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Key Points:

- Regime curves of parameter sensitivities to different modeled hydrological components reveal temporal patterns of parameter dominance
- Detection of a more informative signal of how model parameters are related to individual modeled hydrological components in time
- Using rate of change as response variable provides additional diagnostic information about dominance of individual hydrological components

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Demasking the integrated information of discharge: Advancing sensitivity analysis to consider different hydrological components and their rates of change

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Abstract Discharge as an integrated representation of all hydrological processes is the most common response variable used in sensitivity analyses. However, due to overlaying effects of all hydrological processes, the sensitivity signal of certain parameters to discharge can be masked. A more informative form of sensitivity analysis can be achieved by investigating how parameter sensitivities are related to individual modeled hydrological components. In our study, the TEDPAS (TEmporal Dynamics of PArameter Sensitivity) methodology is used to calculate daily sensitivities to modeled hydrological components and to detect temporal variations in dominant parameters. As a further enhancement to consider both magnitude and dynamics, temporal variations in parameter dominance are analyzed, both for magnitudes and rates of change of hydrological components. For this purpose, regime curves for parameter sensitivities are constructed. The results demonstrate that sensitivities of parameters increase when using the corresponding hydrological component instead of discharge as response variable. For each hydrological component, seasonal patterns of parameter dominance are detected using both magnitude and rate of change as response variable. Major differences are detected for certain capacity parameters, which are less pronounced using rates of change. Overall, we show that disentangling the diagnostic information hidden in the integrated signal of discharge can lead to a more informative signal regarding the sensitivity of hydrological components. Such advancements in sensitivity analysis can lead to a better understanding of how model parameters control the individual hydrological components in time.

1. Introduction

To represent the hydrological system and the contribution of individual processes of a study catchment realistically, hydrological models need to reproduce the magnitudes and dynamics of all relevant processes. To investigate the representation of processes and their dynamics in models, a better understanding of the process behavior in models is required. With diagnostic model analysis temporal variations of the controlling processes are detected and typical temporal patterns of hydrological behavior are identified [Gupta *et al.*, 2008; Yilmaz *et al.*, 2008; Reusser *et al.*, 2009]. Using techniques of diagnostic model analyses, more precise and helpful information about the hydrological system can be derived from existing data or model results [Gupta *et al.*, 2008; De Vos *et al.*, 2010; Hrachowitz *et al.*, 2013; Montanari *et al.*, 2013; Gupta and Nearing, 2014; Guse *et al.*, 2014; Nearing and Gupta, 2015; Pfannerstill *et al.*, 2015]. It is required to tease out and exploit the information made available via the diagnostic concept [Martinez and Gupta, 2011; Clark *et al.*, 2015; Guse *et al.*, 2016; Pianosi *et al.*, 2016].

Temporal variations in the dominance of processes [Boyle *et al.*, 2000, 2001] result in temporal variations in the dominance of model parameters [Wagner *et al.*, 2003; van Werkhoven *et al.*, 2008; Cibirin *et al.*, 2010; Herman *et al.*, 2013a, 2013b]. These patterns of parameter dominance can be analyzed by means of a temporal parameter sensitivity analysis [Sieber and Uhlenbrook, 2005; Reusser *et al.*, 2011; Guse *et al.*, 2014; Massmann *et al.*, 2014; Pfannerstill *et al.*, 2015; Guse *et al.*, 2016]. Parameter sensitivity is, in this context, defined as the sensitivity of model outputs (e.g., discharge) to changes in values of model parameters.

In contrast to classical sensitivity analyses which are applied in an aggregated manner to the whole time series, a temporally resolved sensitivity analysis on subperiods (such as a daily or monthly time step) considers the temporal variability of sensitivity within the modeling period. By analyzing the temporal dynamics of parameter sensitivity (TEDPAS), information about parameter sensitivity at a daily resolution is obtained and reveals the dominance of model parameters on each day [Sieber and Uhlenbrook, 2005; Reusser et al., 2011; Guse et al., 2014]. As recently pointed out by Razavi and Gupta [2015], it is important that the objectives of a sensitivity analysis are clarified in advance so that a consistent approach can be applied. In TEDPAS, the goal of sensitivity analyses is a factor prioritization, which means that the dominant parameters are identified for each time step [Saltelli et al., 2006; Reusser et al., 2011].

The results of a sensitivity analysis are strongly influenced by the choice of response variable [Goehler et al., 2013; Razavi and Gupta, 2015]. Here one can differentiate between sensitivity analyses applied directly to modeled discharge as response variable [Reusser et al., 2011; Guse et al., 2014] and applied to one or more metrics of model performance [van Werkhoven et al., 2008; Herman et al., 2013a]. In the latter case, the deviation between modeled and measured discharge is summarized via a performance measure that serves the function of response variable. However, the selection of any aggregate performance measure will, inevitably, lead to a higher weighting of specific discharge values while resulting in a dampening signal of the influence of other discharge values in the response variable [Razavi and Gupta, 2015]. The use of multiple performance measures as response variables reflects the fact that the relevance of different hydrological components varies temporally [van Werkhoven et al., 2008]. Herman et al. [2013a] ordered the sensitivity of model parameters on discharge by the magnitude of three major processes in hydrology (discharge, precipitation, potential evapotranspiration) to identify the hydrological conditions leading to high parameter sensitivity. Guse et al. [2016] combined daily parameter sensitivity with different segments of the flow duration curve. By deriving typical patterns of parameter dominance, phases of high parameter sensitivity were precisely characterized in relation to discharge magnitudes and seasonal variations. In all of these studies, the diagnostic information included in the discharge time series was amplified and related to hydrological processes as proposed by several authors [Gupta et al., 2008; Martinez and Gupta, 2011; He et al., 2015; Nearing and Gupta, 2015].

Till now, model diagnostic analyses, and more specifically the temporal analyses of parameter sensitivity, have been focused on the use of total discharge as output variable. The challenge is now to bring sensitivity analysis to bear on the different modeled hydrological components (e.g., runoff components, evaporation, soil water content) which are simulated by complex catchment models. Understanding of the temporal behavior of individual processes is crucial for realistic model results that do not obtain the right model results for the wrong reasons [Kirchner, 2006].

Several studies already show that using other modeled hydrological components in addition to discharge for model calibration lead to a more process-based model parameter value identification [Koren et al., 2008; Parajka and Bloeschl, 2008; Duethmann et al., 2014]. A prerequisite for the use of additional hydrological components for parameter value identification is to understand how they are incorporated into the model structure and which parameters control a hydrological component during which phase.

Consequently, by using other modeled hydrological components in addition to discharge, diagnostic information regarding model behavior can be increased and lead to improved knowledge about the structure and functioning of individual hydrological components [Wagener et al., 2001; Martinez and Gupta, 2011]. Clark et al. [2008] stated that the whole information provided by a model needs to be interpreted, including the hydrological state variables and different fluxes. Massmann and Holzmann [2015] showed that a parameter sensitivity analysis for different hydrological components enables one to derive the impact of hydrological components and to understand their implementation in the model. The diagnostic potential of the temporal dynamics of parameter sensitivity can thus be advanced by applying it to modeled variables other than discharge as suggested by Reusser and Zehe [2011].

Keeping in mind that the results of a sensitivity analysis depend on the nature of the selected response variable [Razavi and Gupta, 2015], the investigation reported in this paper explores how different selections of response variables lead to a better understanding of how parameters control the hydrological components in models.

Thus, this study aims to improve the understanding of the controlling model parameters and their relationship to the different hydrological components by an advanced sensitivity analysis approach.

First, time series from modeled hydrological components other than only discharge are used as response variables for a temporal parameter sensitivity analysis, with the view to increase the information provided about how a hydrological component is controlled by a model parameter. Our hypothesis here was that the sensitivity signal of a model parameter is higher and varies in its temporal patterns when using the corresponding modeled hydrological component as response variable.

Further, to better understand temporal variations in dominance patterns of a hydrological component, it is necessary to investigate its dynamic behavior in addition to its magnitude. Thus, as a second approach, we express the dynamics of a hydrological component in terms of its time rate of change (e.g., the change in a hydrological component from day to day). Accordingly, the rate of change of a modeled hydrological component is included in the sensitivity analyses in addition to the common magnitude-approach based on the values themselves.

To achieve this goal, we demonstrate that

1. the dominance of model parameters in controlling an individual hydrological component change in time
2. the understanding of parameter control can be improved by using the individual hydrological components as response variable for a sensitivity analysis
3. the controlling parameters of hydrological components are different when using their rate of change instead of their magnitude as response variable

2. Methods

To achieve the objectives of this study, the temporal dynamics of parameter sensitivity (TEDPAS) approach served as the central diagnostic method. For the sensitivity analysis, the magnitudes and the rates of change (i.e., their derivatives) of different modeled hydrological components were used as response variable. For estimating parameter sensitivities, TEDPAS provides the parameter settings for model simulations which were carried out using a hydrological model as described in detail in the case study. The methodological approach of analyzing TEDPAS to different hydrological components consisting of two parts is summarized in Figure 1 and explained in detail in the next subsections. While the first part is related to the construction of regime curves for each hydrological component based on model simulations, the second part consists of the temporal parameter sensitivity analyses to the magnitudes and the rates of change of different hydrological components as well as the construction of the regime curve sensitivity.

2.1. From Model Simulations to Regime Curves of Hydrological Components

The first part of the analysis consists of the construction of individual regime curves for the modeled hydrological components based on the results of the model simulations. Regime curves show the mean seasonal variation of a hydrological component and thus represent the mean hydrological behavior within the year [Yokoo and Sivapalan, 2011; Coopersmith et al., 2012; Ye et al., 2012; Berghuijs et al., 2014; Coopersmith et al., 2014]. The regime curves are constructed by averaging the values for each day of the year for the simulation period. Therefore, the regime curve value for 1 January is the average of all values for 1 January available within the selected time series. Accordingly, regime curves serve as signatures of the seasonal hydrological behavior [Berghuijs et al., 2014].

To construct regime curves, model simulations were carried out and daily time series of different hydrological components were extracted from each model simulation (A in Figure 1). Next, for each hydrological component and each day of the modeling period, the median from all model simulations was calculated. Moreover, 5%- and 95%-quantiles were calculated to consider uncertainty in each modeled hydrological component. To analyze each hydrological component with respect to its temporal dynamics, regime curves of averaged daily time series were constructed (B in Figure 1).

To express the variability in the regime curve, the degree of variability was calculated for each regime curve with the seasonality index SI [Coopersmith et al., 2012, equation (1)] as proposed by Walsh and Lawler [1981] and used for hydrological applications by Coopersmith et al. [2012, 2014]. A high value for a seasonality index indicates a high seasonal variability in a given hydrological component.

Figure 1. Flowchart of the methodological approach consisting of two parts which are presented in two separate boxes. The blue box presents the model simulations and ends with the construction of regime curves. The purple box shows the calculation of the parameter sensitivities and ends up with the construction of the regime curve sensitivities. The results of each step are shown for the magnitude (left) and the rate of change (right) exemplarily for one hydrological component and the sensitivities of one parameter.

$$SI = \frac{\sum_{i=1}^{366} |H_i - \frac{\sum_{j=1}^{366} H_j}{366}|}{\sum_{i=1}^{366} H_i} \quad (1)$$

where SI = seasonality index and H_i = regime curve value of the hydrological component for the day of the year i .

2.2. From Parameter Sensitivity Analyses to Sensitivity Regime Curves

The second part of the analysis consists of a temporal parameter sensitivity analysis and demonstrates how to calculate the regime curve sensitivity.

2.2.1. Temporal Dynamics of Parameter Sensitivity (TEDPAS)

In this step, all modeled time series (A in Figure 1) were used to calculate the sensitivity of model parameters to the modeled hydrological components (C in Figure 1). The temporal dynamics of parameter sensitivity method (TEDPAS) [Sieber and Uhlenbrook, 2005; Cloke et al., 2008; Reusser and Zehe, 2011; Reusser et al., 2011] was used to obtain daily time series of parameter sensitivities related to each modeled output of interest.

TEDPAS belongs to the category of factor prioritization methods, and focuses on the detection of dominant model parameters [Saltelli et al., 2006]. TEDPAS can be carried out using any global sampling method that covers the whole parameter space and investigates simultaneous parameter perturbations.

Typical methodological implementations for TEDPAS include the (extended) Fourier Amplitude Sensitivity Test (FAST) and Sobol's method [Saltelli et al., 2006; van Werkhoven et al., 2008; Nossent et al., 2011; Reusser

et al., 2011]. In this study, the FAST algorithm implemented in R (FAST-package) [Reusser, 2013] was used to calculate the sensitivity for each model parameter. The number of model runs depends on the selected number of model parameters [Cukier *et al.*, 1975]. We used this approach due to the lower number of required model runs compared to Sobol's method [Saltelli and Bolado, 1998; Reusser *et al.*, 2011].

Applying the FAST method, the modeled time series are transformed into a Fourier series. Since each parameter is varied with different frequencies, the FAST coefficients can be used to calculate the partial variance of this particular parameter [Reusser *et al.*, 2011]. The first-order partial variance measures the contribution of a single parameter to the total variance V among all parameters that influence the model output [Reusser *et al.*, 2011, equation (2)]. The first-order sensitivity can thus be expressed as ratio of the first-order partial variance and the total variance (equation (3)) [Cukier *et al.*, 1978; Saltelli and Bolado, 1998] and is used here as sensitivity measure.

$$V = \sum_i V_i + \sum_{i < j} V_{ij} + \dots + V_{1,2,3,\dots,n} \quad (2)$$

$$S_i = \frac{V_i}{V} \quad (3)$$

where S_i = first-order sensitivity of parameter i , V = total variance, V_i = variance of parameter i (first-order variance), V_{ij} = covariance of parameters i and j (second-order variance); Terms of higher order include multiple contributions.

According to Reusser *et al.* [2011] and Reusser and Zehe [2011], TEDPAS is based on three steps. At first, the FAST algorithm provides a list of parameter combinations using the sampling scheme of FAST. Second, these parameter sets are applied to a hydrological model. The case-specific details about model and selected parameters for this study are provided in the third chapter. Thirdly, these modeled daily time series for a selected hydrological component are extracted for each model simulation and used to calculate daily parameter sensitivities.

We used the model outputs directly as response variable, instead of the deviation between modeled and measured output. Thus, the weighting problem associated with model performance metrics does not arise. The results of the FAST calculation were used to derive the temporal dynamics in parameter sensitivity analyses (TEDPAS). By doing so, temporal variations in the dominance of model parameters were detected for each hydrological component. For a detailed description of TEDPAS using the FAST algorithm, we refer to Reusser *et al.* [2011].

2.2.2. TEDPAS to Magnitudes and Rates of Change of Different Hydrological Components

To investigate how perturbations in various parameters affect the considered model output, different modeled hydrological components were used as response variable for the sensitivity analysis. Accordingly, TEDPAS generated time series of daily sensitivities for each parameter to different modeled hydrological components (C in Figure 1, left), which enables the detection of dominant parameters for the magnitude of each hydrological component (TEDPASnorm).

A dominant parameter is defined as the parameter with the highest first-order partial variance. Further, at a certain time step more than one parameter can have a substantial first-order partial variance and may be relevant in controlling a hydrological component [Sarrazin *et al.*, 2016].

Similarly to TEDPASnorm, the temporal parameter sensitivity analysis was also applied to the rate of change in the modeled hydrological components (i.e., their derivatives; C in Figure 1, right). This TEDPAS approach was named TEDPASrate. The rate of change in a modeled hydrological component was estimated as the difference between the current daily value and the value of the previous day (i.e., the slope from the previous to the current day). A positive value indicates an increase in slope. TEDPASrate focuses on the dynamics of a modeled hydrological component rather than on the magnitude by explicitly looking at changes in a time series.

2.2.3. Regime Curve Sensitivity

The daily time series of parameter sensitivity to a certain hydrological component was next averaged for each day of the year to construct separate regime curves (regime curve sensitivity) (D in Figure 1). For reasons of consistency, days with no sensitivity were set to a sensitivity of zero. Thus, each value of the regime curve sensitivity is the average of the eleven sensitivity values within the modeling period for each day of

the year. For each model parameter and for each hydrological component the regime curve sensitivity was computed separately using both TEDPASnorm and TEDPASrate.

The regime curves for different modeled hydrological components (B in Figure 1) were compared with the regime curve sensitivity derived from TEDPASnorm and TEDPASrate (D in Figure 1). This comparison aims at detecting the controlling parameters for each hydrological component under consideration of its seasonal variations. It reveals whether a parameter is dominant in phases of high or low values of the hydrological component.

2.2.4. Comparison of Sensitivities to Individual Hydrological Components and to Water Yield

Subsequently, we analyzed whether new diagnostically relevant information could be derived by using the individual hydrological components as response variable. To investigate this, regime curve sensitivities to the individual hydrological components and to water yield were compared. Water yield was used here as a representation for the most often used response variable in a sensitivity analysis. In contrast to discharge, the water yield only includes the catchment processes without considering the routing effect in the river system.

The parameter sensitivities of both TEDPAS approaches on the individual hydrological components were compared with the TEDPASnorm approach to water yield. It is aimed to detect which sensitivity signal is captured using water yield as response variable and which is only detectable in the TEDPAS approach to the individual hydrological components. Further, we analyzed whether the sensitivity signal changes when using the rate of change of a hydrological component instead of its magnitude.

3. Case Study

3.1. Study Catchment

For realizing this methodological approach, the Treene catchment in the Northern German lowlands with a low gradient in elevation (maximum of 80 m asl) was selected as test catchment. The study area has a catchment size of 481 km² (catchment outlet Treia). The land use is dominated by agriculture areas (70%) with a minor contribution of forest (7%) and urban areas (10%) [Guse *et al.*, 2015]. As shown in other studies, groundwater flow is the dominating runoff component as typical for German lowland catchments [Kiesel *et al.*, 2010; Pfannerstill *et al.*, 2014b, 2015].

3.2. Soil and Water Assessment Tool (SWAT)

To carry out the model simulations for this study, the Soil and Water Assessment Tool (SWAT) [Arnold *et al.*, 1998; Arnold and Fohrer, 2005], a complex conceptual process-based model, was used. Its spatial discretization consists of spatially located subbasins, in which lumped hydrological response units (HRUs) are included. The SWAT model solves the water balance continuously to calculate daily changes in the soil storage (Figure 2). Precipitation as rain or snow is the main input. SWAT simulates various hydrological components of the water balance including evapotranspiration and different runoff components ranging from surface and subsurface runoff to groundwater flow [Neitsch *et al.*, 2011]. We used the SWAT3S version developed by Pfannerstill *et al.* [2014b]; this SWAT model version has previously been applied in different studies [Pfannerstill *et al.*, 2014a, 2015; Haas *et al.*, 2015; Guse *et al.*, 2016]. Compared to the original SWAT model, the SWAT3S version contains two active aquifers instead of only one active aquifer, thereby simulating both fast and slow components of groundwater flow.

3.2.1. Input Data

To ensure that the methodological approach is transferable, we used only widely available observed data. Representative long continuous observed daily time series at the catchment scale are generally only available for total discharge and precipitation. As geographical input data a digital elevation model (25m resolution) [LVERMA, 1995], a land use map [LVERMA, 2004] and a soil map [BGR, 1999] were used for the hydrological model. A continuous daily time series of discharge for the catchment outlet Treia was used. Four climate stations with continuous daily values of all required climate variables for the modeling period were used, as provided by the German Weather Service and the Potsdam Institute for Climate Impact Research [Oesterle, 2001; Conradt *et al.*, 2012].

3.2.2. SWAT Model Parameters

For this TEDPAS analysis, nine parameters of the SWAT model were used. The SWAT model structure is schematically depicted in Figure 2 as simplified portrayal including the nine model parameters. These nine

Figure 2. Simplified flowchart of the SWAT model in the version SWAT3S with the most relevant modeled hydrological components for this study. The selected modeled hydrological components are filled in grey. The nine model parameters for the sensitivity analysis are classified in capacity parameters (in blue) and flux parameters (in green) and are explained in Table 1. The hydrological components are separated into storages (in boxes) and processes (in circles). The hydrological components and the SWAT model parameters are described in detail in *Neitsch et al. [2011]* and *Pfannerstill et al. [2014b]*.

parameters represent all relevant hydrological components and are presented briefly in the order of their role in the vertical water redistribution [*Pfannerstill et al., 2015*], starting with surface and ending with groundwater parameters.

Snowfall (SFTMP) and snowmelt temperature (SMTMP) function as threshold parameters. Snow falls when SFTMP is decreased and snow melts when SMTMP is exceeded. Infiltration into the soil, and consequently also the occurrence of surface runoff, is represented in the SWAT model by the curve number method (CN2) [*SCS, 1972*]. The soil moisture conditions are regulated by the available soil water capacity (SOL_AWC), which varies spatially between the different soil types and their layers. Evaporation from the soil is regulated by a soil evaporation factor (ESCO) as a nonlinear parameter to estimate to which depth and to which intensity soil water contributes to evaporation. The tile flow lag time (GDRAIN) regulates the flow travel time within the tile drains. In the aquifer, the timing of percolating water to recharge the fast aquifer is controlled by groundwater retention (GW_DELAYfsh). The recharged water is separated into contributing water for both aquifers. The shares for each aquifer are regulated by the aquifer fraction coefficient (RCHRGssh). The timing of the flowing water from the slow shallow aquifer to the river is controlled by ALPHA_BFssh. Thus, the groundwater component in the SWAT model includes two flux parameters (GW_DELAYfsh, ALPHA_BFssh) and a capacity parameter (RCHRGssh). For a more detailed description of the model parameters, please see *Neitsch et al. [2011]*. The parameter ranges shown in Table 1 were selected based on experience acquired through other SWAT modeling studies [e.g., *Guse et al., 2014, 2016; Pfannerstill et al., 2014a, 2015*].

The model parameters are further classified in Figure 2 into parameter types to demonstrate the role of a parameter in regulating either the timing of a hydrological component (flux) or the amount of water in a hydrological component (capacity). While this classification is not completely crisp, we consider flux parameters to be mainly controlling the timing rather than the amount of water available for a certain hydrological component. Capacity parameters are primarily related to the amount of water that can be stored and made available as contribution for a certain hydrological component. For simplicity, the threshold parameters, which control whether a hydrological component occurs or not, were classified as capacity parameters since they primarily control the amount of available water. Of course they also play a role in controlling the timing of onset or termination of a hydrological component.

3.2.3. Modeled Hydrological Components

Eight modeled hydrological components from the land phase of the SWAT model were selected as response variable for TEDPAS. Four runoff components (surface runoff, tile flow, fast and slow aquifer

Table 1. Overview of SWAT Model Parameters and Their Parameter Types^a

Parameter Name	Abbreviation	Hydrological Component	Parameter Type	Range Type	Lower Range	Upper Range
Snow fall temperature	SFTMP	Snow	Capacity/Threshold	r	−2.5	2.5
Snow melt temperature	SMTMP	Snow	Capacity/Threshold	r	−2.5	2.5
Curve number	CN2	Surface runoff	Capacity/Threshold	a	−15	15
Tile flow lag time	GDRAIN	Tile flow	Flux	m	0.5	1.5
Available soil water capacity of a soil layer	SOL_AWC	Soil water	Capacity	a	−0.02	0.1
Soil evaporation compensation factor	ESCO	Evapotranspiration	Capacity	r	0.2	1
Groundwater delay time (fast aquifer)	GW_DELAYsh	Groundwater	Flux	r	1	25
Aquifer fraction coefficient (slow aquifer)	RCHRGssh	Groundwater	Capacity	r	0.2	0.8
Baseflow alpha factor (slow aquifer)	ALPHA_BFssh	Groundwater	Flux	r	0.001	0.1

^aThe SWAT model parameters were varied in the TEDPAS analysis within these ranges. Lower and upper ranges are given as absolute range (r), additive (a) or multiplicative (m) value. The model parameters were described in detail in the SWAT model documentation [Neitsch *et al.*, 2011].

flow) and the water yield as the sum of the runoff components flowing into the river were included. In addition, snowmelt, actual evapotranspiration and soil water content were also analyzed (Figure 2). The daily time series of measured precipitation, minimum and maximum temperature and modeled snowfall are additionally considered to illustrate the dynamical behavior of the main driving inputs for the water cycle.

3.3. TEDPAS Application for the Case Study

The SWAT model for the Treene was run from 1997 to 2010 using the first 3 years as warm-up period. The model set-up was used as presented in Guse *et al.* [2016]. TEDPAS applications of the SWAT model to simulate discharge are further described in Guse *et al.* [2014, 2016] and Pfannerstill *et al.* [2015] and to simulate nitrate in Haas *et al.* [2015]. To calculate the daily sensitivities of nine model parameters, the FAST method requires 315 model simulations [Reusser *et al.*, 2011]. Reusser *et al.* [2011] showed that even this small number of simulation runs leads to robust sensitivity patterns.

The modeled daily time series from these simulations were used to construct the regime curves for the eight hydrological components (B in Figure 1). At first, for each day the median values among all 315 model simulations were calculated for the individual hydrological components. This led to a median time series of the hydrological component for the whole model period (2000–2010) which was then transferred into a regime curve (with 366 days) by averaging all values within the modeling period for each day of the year. This approach was repeated for each hydrological component leading to eight regime curves; one for each hydrological component.

Next, the same set of model simulations was used to estimate daily parameter sensitivities for each hydrological component using the FAST algorithm [Reusser, 2013]. These daily time series of parameter sensitivity for the whole modeling period were then also transferred into regime curve sensitivity. For the eight hydrological components both the original regime curve and the rate of change of the regime curve were used and a separate regime curve sensitivity was calculated for each of the nine model parameters. This resulted in 144 regime curve sensitivities in total (8x2x9) (see D in Figure 1).

The regime curve sensitivity was analyzed in two ways both for TEDPASnorm and TEDPASrate consecutively. At first, the regime curve sensitivity of a certain parameter was compared with the regime curve of the same hydrological component to analyze whether high sensitivities were related to high/low values in the hydrological component. Second, the regime curve sensitivities to a certain hydrological component were compared with the regime curve sensitivity of the same parameter to water yield. With this comparison, it was analyzed which sensitivity information can only be derived by using an individual hydrological component as response variable. Subsequently, a comparison between the sensitivity signal derived by TEDPASnorm and TEDPASrate was carried out.

4. Results

4.1. Regime Curves for Modeled Hydrological Components

The regime curves illustrate the seasonal variability of different modeled hydrological components as shown in Figure 3. Statistical indices such as the seasonality index of the modeled hydrological components were used to further characterize the regime curves of the hydrological components used in the TEDPAS analyses (Table 2). High fluctuations in precipitation occur during the year with the lowest mean daily precipitation in spring and the highest in summer ranging from 0.5 to 9 mm/d for the day of the year (Figure 3). The regime curves show the typical seasonal patterns of the catchment with the highest temperatures in summer and the highest relevance of snowfall and snowmelt at the beginning of the year. Since snow processes do not occur from late spring to autumn, snowmelt has the highest seasonality index. The highest actual evapotranspiration occurs in summer resulting in the lowest values for soil water content.

Among runoff components the seasonality index decreases as we proceed from the surface (e.g., surface runoff) to deeper zones (e.g., slow aquifer flow). Surface runoff has the largest seasonal variation with the highest values in summer, but only a low contribution to total water yield (Table 2). In winter, tile and groundwater flow are dominant. The slow groundwater flow has a smoothed response with a maximum value in spring and a minimum in autumn (Figure 3).

For water yield, the highest values are estimated in winter (up to 2.5 mm/d) and the lowest in summer (0.3 mm/d). As the hydrological component contributing most significantly to runoff, the seasonal regime curve of the fast groundwater flow is similar to those of water yield with the highest values in winter. Additionally, regime curves of actual evapotranspiration and water yield indicate a relevant contribution of evapotranspiration on water yield dynamics.

Figure 3. The averaged regime curves for different modeled hydrological components for the whole modeling period. The regime curves are classified into model inputs as well as into surface, soil and groundwater processes. The 5%- and 95%-uncertainty bands among all model simulations are additionally shown.

Table 2. Statistical Indices of Regime Curves for the Different Modeled Hydrological Components

Hydrological Component	Minimum (mm/d)	Mean (mm/d)	Maximum (mm/d)	Seasonality Index	Day of the Year of Maximum Value
Snowmelt	0.00	0.06	1.04	1.67	37
Surface runoff	0.00	0.10	1.87	0.84	235
Tile flow	0.00	0.19	0.57	0.72	20
Soil water content	263.0	304.1	332.9	0.07	31
Actual evapotranspiration	0.05	1.37	3.50	0.69	160
Fast groundwater flow	0.02	0.46	1.01	0.65	319
Slow groundwater flow	0.17	0.42	0.74	0.48	77
Water yield	0.29	1.27	2.59	0.48	31

The 5%- and 95%-uncertainty bands among all model simulations in Figure 3 illustrate similar seasonal patterns as detected in the median regime curve. In the model simulations with an overall higher water yield, the higher flow conditions in winter are even more emphasized. The largest differences between the median regime curves and the 95%-uncertainty bands are detected for snowmelt.

4.2. Regime Curve Sensitivity to Different Hydrological Components (TEDPASnorm)

The results of TEDPASnorm are presented in Figure 4. Regime curves of the eight modeled hydrological components are normalized by their maximum values (first column) and compared with the regime curve of parameter sensitivities (regime curve sensitivity, columns 2–4) individually for each hydrological component. Next, they are compared with the regime curve sensitivity for water yield as a representative for a typical response variable in sensitivity analyses.

The regime curve sensitivity to snowmelt shows a dominance of both snow parameters (SFTMP and SMTMP) in the winter half-year. At the beginning of the winter, a higher sensitivity of snowfall temperature (SFTMP) is detected, whilst snowmelt temperature (SMTMP) is dominant about one month later up to the end of the winter.

Surface runoff is always dominated by the curve number (CN2) during the whole year. The tile flow lag time (GDRAIN) has the highest regime curve sensitivity to tile flow especially in winter in phases of a high tile flow. By contrast, in the middle of the year in phases of lower tile flow values the soil evaporation coefficient (ESCO) is more sensitive than GDRAIN.

Soil water content is overall dominated by the available soil water capacity (SOL_AWC) during the whole period with the highest sensitivity indices among all cases and with small fluctuations. In the case of actual evapotranspiration, high sensitivities of SOL_AWC are detected in the middle of the year in phases of high actual evapotranspiration, whilst ESCO has a high sensitivity in spring as well as in summer-autumn. The snow parameters (SFTMP, SMTMP) are additionally sensitive in winter.

The parameter sensitivity to fast aquifer shows that the regime curve sensitivities of the aquifer fraction coefficient (RCHRGssh) is similar to the regime curve of fast aquifer flow. Thus, RCHRGssh dominates during high values of fast aquifer flow in winter. High sensitivities of the groundwater retention of the fast aquifer (GW_DELAYfsh) are detected in spring when the contribution of fast aquifer flow to water yield is rather low. ESCO is also sensitive to fast aquifer flow in summer in phases of low fast aquifer flow.

For slow aquifer flow, both, regime curve and regime curve sensitivities are smoothed. RCHRGssh is sensitive to slow aquifer flow during the whole year with the highest sensitivity in spring when slow aquifer flow is high. The regime curve sensitivity of the baseflow recession coefficient (ALPHA_BFssh) is inverse to those for the aquifer fraction coefficient with the highest sensitivity in the middle of the year in phases of low slow aquifer flow.

The regime curve for water yield shows a strong dominance of groundwater parameters during the whole year with seasonal variations in the dominance of these three parameters. Soil parameters (SOL_AWC, ESCO) mainly contribute in late summer and autumn, while the snow parameters are sensitive to a small extent in early spring.

The comparison of regime curve sensitivities of individual hydrological components and water yield shows that the highest similarity is detected between water yield and both fast and slow aquifer flow. In contrast,

Figure 4. Regime curves of eight modeled hydrological components (column 1) and regime curve sensitivities on these hydrological components for the nine model parameters (columns 2–4). The first column presents the regime curve of hydrological components as average value for each day of the year as normalized values in the scale from 0 to 1. The second to fourth column presents the regime curve sensitivities to the hydrological component as defined on the left side. Vertical lines are shown in a 3 months distance.

the regime curve sensitivities for the first four hydrological components (snowmelt, surface runoff, tile flow and soil water content) are highly different from those to water yield. Even for the most controlling parameters of these hydrological components, only a low sensitivity signal to water yield is detected. Overall, the sensitivity of a parameter is higher to the associated hydrological component compared to those to water yield.

4.3. Regime Curve Sensitivity to Rate of Change in Different Hydrological Components (TEDPASrate)

Next, the regime curve sensitivities to rates of change in the different modeled hydrological components are presented based on the results from TEDPASrate (Figure 5). The regime curve (first column) was presented with normalized values and thus, ranges from -1 to 1 illustrating positive and negative changes. Such as in the last chapter, the regime curve sensitivities of each hydrological component are firstly analyzed individually and after that, they are compared with the regime curve sensitivity for water yield.

The rate of change in snowmelt is characterized by strong fluctuations and is dominated by snow parameters in the winter half-year. For surface runoff, the highest rate of change is detected in summer. Its rate of change is mainly controlled by the curve number (CN2) with small seasonal variations.

The highest absolute rate of change in the regime curve for tile flow is detected in winter half-year, when tile flow lag time (GDRAIN) has the highest sensitivity, while soil evaporation (ESCO) dominates in early summer. The rates of change for soil water content are increasing from spring to autumn. The regime curve sensitivity to soil water content is dominated by the available soil water capacity (SOL_AWC) in particular by the end of the year and by soil evaporation in summer half-year. The highest rates of change for actual evapotranspiration are detected in the middle of the year. The sensitivity pattern of actual evapotranspiration is similar to those of soil water content but without a dominant phase of available soil water capacity by the end of the year.

The regime curve of the fast aquifer flow shows a slight increase from negative to positive rate of change in the summer half-year. The regime curve sensitivities for groundwater retention (GW_DELAYfsh) and aquifer partitioning (RCHRGssh) are similar. The regime curve of slow aquifer flow has a typical pattern with an increase from negative values in spring to the most positive values by the end of the year. All three groundwater parameters are sensitive to the rates of change in slow aquifer flow, but with small sensitivities.

The regime curve of water yield indicates that the highest increasing values occur in the middle of the year. The decrease in water yield is rather small demonstrating that rising limbs of peaks are steeper than falling limbs. The regime curve sensitivities to rate of change in water yield demonstrate that all parameters are sensitive at least for a short time of the year. The curve number (CN2) and the soil evaporation (ESCO) are in particular sensitive in the middle of the year. Tile flow lag time (GDRAIN) and the groundwater parameters are relevant in winter.

The regime curve sensitivities of the groundwater parameters to water yield and to fast aquifer flow are very similar. The general dynamic of regime curve sensitivity of CN2 and GDRAIN to water yield and to their associated hydrological components, i.e., surface runoff or tile flow, respectively, is similar, but the sensitivity values to the individual hydrological component are higher.

4.4. Comparison of Regime Curve Sensitivities Between TEDPASnorm and TEDPASrate

The diagnostic information as derived from TEDPASnorm and TEDPASrate (see Figures 4 and 5) is compared as follows. For this, the differences between both approaches are summarized in Figure 6. For this, the partial sensitivities are temporally averaged for the whole modeling period. The relevance of each parameter is shown as share of its first-order partial sensitivity to the sum of all first-order partial sensitivities to facilitate the analysis of similarities and differences between TEDPASnorm and TEDPASrate.

The strongest differences between TEDPASnorm and TEDPASrate are found for soil water content. The relevance of the available soil water capacity (SOL_AWC) to the soil water content is strongly lower in TEDPASrate, while soil evaporation (ESCO) is more relevant to the soil water content in TEDPASrate. While SOL_AWC is completely controlling the magnitudes of soil water content in TEDPASnorm, the change in soil water content in TEDPASrate is controlled in winter by SOL_AWC, but in summer both by SOL_AWC and ESCO.

Figure 5. Regime curves of rate of change in eight modeled hydrological components (column 1) and regime curve sensitivities on these hydrological components for the nine model parameters (columns 2–4). The first column presents the regime curve of hydrological components as average value for each day of the year as normalized values in the scale from -1 to 1 using their maximum absolute values. The second to fourth column presents the regime curve sensitivities to the hydrological component as defined on the left side. Vertical lines are shown in a 3 months distance.

Figure 6. Comparison of the share of the first-order partial sensitivity of a model parameter to the sum of all first-order partial sensitivities on the different hydrological components for the whole modeling period both for TEDPASnorm and TEDPASrate (each row sums up to 1).

As an intermediate groundwater parameter between fast and slow aquifers, the aquifer fraction coefficient (RCHRGssh) is sensitive to both fast and slow aquifer flow in TEDPASnorm, but only to a low extent in TEDPASrate. Fast aquifer flow is, in particular, strongly dominated in TEDPASnorm by RCHRGssh in the winter half-year. In contrast, the rate of change in fast aquifer flow (in TEDPASrate) is to a similar extent controlled by a delay in groundwater inflow (GW_DELAYfsh). Slow aquifer flow is governed by RCHRGssh during the year and to a lower extent by baseflow retention (ALPHA_BFssh) in TEDPASnorm.

In contrast, almost no differences between TEDPASnorm and TEDPASrate are detected for other hydrological components (snowmelt, surface runoff, tile flow and actual evapotranspiration) (Figure 6). One example is the strong relationship of surface runoff and curve number (CN2). CN2 has a high sensitivity to the surface runoff in both TEDPAS approaches. Neither the curve number is sensitive to other hydrological components nor do other parameters show a high sensitivity to surface runoff. This shows how strongly surface runoff and its dynamic are regulated by the curve number.

In both TEDPAS approaches, the tile flow is not only controlled by the associated parameter (tile flow lag time, GDRAIN), but also by soil evaporation (ESCO) showing that both magnitudes and dynamics of tile flow are affected by the retention time in tile flow and also by evaporation as the another hydrological component which affects the available water in soil.

As shown in Figure 6, the water yield in TEDPASnorm is controlled by four parameters, namely ESCO and the three groundwater parameters. In contrast, in TEDPASrate curve number (CN2) and tile flow lag time (GDRAIN) have a largely higher relevance, while three of the four sensitive parameters in TEDPASnorm show a lower relevance in TEDPASrate.

5. Discussion

Recent studies provided detailed investigations related to the advanced use of sensitivity analyses results for diagnostic interpretation [Herman et al., 2013b; Massmann et al., 2014; Pfannerstill et al., 2015; Guse et al., 2016; Pianosi et al., 2016; Pianosi and Wagener, 2016]. In this study, the temporal behavior of dominant

model parameters using different hydrological components as response variable in a sensitivity analysis was investigated. Further, the effect of using magnitudes or rates of change of different hydrological components as response variable was analyzed. Our results show that the sensitivity of a parameter varies both by using different hydrological components and by using either their magnitude or their rates of change as response variable. In this way, additional knowledge of how parameters control the hydrological system in models is gained. Based on our results, we discuss below the benefits of these sensitivity analyses toward a better understanding of how hydrological components and parameters are handled in models, and how these insights could be useful for model calibration.

5.1. Which Diagnostic Information for Parameter Behavior Is Obtained From the Temporally Resolved Sensitivity Signal?

Our study highlights that each hydrological component is affected by different model parameters and each parameter has active and inactive phases during the modeling period. The role of a parameter in the model can be disentangled by detecting which hydrological components are controlled by a parameter at a certain time of the year. Analyzing the temporal behavior in dominant parameters on individual hydrological components clarifies how model parameters and associated hydrological components are really related in time.

The regime curve sensitivities to snowmelt clearly show that both of the snow parameters are dominant at the same time. However, the sensitivity patterns change in time from a dominance of snowfall temperature (SFTMP) to snowmelt temperature (SMTMP). Another example is related to the temporal sensitivity patterns of both aquifer flows. We find that the aquifer partitioning coefficient (RCHRGssh) controls both of the aquifer flows in times when they are of high relevance, while the retention parameters (GW_DELAYfsh for the fast aquifer flow and ALPHA_BFssh for the slow aquifer flow) are dominant under low aquifer flow conditions.

This time dependence of model fluxes to parameters is important information that can be used, for example, in a parameter estimation procedure, as it reveals time periods during which the parameter can be estimated more precisely [Wagner *et al.*, 2003]. Our study shows how each parameter affects certain hydrological components at a certain time of the year. By extracting these phases for individual hydrological components, a more constrained parameter identification might be possible. Based on this knowledge, the dominance of the model parameter can be more effectively considered during the parameter identification and can be used to improve the representation of hydrological components in models [Wagner *et al.*, 2003; Herman *et al.*, 2013b; Clark *et al.*, 2015; Massmann and Holzmann, 2015].

5.2. How Informative Is the Sensitivity Signal to Individual Hydrological Components Compared to Water Yield?

The results of the sensitivity analyses were found to be highly influenced by the choice of response variable; i.e., the hydrological component. The comparison between the sensitivity analyses conducted on an individual hydrological component, versus that on water yield, shows that the sensitivity signal is dampened when using the latter. This results in a smoothed regime curve sensitivity to water yield as an integrated value of all hydrological components. In contrast, the sensitivity analysis conducted on different hydrological components demasks this dampening effect. Therefore, the regime curve sensitivities to a certain hydrological component provide a more informative signal of how and when the corresponding model parameters control this hydrological component in the model.

For hydrological components with minor relevance (snowmelt, surface runoff), the necessarily high sensitivities of the controlling parameter(s) to the specific hydrological component are not revealed in the sensitivity patterns for water yield due to the minor role of the corresponding hydrological components in influencing water yield.

Thus, a sensitivity analysis based on water yield provides precise information only for the dominant hydrological components, while the effect of hydrological components with minor relevance is masked. The latter is better characterized by analyzing TEDPAS for the associated hydrological component.

The high differences in the sensitivity signal using individual hydrological components or water yield as response variable is of high relevance for a precise parameter identification. This can be demonstrated exemplarily for snowmelt and the associated model parameters (snowfall (SFTMP) and snowmelt

temperature (SMTMP)). Our results clearly show that snow parameters are not sensitive to water yield. Due to the low identifiability of both snow parameters, it might not be possible to identify reasonable parameter values using water yield as response variable. However, our results also show the relevance of SFTMP and SMTMP in controlling the snowmelt process. It is further possible to extract the phases of the year in which snowfall or snowmelt temperature regulate the snowmelt process. Based on the diagnostic information as obtained in this study, a typical calibration of snow parameters on water yield might not be appropriate. In contrast, since snow parameters are only sensitive in the winter half-year, a calibration of these parameters only for this period could be more beneficial. Thus, a sensitivity analysis to individual hydrological components demasks the phase of the year in which snow parameters are of relevance.

This sensitivity approach is assumed to be transferable. We expect that a clearer sensitivity signal would also be obtained for individual hydrological components in other catchments or with other models. Different results in the sensitivity patterns might be estimated in contrasting catchments with a dominance of other processes such as snow or fast occurring runoff processes. In these cases, we expect a change both in the dominance of model parameters and in their temporal sensitivity patterns.

5.3. Are Hydrological Components Only Controlled by the Associated Model Parameters?

In this study, it was hypothesized that a more precise sensitivity signal for a model parameter can be obtained using the associated hydrological component as response variable. As expected, in the majority of the cases, a hydrological component was controlled by associated model parameters. Typical pairs for this relationship are surface runoff and curve number (CN2), snowmelt and snowfall (SFTMP) and snowmelt (SFTMP) temperature, and both aquifer flows and the three groundwater parameters.

However, in specific cases, also parameters are sensitive to hydrological components to which they are not directly associated. One example is the sensitivity of the soil evaporation (ESCO) to tile flow in particular in summer times when tile flow is low. ESCO regulates the amount of water available from deeper zones for evaporation. The more water is evaporated in summer and autumn from deeper soil layers, the less is available for tile flow. We see here an effect of a parameter associated to one hydrological component (evapotranspiration), which is relevant in times (summer) before another hydrological component (tile flow in winter) becomes of major relevance. The timing and extent of the sensitivity of ESCO to tile flow becomes only apparent by analyzing the individual hydrological component in time.

The sensitivity analyses on individual hydrological components reveal how strongly a model parameter is related to a hydrological component. It shows whether hydrological components are only dominated by their directly associated parameters or also by parameters which are primarily related to other hydrological components. A better understanding of model parameters and their relationship to the modeled hydrological components can help in detecting whether the parameters are really functioning in the model as conceptually intended [Wagener *et al.*, 2003; Clark *et al.*, 2008; Fenicia *et al.*, 2008; Clark *et al.*, 2011].

5.4. How to Explain Differences in the Sensitivity Signal Between TEDPASnorm and TEDPASrate?

In specific cases, highly different regime curve sensitivities of different parameters to an individual hydrological component are provided by TEDPASnorm and TEDPASrate. This can be particularly seen in the sensitivity of soil water content. The soil water content in TEDPASnorm is strongly controlled by the available soil water capacity (SOL_AWC) (see Figure 4) whereas in TEDPASrate the rate of change in soil water content is dominated not only by SOL_AWC, but also by parameters associated to other hydrological components such as evapotranspiration (ESCO) and snowmelt (SMTMP) (see Figure 5). In TEDPASnorm, the controlling function of these parameters on soil water dynamic is masked by the high dominance of SOL_AWC on the magnitude of soil water content. The sensitivity of parameters affecting the soil water dynamic increases in TEDPASrate, while SOL_AWC has a lower relevance. Thus, the relevance of other parameters on soil water dynamic is demasked in TEDPASrate.

These results can be explained by looking at the model parameters in detail. The available soil water capacity (SOL_AWC) defines the amount of water which can be stored in the soil. A higher value of SOL_AWC results in an increase in the magnitude of soil water content. As shown in Table 2, the values of SOL_AWC are highly variable. A change of another parameter affects soil water content but to a lower extent compared to the impact of the available soil water capacity. A different situation is given for changes in soil

water content. The rate of change is not mainly influenced by the magnitudes but by the changes in the hydrological component.

A second example showing the differences in the calculated sensitivity between TEDPASnorm and TEDPASrate is related to groundwater. Both groundwater aquifers are controlled by two parameters: the aquifer fraction coefficient (RCHRGssh) as a capacity parameter which regulates the water volume in both aquifers and a flux parameter which regulates the retention time of the groundwater flow. The groundwater delay (GW_DELAYfsh) controls the retention of water flowing into the fast aquifer and the baseflow recession (ALPHA_BFssh) describes the retention of the outflow of the slow aquifer. In TEDPASnorm, both aquifers are controlled by the aquifer partitioning (RCHRGssh), while their rates of changes are regulated to a similar extent by a retention parameter.

Thus, to understand the differences between TEDPASnorm and TEDPASrate, it is worth looking at the type of model parameters. While interpreting sensitivity patterns with regard to a classification into capacity or flux parameter seems intuitive, it has rarely been recognized how the results of a parameter sensitivity analysis are impacted by the parameter type. Our investigation of the literature found no instance where it has been demonstrated that capacity parameters tend to be emphasized in the typical approach to a sensitivity analysis based on the magnitude of the modeled hydrological component. A comparable idea was considered in *Goehler et al.* [2013] in performing a gradient-based sensitivity analysis to different response variables of a land surface model. They gave higher weights to sensitivities in times of higher fluxes.

Therefore, to identify the controlling parameters both in magnitude and dynamics, one should also analyze how the parameter sensitivity changes when using the rates of change as response variable in addition to the magnitude. In this way, it can be extracted whether the sensitivity signal decreases for capacity parameters and other parameters on the dynamic behavior become relevant.

TEDPASrate as a supplementary approach to TEDPASnorm thus provides further diagnostically relevant information of how model parameters control a certain hydrological component. On the one side, with TEDPASrate it can be disentangled whether a high sensitivity is mainly explained by water volume which results in a decrease in sensitivity in TEDPASrate in comparison to TEDPASnorm such as in the case of the available soil water capacity (SOL_AWC) on soil moisture or of the aquifer partitioning coefficient (RCHRGssh) on the two aquifer flows. On the other side, it is derived whether both magnitude and dynamic of a hydrological component are controlled by the same model parameters such as in the case of the curve number (CN2) on surface runoff or by snow parameters on snowmelt, which show the strong relationship between model parameters and hydrological component.

The joint approach of using magnitude and rates of change of hydrological components as response variable provides insights for a better parameter value identification. Looking at water yield as response variable, we showed that four model parameters are sensitive using its magnitude. Thus, based on this classical approach these four parameters are relevant for model calibration. However, by using the rate of change in water yield in TEDPASrate as response variable, two additional parameters are relevant in controlling the dynamics in water yield leading to six sensitive parameters in total. Thus, the sensitivity analyses to rates of change can disentangle effects of model parameters on water yield which are masked by using its magnitude.

6. Conclusion

Our study clearly demonstrated one of the important ways how the selection of response variables affect the outcomes of sensitivity analysis, as proposed by *Razavi and Gupta* [2015]. Additional diagnostic information is provided of how model parameters control the different hydrological components. TEDPAS reveals how the temporal dominance of parameters varies in time for magnitudes and rates of change of different hydrological components. This information can be helpful for a more process-based model calibration.

The main outcomes of this study are:

1. The regime curve sensitivities to different hydrological components reveal how model parameters are temporally related to different hydrological components and how parameter dominance patterns change in time.

2. A more precise sensitivity signal for model parameters is obtained using the individual hydrological components instead of water yield as response variable.
3. The regime curve sensitivities are highly varying when using different hydrological components as response variable. While the highest relationship is detected between model parameters and their associated hydrological components, in specific cases, also an impact on other hydrological component is detected.
4. The sensitivity analyses applied to the magnitudes of modeled hydrological components (TEDPASnorm) and their rates of change (TEDPASrate) show that the controlling parameters change for certain hydrological components. These differences are related to a relaxing dominance of a capacity parameter in TEDPASrate compared to TEDPASnorm.

Overall, sensitivity analyses to different modeled hydrological components and the separate TEDPAS approaches on magnitude and rates of change provide a more informative signal of how the temporal varying dominance of a parameter are related to the hydrological component and how these patterns are transferred into the sensitivity signal on water yield. The masking effect that occurs in a conventional sensitivity analysis to discharge is thereby disentangled in this approach. We emphasize that there is considerable potential in the use of diagnostic information regarding the temporal patterns of parameter dominance on the different hydrologically components to better constrain model parameters individually for the associated hydrological components [Pokhrel *et al.*, 2012]. In this way, our study contributes to the goal of hydrologically consistent modeling as emphasized in several recent studies [Wagener and Gupta, 2005; Martinez and Gupta, 2011; Pokhrel *et al.*, 2012; Euser *et al.*, 2013; Hrachowitz *et al.*, 2014; Pfannerstill *et al.*, 2015; Pianosi *et al.*, 2016].

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