Nature Conservation, Environment and Geology (HLNUG) (https://www.hlnug.de/service/english.html).

Competing interests. The authors declare that they have no conflict of interests.

Acknowledgements. We thank the "Hessisches Landesamt für Naturschutz, Umwelt und Geologie" for providing the meteorological and discharge data.

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