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Key Points:

- This study presents the first temporal parameter sensitivity analysis of a hydrologic model with multiscale parameter regionalization
- Spatio-temporal variability in dominant parameters changes with target variables (runoff, evapotranspiration, soil moisture, recharge)
- Daily sensitivities of some parameters are related to magnitude of corresponding process

Supporting Information:

Supporting Information may be found in the online version of this article.

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Spatio-Temporal Consistency and Variability in Parameter Dominance on Simulated Hydrological Fluxes and State Variables

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Abstract Hydrological parameters are used to tailor simulation models to the specific characteristics of a catchment so that models can accurately represent processes under different catchment conditions. In the case of the mesoscale Hydrological Model (mHM), its parameters are estimated via transfer functions using the Multiscale Parameter Regionalization (MPR) approach. In this study, the spatial and temporal variability in the sensitivity of transfer function parameters (TFP) and their relationships to corresponding simulated processes are investigated to understand how these TFP control simulated hydrological fluxes and state variables. Daily dominant model parameters are identified for 102 German catchments as a study domain with temperate climate using a temporally resolved parameter sensitivity analysis. This approach allows the comparison of spatial and temporal variability of TFP dominance. Three simulated hydrological fluxes and one state variable are used as target variables for the sensitivity analysis: runoff, actual evapotranspiration, soil moisture (SM), and groundwater recharge. The analysis leads to consistent and plausible patterns of parameter dominance in space. An evapotranspiration parameter dominates actual evapotranspiration and SM. Runoff and recharge are mainly controlled by soil texture, subsurface, and percolation parameters. The relevance of spatial versus temporal variability varies among model parameters and target variables. In some cases, parameter sensitivities are related to the magnitude of corresponding processes. Low spatial and temporal variability of dominant parameters is explained by MPR. In light of these results, a joint spatio-temporal analysis is recommended to better understand how model parameters drive simulated states and fluxes in hydrological models to improve process accuracy.

Plain Language Summary Hydrological models use parameters to represent the hydrologic system under varying climate and landscape conditions. The mesoscale hydrological model (mHM) uses a special regionalization approach (Multiscale Parameter Regionalization, MPR) to ensure spatial consistency in parameter patterns. In this study, we conducted a temporally resolved parameter sensitivity analysis that estimates daily parameter sensitivities for four hydrological variables (runoff, actual evapotranspiration, soil moisture (SM), recharge) across 102 gauges. In this way, we investigated how the parameter sensitivity varies across space and time. Our results indicate that an evapotranspiration parameter dominates not only simulated evapotranspiration but also SM. Runoff and recharge are mainly controlled by soil texture, subsurface and percolation parameters. The MPR approach ensures that the parameter sensitivity patterns are consistent across space. Additionally, our analysis reveals that in multiple cases the parameter sensitivity depends on the magnitude of the corresponding process. We see our analysis as a valuable contribution toward a better understanding of how parameters govern hydrological models.

1. Introduction

The complexity of hydrological systems can be reproduced in hydrological models only in a simplified way. To overcome this greater constraint, model parameters are estimated to adapt the general model to specific catchment conditions so that they represent the corresponding hydrological process adequately. Consequently, the role of parameters in controlling the simulated hydrological system needs to be analyzed in detail (Kirchner, 2006; Wagener et al., 2003, 2022). For these reasons, spatio-temporal diagnostic parameter analysis methods are used to

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investigate dynamics and variability of hydrological states and fluxes in models, aiming to improve the model understanding (Gupta et al., 2008; Reusser et al., 2009; Yilmaz et al., 2008). In this regard, Wagener et al. (2022) argues that reliable modeling requires checking process adequacy and internal consistency in representing hydrological states and fluxes in models.

Hydrological processes vary in space across catchments due to the differences in physiographical and climatological conditions. Thus, the relevance of simulated processes and parameter dominance also varies across catchments with contrasting characteristics in topography, landscape, or soil (Guse et al., 2019; Mai et al., 2022; Markstrom et al., 2016; Merz & Blöschl, 2004; van Werkhoven et al., 2008). Furthermore, hydrological processes can vary inter- and intra-annually resulting in typical temporal process patterns. The relevance of processes and the parameter dominance, however, also changes within different seasons, periods, or between different years (Guse et al., 2019; Herman, Reed, & Wagener, 2013; Wagener et al., 2003), as well as under changing climate conditions (Melsen & Guse, 2021).

Sensitivity analysis identifies the role of parameters for a given model structure. A temporally resolved parameter sensitivity analysis in different catchments is required to detect the spatio-temporal variability in process relevance and parameter dominance (Cloke et al., 2008; Guse et al., 2019; Herman, Kollat, et al., 2013; Herman, Reed, & Wagener, 2013; Kelleher et al., 2013; Mai et al., 2022; Massmann et al., 2014; Reusser et al., 2011; Wagener et al., 2003) for the reasons mentioned above. In this way, periods exhibiting the highest sensitivity of a given parameter can be identified (Guse et al., 2014; Reusser et al., 2009; Wagener et al., 2003). It could be tested whether model parameters are sensitive only during phases of high process relevance. Model parameters related to seasonally varying processes such as actual evapotranspiration or snowmelt are expected to show a high variability in parameter sensitivity. While their average sensitivity could be low, their impact could be high during specific phases, for example, snowmelt periods (Guse, Pfannerstill, Gafurov, et al., 2016). Concerning hydrological conditions such as floods and droughts, different processes and, thus, model parameters are relevant. Therefore, parameter sensitivity also changes with process magnitude. In addition to the temporal parameter dominance patterns, the spatial variability in parameter sensitivity was analyzed to provide the parameter control for different parts of the catchments and under different hydrologic conditions (Herman, Kollat, et al., 2013; Mai et al., 2022; Markstrom et al., 2016; Tang et al., 2007). In temporal diagnostic analysis, sensitivity analyses are often applied to contrasting catchments but rarely to a large number of catchments to analyze consistency in spatial patterns (Guse et al., 2019; Herman, Kollat, et al., 2013; van Werkhoven et al., 2008). Recently, Mai et al. (2022) analyzed the parameter sensitivity using the Raven model framework for a large set of North American catchments and presented the temporal parameter sensitivity for eight representative basins from contrasting regions.

Applying sensitivity analysis to hydrological states and fluxes besides discharge, for example, actual evapotranspiration, runoff components, and soil moisture, could demonstrate how these parameters are related to the corresponding processes and their influence on the discharge simulation. The best model parameter identification can be achieved when the corresponding process is used as the target variable (Guse, Pfannerstill, Gafurov, et al., 2016; Markstrom et al., 2016) which is based on the assumption that a parameter is dominant in phases with high relevance and/or variability of the corresponding process (Cuntz et al., 2015). A comparison of sensitivity patterns between the corresponding process and the integrated value of discharge shows how well a parameter could be identified using discharge.

The mesoscale hydrological model (mHM) is a process-based gridded model (Kumar, Samaniego, & Attinger, 2013; Samaniego et al., 2010; Thober et al., 2019). A major characteristic of mHM is the use of the multiscale parameter regionalization (MPR) approach to identify and optimize its model parameters. MPR in mHM encompasses two types of model parameters: The first type of parameters encompasses the globally consistent (gamma) parameters of the transfer functions. These are utilized in conjunction with the physiographic features of the catchments to determine the second type of parameters. These are the effective model (beta) parameters which vary spatially and temporally and are employed to simulate the hydrological states and fluxes.

mHM has already been used in a couple of model diagnostic studies. For example, Cuntz et al. (2015) used a screening method to identify dominant and less dominant parameters for mHM based on a global sensitivity analysis using the Sobol' algorithm. In this study, parameters were grouped into different process groups. The screening approach leads to a reduction in the number of model runs. The first-order index was found to exhibit a higher explanatory power, indicating the presence of low parameter interactions. However, this study was only

applied to three basins. Thus, a consistent analysis of temporal and spatial variability of parameter sensitivities for a large set of gauges is still needed. Zink et al. (2017) presented long-term data sets based on mHM model results for different states and fluxes that were constrained by different data sources. They showed the uncertainty in states and fluxes due to parameter uncertainties in applications to several basins in Germany. Later, Zink et al. (2018) emphasized that streamflow-only calibration did not guarantee realistic simulations of internal states and fluxes and highlighted the benefit of reduced uncertainty in constraining model states and fluxes by observation from other hydrological variables. It is most promising to constrain simulations of states and fluxes using observations of hydrological variables (e.g., SM, actual evapotranspiration) (Rakovec et al., 2016).

For mHM, it has not yet been analyzed which parameters control which states and fluxes. Moreover, a large-basin study is needed to investigate the consistency and variability in spatial patterns of dominant parameters. In addition, an analysis of temporal variability in parameter sensitivity has not yet been carried out with mHM. For this model, it is relevant to analyze how the temporal variability in parameter dominance is considered, keeping in mind that the MPR approach focuses on spatial variability. We tested the applicability of a temporal parameter sensitivity method therefore for a model with MPR to check whether the spatially consistent parameter regionalization approach also led to spatially consistent parameter dominance patterns. It is necessary to ascertain whether this leads to greater temporal than spatial variability of how model parameters control the processes in mHM. This knowledge could also be helpful for reliable model optimization needed for practical applications such as flood forecasting or SM drought monitoring.

In this study, a temporally resolved sensitivity analysis for mHM was carried out with a large set of 102 basins to analyze the variability of parameter dominance in time and space under different hydrological conditions and to improve the understanding of how the model parameters control the simulated states and fluxes in mHM. In addition to previous studies, we used four different target variables for the sensitivity analysis, namely runoff, actual evapotranspiration, SM, and groundwater recharge.

Here we aim to investigate the following research questions: (a) Which parameters, categorized by their respective process groups in mHM, exert dominance over specific hydrological states and fluxes, and how does their sensitivity evolve over time? (b) Do the sensitivity patterns of the model parameters remain constant in space, and how do they vary in relation to different hydrological target variables? (c) What are the differences between the spatial and temporal variability of the target variables (i.e., model outputs), and which type of variability predominates under specific circumstances? And, (d) How does parameter sensitivity vary across different magnitudes of the four selected hydrological states and fluxes?

Based on these research questions, we postulate the following hypotheses: (a) The temporal variability of the dominant parameters changes in accordance with the variability of the corresponding processes. (b) The patterns of dominant parameters in mHM exhibit spatial continuity due to MPR and show significant variations primarily between different regions. (c) The temporal variability of parameter sensitivity is higher than the spatial variability, primarily attributed to the focus of the MPR on ensuring spatial consistency. And, (d) The variability in parameter sensitivity is linked to the magnitude of the associated process, leading to high sensitivities for either high or low values of that particular process.

2. A Short Description of mHM

In this study we used the process-based gridded mHM version 5.10.2 (Kumar, Samaniego, & Attinger, 2013; Samaniego et al., 2010; Thober et al., 2019). In mHM, the water balance is closed on every grid cell level and different hydrologic fluxes and state variables are calculated for every cell.

2.1. The Multiscale Parameter Regionalization Approach

mHM distinguishes between three different levels that can have different spatial resolutions. In this way, for each level, the optimal spatial resolution for the input data and hydrological states is used. These spatial levels are: Level-0 includes the main terrain features, soil properties, and land cover. Level-1 is related to the dominant processes and geology, representing the spatial unit for the simulation of hydrological processes. Finally, Level-2 is related to the meteorological forcing data.

The linkage between the three levels with the different spatial resolutions is realized with the MPR (Kumar, Samaniego, & Attinger, 2013; Samaniego et al., 2010). MPR is used to obtain accurate spatial distribution of

Table 1

Explanation of Gamma Parameter Used in the Example as Introduced by Zacharias and Wessolek (2007)

Gamma number	Parameter	Parameter description
gamma_1	PTF_lower66_5_constant	Zacharias PTF parameters below 66.5% sand content
gamma_2	PTF_lower66_5_clay	Zacharias PTF parameters below 66.5% sand content for clay
gamma_3	PTF_lower66_5_Db	Zacharias PTF parameters below 66.5% sand content for mineral bulk density
gamma_4	PTF_higher66_5_constant	Zacharias PTF parameters above 66.5% sand content
gamma_5	PTF_higher66_5_clay	Zacharias PTF parameters above 66.5% sand content for clay
gamma_6	PTF_higher66_5_Db	Zacharias PTF parameters above 66.5% sand content for mineral bulk density

parameter fields. Therefore, the variability of physiographical and morphological input data is used at a subgrid level to estimate the grid field of effective model parameters.

MPR consists of two major steps and distinguishes between two types of parameters. The global (gamma) parameters are used to relate the subgrid (fine-scale) values of geophysical characteristics (e.g., slope, sand content) to the hydrological model parameters at level-0 (beta-0). In this transformation step, the gamma parameters are the transfer function parameters (TFP) and linked to catchment descriptors.

The beta parameters are the hydrological model parameters at level-0 (beta-0). In a second step, the beta-0 parameters are aggregated to a level-1 resolution (beta-1) to obtain grid fields of effective model parameters through upscaling operators (e.g., arithmetic or harmonic mean, majority etc.). With the help of upscaling operators, the subgrid variability is included in the model parameterization approach. Therefore, the beta parameters vary depending on the spatial variability in catchment characteristics and represent the subgrid variability.

To further illustrate the two-step approach of MPR for estimating mHM hydrologic parameters, we take an example of a key soil parameter—porosity (θ) or saturated soil water content—the latter being estimated when multiplied by the depth of the soil layer. In the first step of MPR, the porosity parameter is regionalized via pedo-transfer functions based on fine-scale soil textural properties (θ^0 at level-0; 100 m spatial resolution) following Zacharias and Wessolek (2007).

$$\theta^0 = \begin{cases} \gamma_1 + \gamma_2 u_1^0 + \gamma_3 \varphi^0 & u_2^0 < \tau^0 \\ \gamma_4 + \gamma_5 u_1^0 + \gamma_6 \varphi^0 & \text{otherwise} \end{cases} \quad (1)$$

Where, γ_i , $i = 1-6$ (see explanation in Table 1) are the calibration parameters defined within their proposed ranges. u_1 , u_2 , and φ^0 are the clay and sand contents, and bulk density, respectively; these are derived based on fine-resolution soil databases (at level-0). $\tau^0 = 66.5\%$ is the threshold limit related to sand content (Zacharias & Wessolek, 2007). In the second step of MPR, θ^0 is aggregated to generate the effective field of θ^1 at the modeling resolution (at grid level-1; 5 km spatial resolution) using the harmonic mean (H) as an upscaling operator (Zhu & Mohanty, 2002).

$$\theta^1 = H\langle\theta^0\rangle \quad (2)$$

It is worth noting that in the MPR approach, the calibration or sensitivity analysis is performed for a set of global parameters (γ) from which the hydrologic parameters (β) are derived which eventually affect modeled fluxes and storages within mHM. The impact of the gamma parameters is calculated via transfer functions which are employed to regionalize model parameters. A spatially consistent set of gamma parameters is used for the entire study area. However, since the catchment descriptors vary in space and due to the use of MPR, spatial process variability is considered while estimating the beta parameters.

An example of regionalization via the pedo-transfer function is given here. For a complete overview of all pedo-transfer functions as implemented in mHM, we refer to Samaniego et al. (2010) and Kumar, Samaniego, and Attinger (2013). It is noteworthy that certain transfer functions incorporate multiple gamma parameters, and

Table 2
List of Global Mesoscale Hydrological Model Gamma Parameters

Process	Parameter	Parameter description	Min	Max
Snow	snowThresholdTemperature	Threshold for rain/snow partitioning (degC)	−2	2
Soil moisture	orgMatterContent_forest	Organic matter content (%) for forest	5	10
	orgMatterContent_impervious	Organic matter content (%) for impervious	0	1
	orgMatterContent_pervious	Organic matter content (%) for pervious	1	5
	PTF_lower66_5_constant	Zacharias PTF parameters below 66.5% sand content	0.75	0.8
	PTF_lower66_5_Db	Zacharias PTF parameters below 66.5% for mineral bulk density	−0.27	−0.25
	PTF_Ks_constant	PTF parameters for saturated hydraulic conductivity	−1.2	−0.285
	PTF_Ks_sand	PTF parameters for saturated hydraulic conductivity for sand	0.06	0.026
	PTF_Ks_clay	PTF parameters for saturated hydraulic conductivity for clay	0.003	0.013
Infiltration	infiltrationShapeFactor	Shape factor for partitioning effective precipitation into runoff and infiltration based on soil wetness (−)	1	4
Evapotranspiration	minCorrectionFactorPET	Minimum factor for PET correction with aspect	0.7	1.3
Subsurface flow	slowInterflowRecession_Ks	Multiplier for variability of saturated hydraulic conductivity to derive slow interflow recession constant	1	30
	exponentSlowInterflow	Multiplier for variability of saturated hydraulic conductivity to derive slow interflow exponent	0.05	3
Percolation	rechargeCoefficient	Groundwater rate parameter	0	50

sometimes gamma parameters are also implemented in different transfer functions. This is important to note better to understand the sensitivity of gamma parameters on the simulated processes.

MPR was originally designed for mHM, but has been used in other models such as demonstrated in Lane et al. (2021) to derive spatially consistent parameter fields for the Decipher model in the United Kingdom (Coxon et al., 2019). MPR has also been applied in the VIC model (Mizukami et al., 2017), PCR-GlobeWB (Samaniego et al., 2017), and recently to ECLand, the land surface model of ECMWF (Boussetta et al., 2021). Thus, it was already successfully demonstrated that MPR is a model-agnostic tool applicable to models other than mHM.

2.2. Mesoscale Processes and Transfer Function Parameters

Based on initial screening and expert knowledge, 14 gamma parameters of mHM that are used in the transfer functions were selected for this study (Table 2) and represent different fluxes and states in mHM. The parameter ranges were selected based on many years of extensive modeling experiences in the core developing team of the mHM model and have been adjusted over the years.

The beta parameters vary based on different arrangements of transfer functions, catchment characteristics and related global parameters. An overview of the model structure of mHM and implemented parameters is given in Figure 1 to understand which parameters are related to which processes. More information on the model structure and the role of the parameters is given in Kumar et al. (2010) and Kumar (2010).

Snow processes are calculated using the day-degree method (see Hundecha and Bárdossy (2004)). To simulate snow accumulation and melting, a threshold temperature (SnowThresholdTemperature) is set to distinguish whether precipitation falls as rain (observed temperature above the threshold) or snowfall (below the threshold) and determine when snowmelt is triggered. The partitioning between effective precipitation and infiltration into the soil depends on the soil's wetness and can be regulated by an infiltrationShapeFactor.

Potential evapotranspiration (PET) is corrected to account for the spatial variability in terrain characteristics (Shevenell, 1999). Specifically, in south-facing terrain in the northern hemisphere which generally receives more sunlight compared to their northern counterparts, the PET is adjusted accordingly to reflect this variation with adjustment factors (minCorrectionFactorPET). Actual evapotranspiration is then calculated in the interaction with soil infiltration as a function of SM and root fraction, separately for each soil layer.

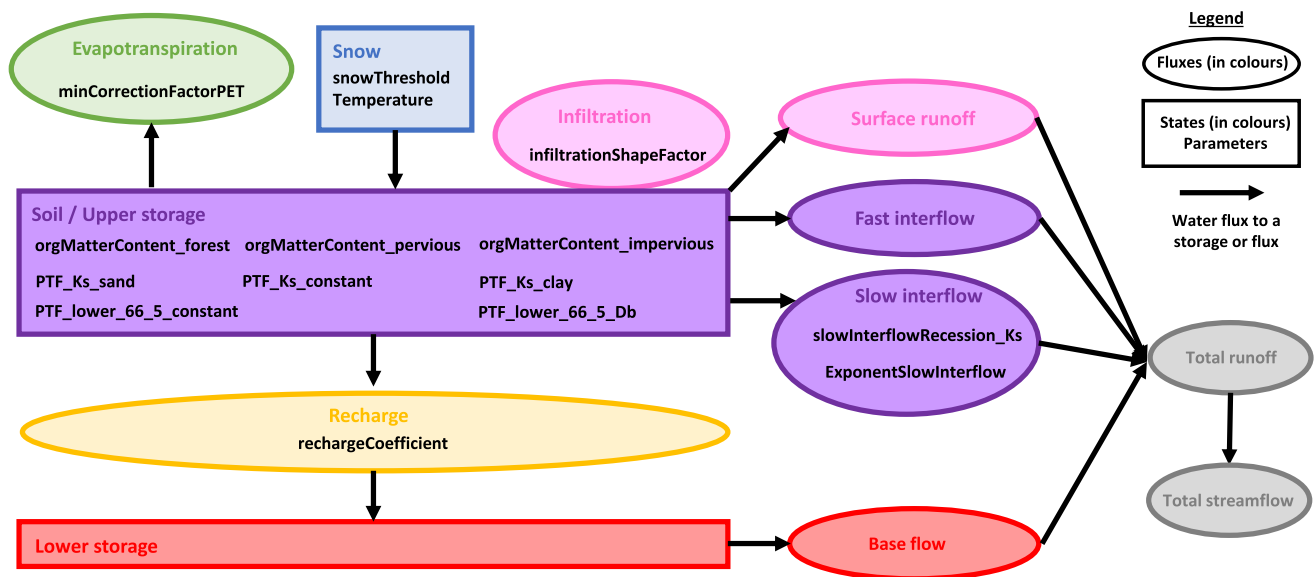


Figure 1. Model structure of mesoscale hydrological model with processes, states, and fluxes. Model parameters are written in black. Based on Samanieo et al. (2010) and Kumar, Livneh, and Samanieo (2013). Each process is represented in a different color of the box. States are presented as filled boxes.

In the subsurface, mHM consists of three deep layers or storages, two of which are unsaturated and one is assumed saturated. The top soil layer consists of different soil horizons, including the upper root zone, regulating surface runoff and infiltration. Surface runoff only occurs in impervious areas. In this soil layer, no lateral flow is simulated. Water infiltrates from the soil to the next storage, which is the upper subsurface storage, as the lower part of the unsaturated zone. The soil and upper storages are shown in Figure 1 in one box as they represent the unsaturated zone in mHM. There are several soil parameters in mHM. The organic matter content (orgMatterContent) is distinguished between the three land uses (forests, impervious, pervious). The pedo-transfer function parameters for the saturated soil water content, following Zacharias and Wessolek (2007), are set differently depending on the sand content (PTF_lower_66_5_constant) and the mineral bulk density (PTF_lower_66_5_Db). The parameters for the pedo-transfer function to calculate the saturated hydraulic conductivity are set to a default value and then specifically increased for sand and decreased for clay (PTF_Ks_constant/sand/clay).

The runoff generation is subdivided into two subsurface reservoirs, an upper and a lower layer. For the upper reservoir, both fast and slow subsurface flows are generated as near-surface flow. While fast subsurface flow is considered as a direct fast water flow from the unsaturated zone to the channel, the slow interflow flows more slowly out of the unsaturated reservoir depending on the water level. In this analysis, two parameters are included to regulate the slow interflow (slowInterflowRecession_Ks, exponentSlowInterflow).

Finally, the lower subsurface storage is the saturated zone, which is fed by percolation from the unsaturated zone. Groundwater recharge in mHM is conceptualized as an outgoing flux leaving the unsaturated compartment to the lower saturated groundwater compartment. It is controlled by a rate parameter (rechargeCoefficient) and the available water storage in the unsaturated compartment. Baseflow is generated as gravity-based water flow as a function of water level and recession coefficient (Livneh et al., 2015).

For each grid cell, the sum of all four runoff components, that is, surface runoff, fast interflow, slow interflow, and baseflow, is calculated. Based on the gradient between the cells, runoff is routed from cell to cell using regionalized Muskingum–Cunge routing (Thober et al., 2019).

In this study, four hydrological output variables were simulated for all gauges. We have selected three fluxes, namely the total runoff generated by every cell (Q), actual evapotranspiration (ET), and groundwater recharge (R), and one state variable, namely average SM over all layers (SM). All of these four variables are generated for each grid cell. Subsequently, the hydrological variables were spatially averaged for each catchment.

3. Experimental Design

One hundred and two hydrological gauges with daily discharge data that are spatially distributed in Germany were used for this study (Figure 2). The study region belongs to the temperate climates and represents variability in catchment characteristics such as topography, soils, land cover, and to a certain degree also in climate. Germany can be separated into four major natural regions (see classification in Tarasova et al. (2020)). The north and the northeast belong to the North German Plains. Most of the Elbe basin and the lower parts of Weser and Rhine, belong to this region. The Central Uplands in the middle of Germany range from the Rhenish Massif to the Ore Mountains (Middle Rhine, Upper Weser and Upper Elbe parts). The South German Scarplands cover south-western Germany. Subsequently, the Alpine Foreland is in the south of Germany, separated from the South German Scarplands by the Danube River. Thus, the right-sided alpine confluences to the Danube are in this region.

For this study, mHM was set up for the entire headwaters and river network of all German rivers. The description of this setup corresponds to the European data set described in Thober et al. (2015); Rakovec et al. (2016); Samaniego et al. (2019).

The three levels in mHM are considered with the following spatial resolutions: Level-0 with the main terrain features, soil properties and land cover was used with a typical spatial resolution of $500\text{ m} \times 500\text{ m}$ based on the aggregation of the Digital elevation model EU-DEM (EEA) (www.eea.europa.eu/data-and-maps/data/eu-dem). See more details in Samaniego et al. (2019). The CORINE land-cover data set was aggregated to the spatial resolution of level-0. For Level-1 as the spatial resolution for the simulation of the hydrological processes, a 5 km grid resolution was used as a trade-off between accuracy in process representation, computational runtime, and handling of the final size of model outputs as used in Samaniego et al. (2019). Finally, the common resolution for Level-2 with the meteorological data was 0.25° (daily E-OBS product (Haylock et al., 2008)).

Soils were discretized in six layers with different soil depth (0–50, 50–100, 100–300, 300–600, 600–1,000, 1,000–2,000 mm). The tillage depth was set to 300 mm as the depth with organic matter effects. In this study, the Hargreaves-Samani method (Hargreaves & Samani, 1985) was used to calculate potential evapotranspiration. The simulation period was from 2001 to 2006 with 2000 as 1 year of spin-up period before.

4. Temporally Resolved Parameter Sensitivity

4.1. Brief Overview of the Fourier Amplitude Sensitivity Test (FAST)

To estimate the parameter sensitivity, a temporally resolved approach is used. This means that the sensitivity index is calculated for each time step. The temporal parameter sensitivity analysis provides a daily time series of parameter sensitivity (for details, see Reusser et al. (2011) and Guse et al. (2014)). We use a global sensitivity analysis using the Fourier Amplitude Sensitivity Test (FAST) algorithm (Cukier et al., 1973) and the R-package FAST (Reusser, 2013).

The FAST algorithm produces a list of parameter combinations for which mHM needs to be run. The number of model simulations is increasing non-linearly with the number of parameters. In FAST, the amount of parameter combinations that are simulated is fixed for a given number of parameters. The parameter values are not changed during the simulation period, but between different simulation runs.

As the sensitivity index, the partial sensitivity of the first-order variance divided by the total variance of all parameters is used. Thus, the sensitivity index ranges from 0 to 1. In this study, sensitivity analysis directly uses the model outputs without calculating a performance metric, but also an application to a metric is possible (Markstrom et al., 2016).

4.2. Application of FAST to mHM

The methodological approach is described as follows. For the model simulation, at first 907 parameter combinations as required for 14 model parameters were provided by FAST to calculate the daily sensitivities for each model parameter. The same parameter sets are used for all gauges. Reusser et al. (2011) demonstrated that this size of parameter sets (here 907 runs) is sufficient to detect dominant parameters (here 14) and to obtain robust results of the sensitivity analysis.



Figure 2. Hydrological gauges used in this study and the major rivers. The elevation is shown in the background. River network has been delineated using Heberger (2022). DEM200 (©GeoBasis-DE/BKG) was used (BKG, 2013).

mHM was firstly simulated in daily resolution for all pre-defined parameter combinations consistently for the entire spatial domain, that is, 102 German catchments. Daily simulated time series of runoff (Q), actual evapotranspiration (ET), SM and recharge (R) were stored for all 907 simulations. Then, daily parameter sensitivities were calculated separately for each gauge and each target variable. The daily parameter sensitivities are further aggregated to mean monthly sensitivities to derive typical temporal patterns of parameter sensitivities. A monthly averaging of parameter sensitivities was suggested in Guse, Pfannerstill, Strauch, et al. (2016) to aggregate the results and facilitate the identification of typical temporal patterns.

The coefficient of variation was calculated between all gauges for a fixed month (CV_space) and among all monthly values for a given gauge (CV_time) to assess spatial and temporal variability. Moreover, the parameter sensitivities were related to the simulated values of the state and fluxes to detect whether the parameter sensitivity is higher for high or low values of a hydrological component. This way, we quantified the parameter sensitivity in space, time and magnitude.

5. Results and Discussion

5.1. Spatial-Temporal Patterns of Fluxes and State Variables

First, the simulation of the key model state and fluxes are analyzed. Therefore, the daily simulated model state and fluxes are averaged among all simulations of the parameter sensitivity analysis and aggregated to monthly averaged values separately for each gauge.

The simulation results for runoff show a spatial gradient with the highest runoff south of the Danube and the lowest in northeastern Germany (Elbe basin) (Figure 3). Overall, the highest runoff was computed for the winter half-year (November to March). South of the Danube, runoff is even higher in summer. In the northeast, the lowest runoff was recorded from spring to autumn (April to October). These spatial patterns result from an elevation gradient from north to south (increasing elevation) and a dryness gradient from west to east (increasing dryness). As indicated in Table 3, the spatial variability of runoff among the gauges is greater than the temporal (monthly) variability.

The hydrological state (SM) and fluxes (actual evapotranspiration and recharge) are presented in addition to runoff as cumulative values in monthly resolution over all gauges for the entire model period (Figure 4). The spatial variability can be found in a map in the attachment in seasonal resolution (Figures S1–S4 in Supporting Information S1).

Actual evapotranspiration has high seasonal variability with the highest values in summer and overall low spatial variability as indicated in the CV in space and time (Table 3). The highest ET values are simulated in the south of the Danube.

The variability in space and time of simulated SM is relatively low. The CV in space is, to a small extent, higher than in time. As indicated in Figure 4, some of the catchments are characterized by lower SM in comparison to the majority of the gauges. The lowest values were detected in the northeast in summer, where in addition a longer rewetting period in autumn was observed. The overall highest SM was simulated in winter. In the south and west, the SM has high simulated values throughout the year.

Also for recharge the spatial variability is larger than the temporal variability. Subsurface processes are known to have a temporal lag. This explains the lower variability in time. For recharge, the highest values were simulated in spring south of the Danube. The lowest recharge was simulated in Central Germany similar to runoff.

5.2. Monthly Variability in Dominant Model Parameters With Regard to Different Hydrological Target Variables

Figure 5 shows the monthly averaged parameter sensitivities on the four target variables across all gauges. The sensitivity analysis is related to the gamma parameters of mHM, which are the parameters used in the transfer functions in MPR and should not be confused with the process parameters that are calculated by MPR.

The most sensitive parameters on runoff (Q) are PTF_Ks_sand, PTF_Ks_constant and exponentSlowInterflow with low monthly variability. According to the model structure, these parameters also govern the interflow compartment and recharge and thus the input of the baseflow compartment. MinCorrectionFactorPET varies

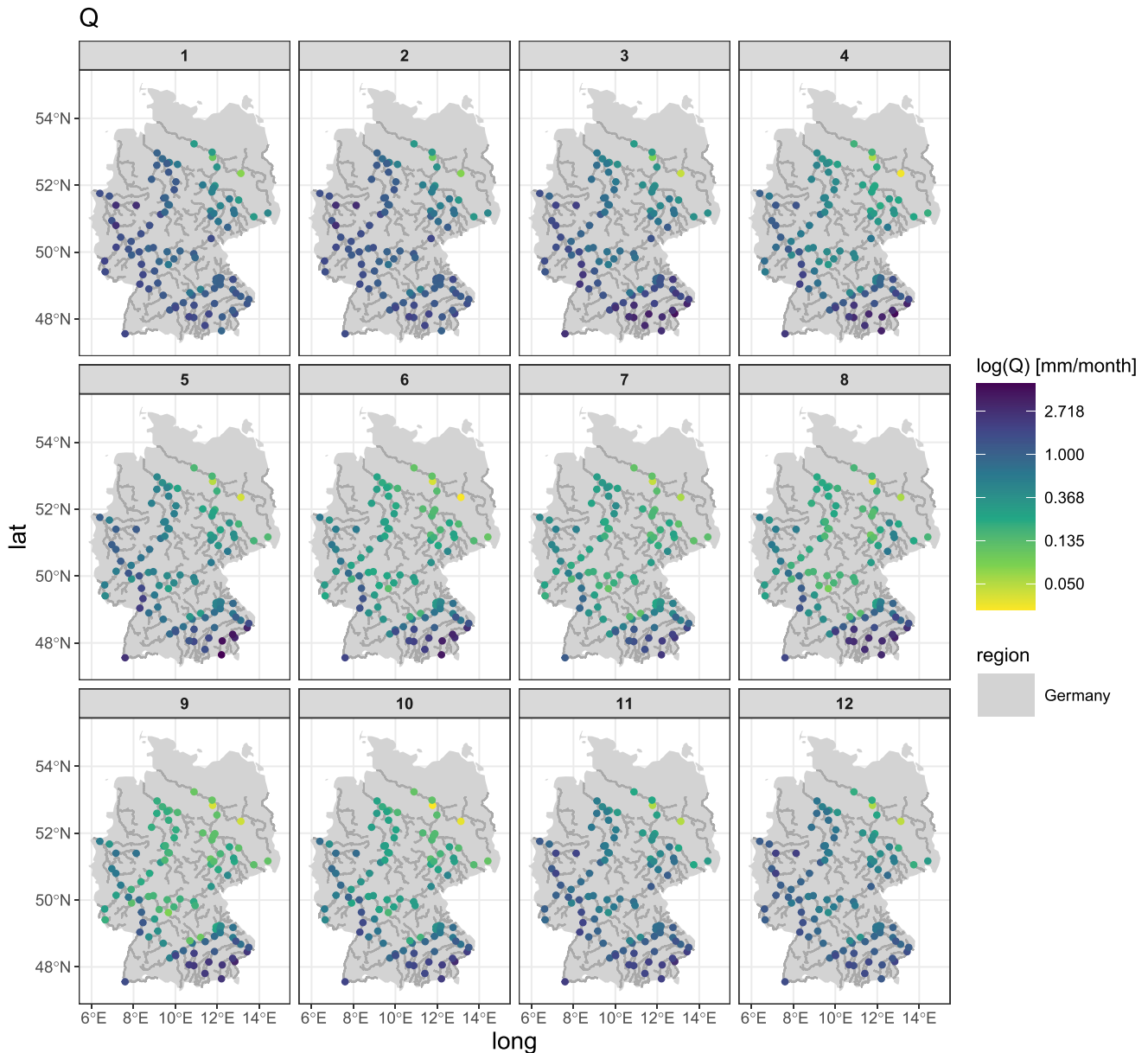


Figure 3. Monthly averaged modeled runoff [mm/month] in log scale. Subtitle numbers indicate the month (from January to December).

seasonally with the highest sensitivity in summer. SnowThresholdTemperature is sensitive in winter from November to April in phases of snow accumulation and melting with a maximum in March in the month with the overall highest impact of snowmelt in Germany. Overall, runoff is highly controlled by subsurface flow conditions and evapotranspiration during summer.

The related parameter minCorrectionFactorPET fully controls actual evapotranspiration (ET) throughout the year. InfiltrationShapeFactor is also sensitive in summer. Thus, actual evapotranspiration depends during summer also on the amount of infiltrated water.

Soil moisture is also controlled by minCorrectionFactorPET, in particular during periods of low SM and high actual evapotranspiration between April and September. During the winter half-year from October to March,

Table 3

Coefficient of Variation in Space and Time for the Four Hydrological Variables

Hydrological variable	CV in space	CV in time
Runoff	0.714	0.291
Actual evapotranspiration	0.061	0.704
Soil moisture	0.088	0.035
Recharge	0.598	0.385

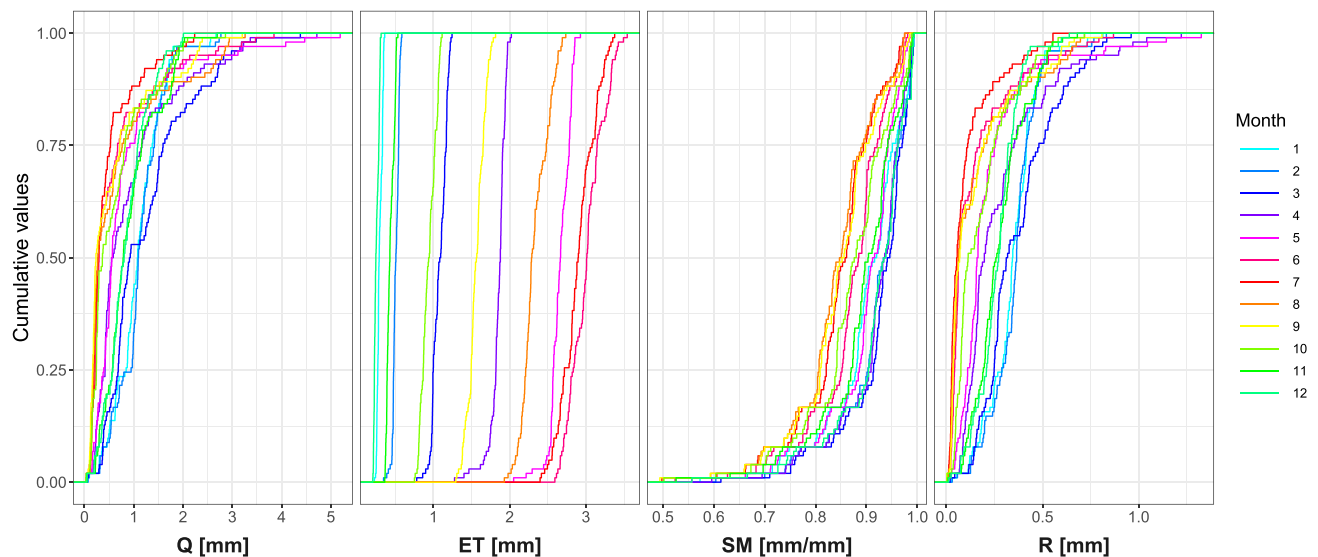


Figure 4. Cumulative distribution function of the mean monthly values of four simulated hydrological variables (Q = runoff, ET = actual evapotranspiration, SM = soil moisture, R = recharge). A cumulative distribution plot sums up the results for all gauges. They are separated by month by colors.

the infiltrationShapeFactor is also sensitive. Therefore, the infiltrationShapeFactor regulates the infiltrating water in phases of high SM conditions. Both parameters are sensitive in phases of high values of the corresponding process. In summer, evapotranspiration regulates SM . Thus, under warmer temperatures and low SM conditions, regulating water that leaves the soil via evapotranspiration is more relevant in the model structure of mHM than the regulation of infiltrating water. In winter snowThresholdTemperature is also sensitive to SM .

Recharge (R) is dominated similarly to runoff by PTF_Ks_sand and $PTF_Ks_constant$ and by exponentSlowInterflow and rechargeCoefficient. Note that the recharge coefficient in mHM is parameterized based on PTF_Ks estimates. Thus, recharge is always controlled by the soil texture and the resulting vertical permeability. ExponentSlowInterflow is sensitive being a regulating parameter for slow interflow. Generally, the temporal variability of these parameters is low. MinCorrectionFactorPET is sensitive in summer. In this period of highest evapotranspiration, the amount of recharge water is therefore also highly regulated by evaporation water.

A parameter-based analysis shows that minCorrectionFactorPET highly controls actual evapotranspiration, but also affects SM and to a lower extent runoff (both in summer). InfiltrationShapeFactor is sensitive to SM in winter. The two parameters PTF_Ks (sand, constant) and exponentSlowInterflow are sensitive to runoff and recharge during the entire year with low temporal variability.

5.3. Space-Time Variability in Parameter Sensitivities

Next, the variability of sensitivities of the significant parameters on the four target variables was analyzed in space (among different gauges) and time (between different months) (Figure 6).

For runoff, snowThresholdTemperature changes both in space and time, while infiltrationShapeFactor has a higher CV in space. For the most sensitive parameters $PTF_Ks_constant$, PTF_Ks_sand and exponentSlowInterflow the spatial CV is higher than the temporal CV.

With regard to actual evapotranspiration, minCorrectionFactorPET is the most sensitive parameter but with low spatial and temporal variability. This shows the constant and strong relationship between minCorrectionFactorPET and the corresponding process of actual evapotranspiration. The infiltrationShapeFactor as the second most relevant parameter varies in its sensitivity more in time than space. All other parameters have lower temporally averaged sensitivities than 0.005.

In relation to SM , the spatial variability in parameter sensitivity is higher in space than in time. Only for minCorrectionFactorPET as the most sensitive parameter on SM the variability is similar in space and time, but also

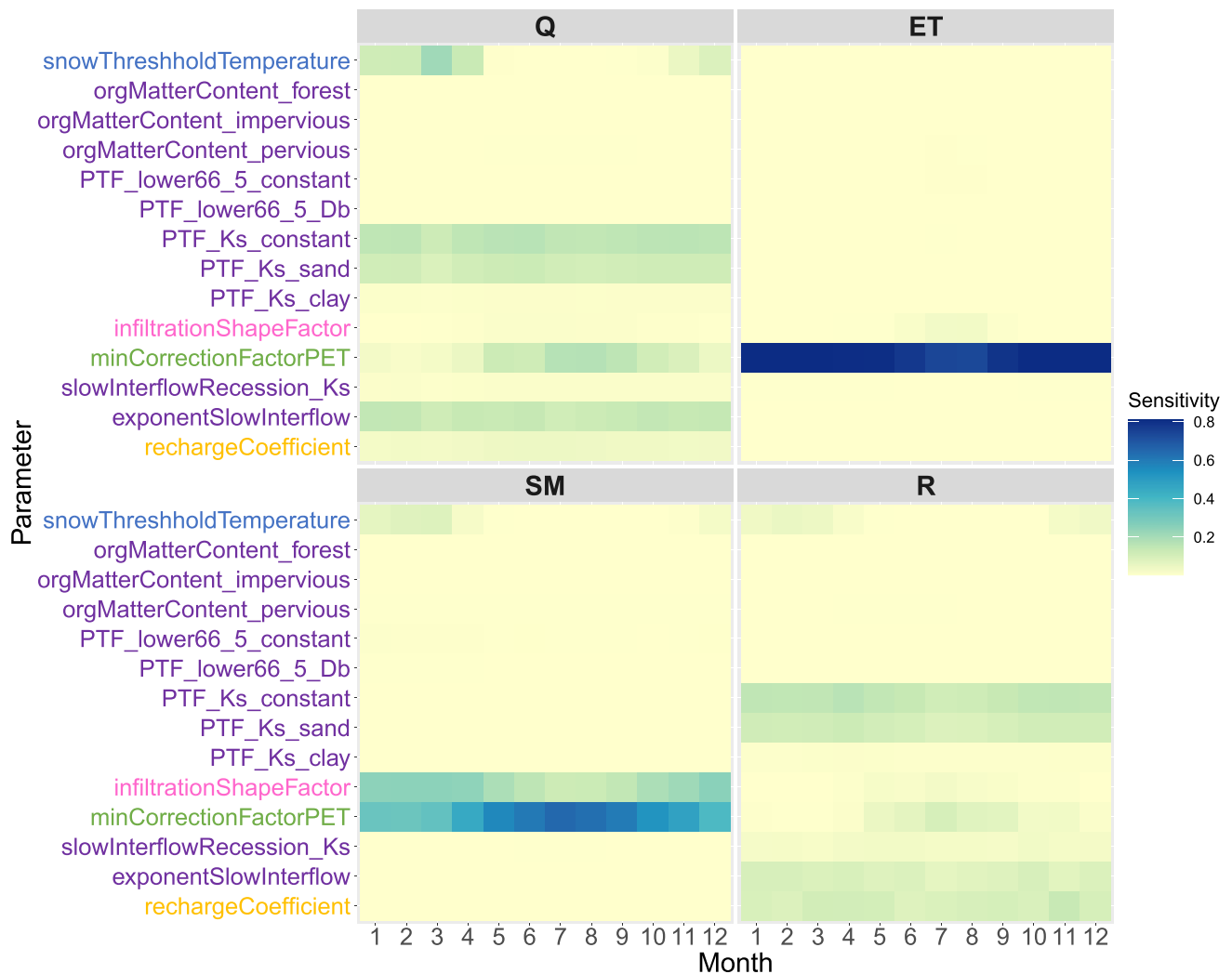


Figure 5. Average monthly parameter sensitivity in relation to different target variables.

here slightly higher in space. The overall highest CV was detected for snowThresholdTemperature on SM, but with low sensitivity values.

In terms of recharge, the variability in parameter sensitivity is similar in space and time. Also here the sensitivity values of snowThresholdTemperature vary most, but here more in time than in space. High temporal variability was detected for four parameters on recharge that are also all sensitive.

Overall, the highest parameter sensitivity is often related to low spatial variability. Also in time the variability in sensitivity of minCorrectionFactorPET on actual evapotranspiration and SM is low despite high sensitivity values. The snowThresholdTemperature is highly variable in time between winter and summer as well as in space between alpine areas and lowlands.

5.4. Spatial Variability in Temporally Averaged Parameter Sensitivities

Next, the variability in parameter sensitivity was analyzed in seasonal resolution for each catchment to identify spatial patterns of higher/lower sensitivity and to detect temporal variations in spatial patterns. The more detailed parameter-based analysis is focused on five major parameters as detected in Figure 5 with seasonal averaged sensitivities on runoff in Figure 7.

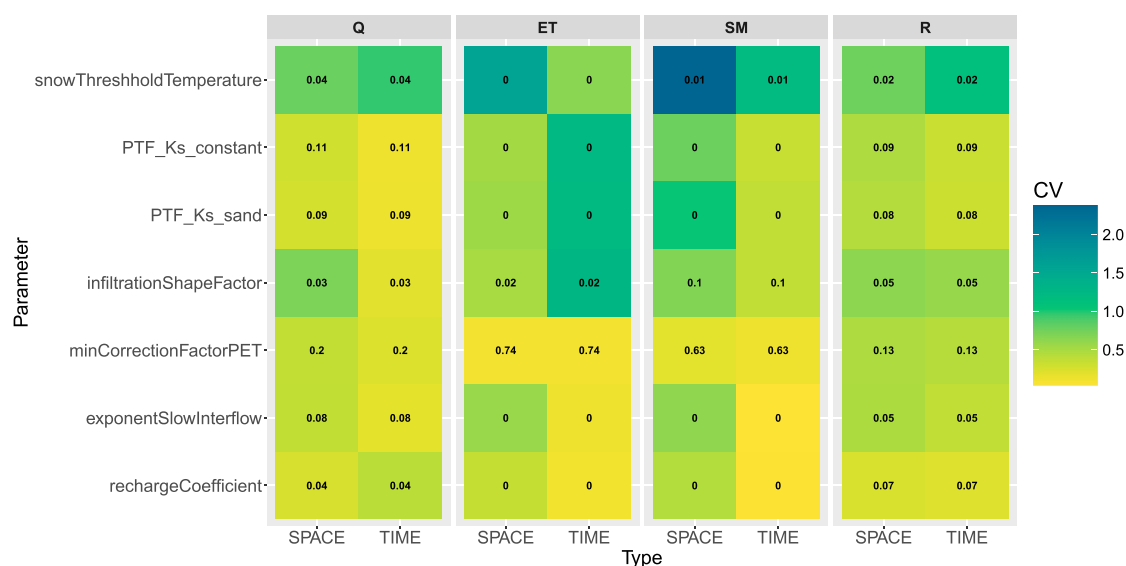


Figure 6. Coefficient variability of parameter sensitivities along space (gauges) and time (month). Labels represent the mean parameter sensitivity in relation to the target variable. Only model parameters with a mean sensitivity larger than 0.02 to at least one of the target variables are considered in this plot. Q = runoff, ET = actual evapotranspiration, SM = soil moisture, R = recharge.

With regard to snow parameters, snowThresholdTemperature is sensitive particularly in spring in the alpine rivers south of the Danube and along the Rhine river. In winter, snowThresholdTemperature is sensitive in the south and southeast of Germany. PTF_Ks_constant and PTF_Ks_sand are sensitive parameters all the time and in all basins with a slightly decreasing gradient toward the northeast and toward lowlands. In total, both parameters have a relatively low variability in space and time with a slight decrease toward the northeast. MinCorrectionFactorPET is sensitive the entire year with the highest sensitivity in the north and decreasing values toward the south. The highest sensitivity of minCorrectionFactorPET is thus detected in autumn. ExponentSlowInterflow is sensitive in winter with decreasing values toward northeast and lowlands similar to PTF_Ks_constant.

Separate maps in the attachment show the spatio-temporal variability in the sensitivity of the major parameters in relation to the specific three other target variables actual evapotranspiration (Figure S2 in Supporting Information S1), SM (Figure S3 in Supporting Information S1) and recharge (Figure S4 in Supporting Information S1).

Spatial variability in the sensitivity of three model parameters on actual evapotranspiration shows that minCorrectionFactorPET is the dominant parameter in all seasons (Figure S2 in Supporting Information S1). Lower sensitivities were detected in summer in the north of Germany in the phases of the highest simulated actual evapotranspiration.

Using SM as the target variable, minCorrectionFactorPET is the most sensitive parameter in almost all catchments in all seasons. The sensitivity is higher in the dry northeast. Lower sensitivity values on SM are in winter in particular south of the Danube and in the southwest of Germany. InfiltrationShapeFactor is sensitive in the south of the Danube mainly in autumn and winter (Figure S3 in Supporting Information S1).

Subsequently, spatial patterns of the parameter sensitivity on recharge were analyzed (Figure S4 in Supporting Information S1). PTF_Ks_constant and PTF_Ks_sand are mainly sensitive south of the Danube and in the west of Germany (Rhine basin) during the entire year. The lowest sensitivity was simulated in summer in the north and center of Germany. MinCorrectionFactor PET is the dominant parameter in particular in summer and autumn in northern and central Germany. The sensitivity is low in the south of Germany. RechargeCoefficient is sensitive in autumn and winter with lower spatial variability as the other parameters in the south and west. In summer the lowest sensitivities were simulated in the north.

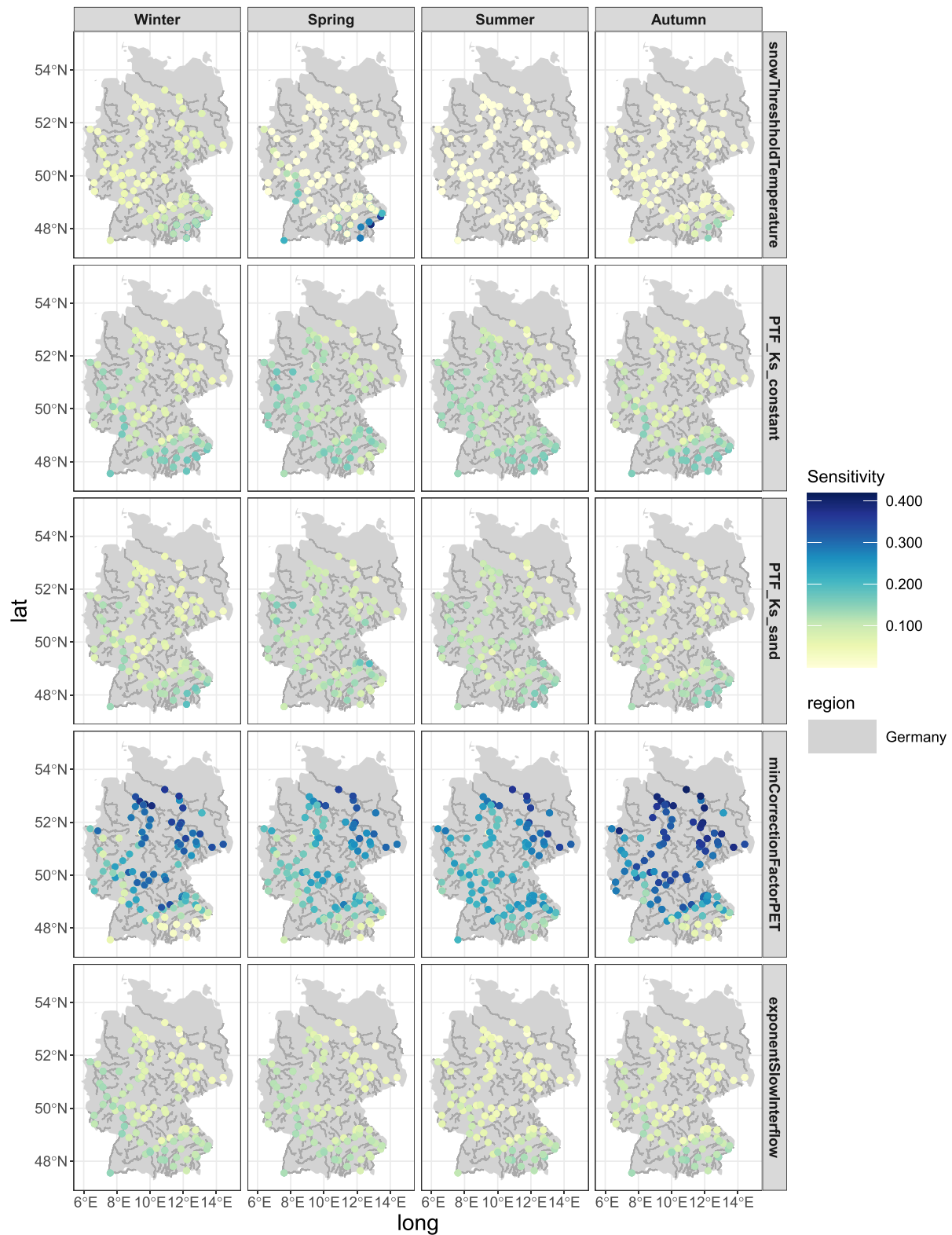


Figure 7. Mapping of mean seasonal sensitivity of the five major model parameters on Q .

5.5. Magnitude-Based Impact on Parameter Sensitivity

Next, the parameter sensitivities are related to the simulated states and fluxes in order to check whether high parameter sensitivity is related to high/low values of the state and fluxes. In this way, it is detected whether a parameter is mainly active under high/low values of the hydrological component.

Figure 8 shows the relationship between the mean simulated values of the hydrological variables and the temporally averaged sensitivity of seven selected parameters in relation to the four hydrological target variables under consideration of seasonal variability. The Spearman correlation coefficient between hydrological variable and parameter sensitivity was added to each subplot. We emphasized in the following relationships with a maximum sensitivity larger than 0.1.

Using runoff as the target variable (first row), simulated values negatively correlate with infiltrationShapeFactor (-0.82) and minCorrectionFactorPET (-0.67). In both cases, high sensitivities of these parameters were related to low flows. In contrast, for exponentSlowInterflow (0.83) and snowThresholdTemperature (0.68), the sensitivities increase with increasing runoff. The sensitivities of the three soil substrate parameters are correlated to a lower value with runoff values.

Three parameters have a positive correlation with actual evapotranspiration (between 0.69 and 0.75). These are the two soil parameters showing a very low overall sensitivity and infiltrationShapeFactor. A negative correlation is simulated for minCorrectionFactorPET (-0.66). Thus, high sensitivities are related to low actual evapotranspiration, while the lowest sensitivities of minCorrectionFactorPET are related to high actual evapotranspiration in summer. Thus, with increasing actual evapotranspiration, several parameters are sensitive.

InfiltrationShapeFactor (0.95) is highly correlated with SM values with higher sensitivity for high values of SM. This parameter is more relevant under high SM conditions. The sensitivity of minCorrectionFactorPET (-0.9) decreases with increasing SM values. Thus, the evapotranspiration parameter is more relevant under low SM conditions while the infiltration parameter is more sensitive in high SM conditions. SnowThresholdTemperature is also correlated with SM (0.68). However, this is mainly related to the seasonal overlapping of high snow and SM conditions in winter. The sensitivities of soil substrate parameters correlate with simulated SM values, but the sensitivities are rather low in general.

High correlations were also calculated for recharge. Here, infiltrationShapeFactor (-0.9) and minCorrectionFactorPET (-0.83) are more relevant for low recharge values. Hereby, the highest sensitivities are found in summer for infiltrationShapeFactor and in summer and autumn for minCorrectionFactorPET. In contrast, PTF_Ks_constant (0.9) and PTF_Ks_sand (0.9), as well as exponentSlowInterflow (0.86) and rechargeCoefficient (0.79), are more relevant for high recharge values that are occurring in spring.

Overall, we see that in several cases the sensitivity of model parameters depends on process magnitudes. These parameters are either highly sensitive for high and low magnitudes of state and fluxes. The variability in the relationship between model parameters and parameter sensitivity reflects that a given parameter might be important for different catchment conditions. And high or low values of the same parameter can produce good results depending on the conditions (Wagener et al., 2003).

6. Summary of the Results and Discussion

Our analyses reveal how the model parameters in mHM control four hydrological variables. The sensitivity was analyzed in spatial, temporal and magnitude-based patterns. The results were graphically summarized in Figure 9 similarly as presented in Herman, Reed, and Wagener (2013). For the four target variables of the sensitivity analysis, the mean parameter dominance is shown separately for the hydrological summer half-year (May to October) and winter half-year (November to April). If the high parameter sensitivity is related to process magnitudes, this is shown in addition by arrows. Moreover, the detected sensitivity patterns are summarized in Table 4 with regard to the three criteria: (a) Temporal variability, (b) spatial variability, and (c) magnitude-related variability.

Temporal variability in dominant parameters is mainly related to parameters whose corresponding processes have strong seasonal patterns, for example, evapotranspiration and snow. Cuntz et al. (2015) have demonstrated the temporal variability in the sensitivity of an evapotranspiration parameter for mHM. The other parameters are mostly constant in time. Other studies on temporally resolved sensitivity analysis reveal that also soil or

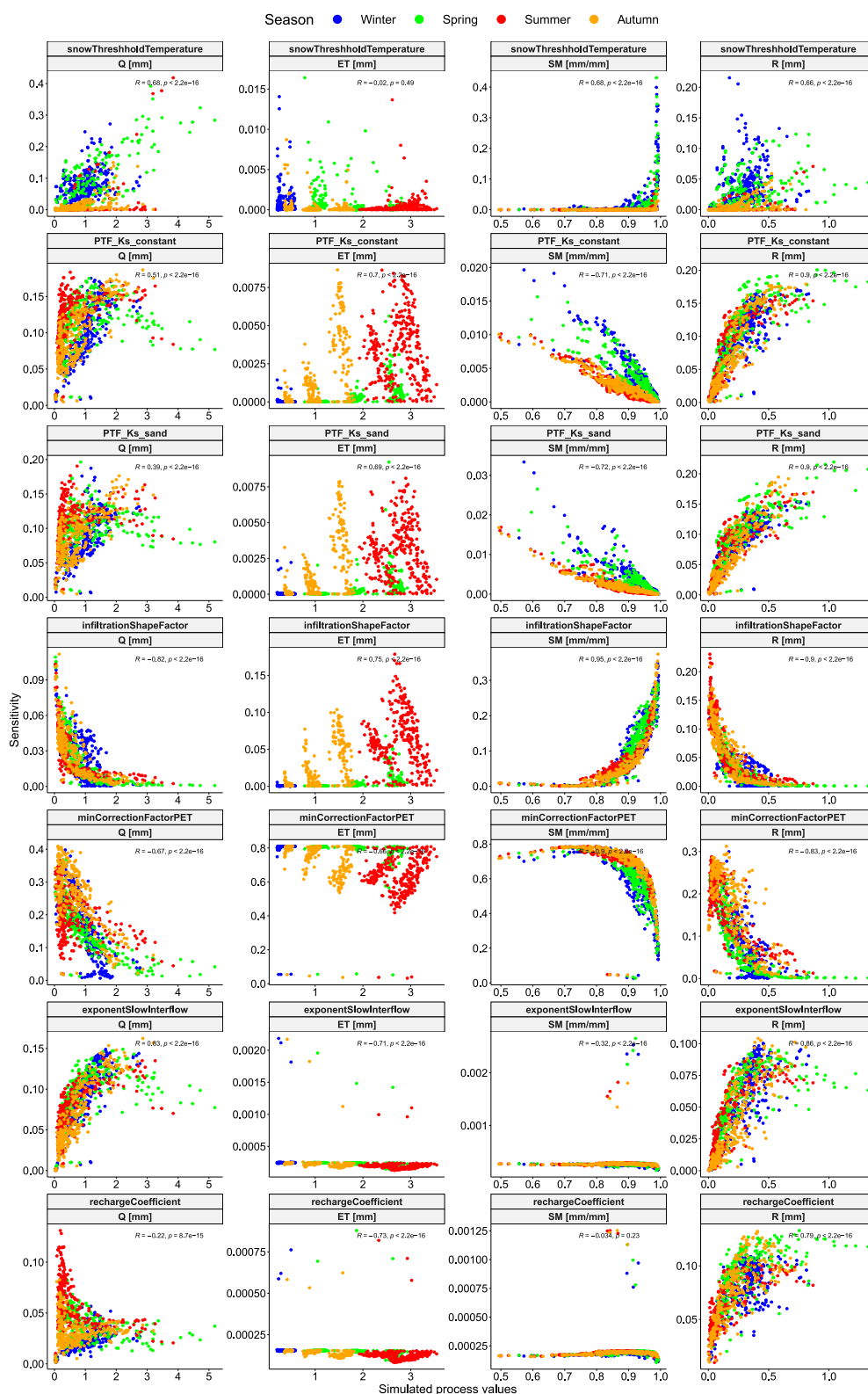


Figure 8. Relationship of monthly simulated values of the four hydrological variables to parameter sensitivity with regard to four hydrological target variables. Seasons are shown in colors. In each subplot, the first line of the header shows the model parameter, the second the target variable.

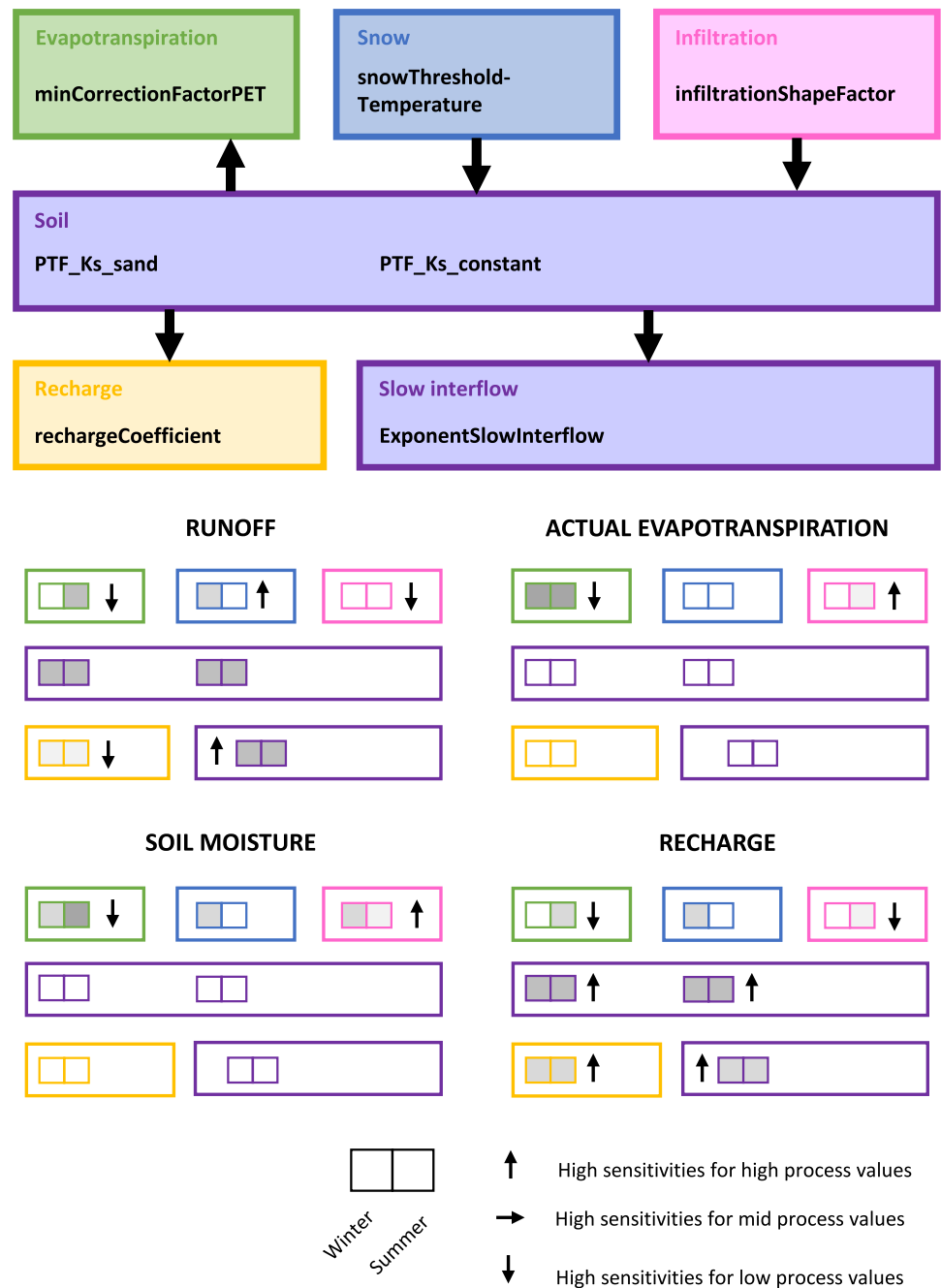


Figure 9. Graphical summary of temporal variability in parameter dominance on four hydrological variables. The mesoscale hydrological model parameters are explained in the upper panel. In the middle and lower panels, the boxes show the sensitivities of these parameters on the hydrological variables. The left box is the average sensitivity in winter, the right in summer. The arrows show that there is a relation between process values and parameter sensitivity. The direction of the arrows symbolize for which magnitudes the highest sensitivity was detected. Increasing arrow means high flow, decreasing low flow.

groundwater parameters vary in time and identified differences in dominant model parameters between wet and dry periods as well (Guse et al., 2019; Herman, Kollat, et al., 2013; Mai et al., 2022).

In this study, parameter sensitivities were calculated at a daily resolution to accurately represent the different hydrological states and fluxes. The temporal resolution chosen for the analysis can influence the results of the sensitivity analysis. Fast-evolving processes are more emphasized at a high temporal resolution, while slow-

Table 4

Summary of Relationships of High Parameter Sensitivity of the Major Mesoscale Hydrological Model Parameters to Four Hydrological Variables (Q = Runoff, ET = Actual Evapotranspiration, SM = Soil Moisture, R = Recharge) With Regard to Time, Space and Magnitude

Process group	Parameter	Sensitive hyd. Var.	Temporal phases	Spatial location	Magnitudes
Snow	snowThresholdTemperature	Q	winter	high altitudes	high Q
Soil moisture	PTF_Ks_constant	Q, R	none	Rhine + Danube basins	mid and high R
	PTF_Ks_sand	Q, R	none	Rhine + Danube basins	mid and high R
Infiltration	infiltrationShapeFactor	SM	in winter on SM	none	low Q and R
			in summer on ET and R		high SM
Evapotranspiration	minCorrectionFactorPET	ET, SM,	in winter on SM,	Lowlands and	low Q and R
		Q, R	in summer on Q and R	Central Uplands	
Subsurface flow	exponentSlowInterflow	Q, R	none	none	mid to high Q and R
Percolation	rechargeCoefficient	Q, R	none	none	low Q + mid to high R

reacting processes are more prominent at a low temporal resolution. To facilitate the interpretation of typical temporal patterns, the daily parameter sensitivities were aggregated to mean monthly averages. This aggregation may be critical when parameters of fast-evolving processes are sensitive on only one or a few days, as the sensitivity peak is averaged out over the remaining days of the month with low sensitivities. Future studies may focus on analyzing parameter sensitivity focusing on different temporal resolutions (from days to weeks and months) and corresponding impacts on modeled fluxes and storages.

Spatial variability among the catchments and absolute values of the sensitivities changes in space as shown in former sensitivity studies (Mai et al., 2022; Markstrom et al., 2016). However, the general patterns as described above are valid for the entire Germany. In total, spatial variability in parameter sensitivity is low as hypothesized. In a sensitivity analysis on selected event-periods using the HL-RDHM model, Herman, Kollat et al. (2013) identified a higher variability in sensitivities within the study catchment. In Guse et al. (2019) the variability in parameter sensitivities of the SWAT model across different catchments was also larger as in this study.

The application of MPR has resulted in the emergence of similar patterns of parameter sensitivity for the same catchment characteristics. The monthly spatial sensitivity patterns exhibited by a specific (corresponding) process remain consistent in space, thereby demonstrating the effectiveness of the parameter transfer function approach. The spatial variability in runoff sensitivity patterns can be attributed to the relevance of the process to the integrated value of runoff.

The results demonstrate temporal and spatial consistency in parameter dominance. In comparison to Guse et al. (2019), the spatial and temporal variability is lower because the impact of parameter variations on the simulated hydrological component is less pronounced when MPR is employed. Whether spatial or temporal variability is higher depends on the model parameter and the corresponding hydrological component.

This sensitivity analysis was carried out in a study domain with temperate climate. In a further study, the sensitivity analysis could be repeated with mHM as presented here in more contrasting climate regions (as used in Markstrom et al. (2016) or Mai et al. (2022)) to test whether the spatial variability in parameter sensitivity is also lower in these regions when using MPR in the model structure. In addition, it would be of interest to compare temporally resolved parameter sensitivities for a large set of gauges between mHM and another model without MPR in order to ascertain the difference in spatial and temporal variability in dominant parameters.

With regard to the magnitudes of the hydrological variables, some remarkable patterns of parameter sensitivities are derived as hypothesized. Soil texture parameters control high recharge. Low recharge and also runoff are regulated by infiltrationShapeFactor and minCorrectionFactorPET. The parameter dominance patterns on SM are highly dependent on the conditions. Under wet soil conditions, infiltrationShapeFactor is dominant, while under dry conditions minCorrectionFactorPET is the most sensitive parameter. Evapotranspiration parameters have also been shown before to be sensitive in particular during dry phases (Guse et al., 2014; Mai et al., 2022). Based on these results, it is recommended to consider changes in parameter sensitivity between low and high values of the corresponding hydrological component. These results are consistent with Massmann and Holzmann (2012) and

Herman, Reed, and Wagener (2013). Herman, Reed, and Wagener (2013) showed in a three-model study that the sensitivity of several parameters in particular of the SAC-SMA model is high/low for high/low values of runoff, precipitation or potential evapotranspiration. In addition, this relationship between simulated variables and parameter sensitivities varies in space across different catchments. For different runoff conditions, van Werkhoven et al. (2008) have shown that the sensitivity of SAC-SMA parameters change along a dry-wet gradient across 14 catchments in the United States. As summarized in Table 4, our analysis has disentangled a precise description of conditions of high sensitivities for each model parameter. This information helps for parameter identification that could be focused on the specific conditions for each parameter. In the case of a major model error for low flows (high flows), the calibration could be focused on parameters that are sensitive under low flows (high flows). Similarly, this is valid for the other hydrological variables. This information might be in particular helpful if model studies are focused on specific conditions such as floods or droughts.

The differences in parameter sensitivity between wet and dry conditions could also be relevant when evaluating models in climate change projections (Wagener et al., 2022). The role of model parameters in controlling the simulated hydrological system might change under a changed climate. As emphasized in Melsen and Guse (2021), the ranking of model parameters in terms of their sensitivity is expected to change between recent and future simulations. Based on the results of this study, we expect that the minCorrectionFactorPET will be more sensitive under drier conditions in the future, while the sensitivity of the infiltrationShapeFactor might decrease.

With regard to specific parameter regionalization approach (MPR) used in mHM, it is worth noting that analyzing the relationship between global gamma parameters and the model outputs is not simple and straightforward. There is no direct effect of gamma (or calibration) parameters on modeled fluxes and storages because these gamma parameters need to be translated to beta parameters—which directly interact with model processes. Furthermore, one needs to consider the interactions between different pedo-transfer functions and dependencies among them to infer beta parameters (Kumar et al., 2010; Kumar, Livneh, & Samaniego, 2013). The gamma parameters are part of one or more transfer functions and some pedo-transfer functions even can include more than one gamma parameter. Despite these inherent complexities, this study shows that important insights can be gained about parameter behavior and variability in space and time. The method of temporal parameter sensitivity analysis is thus applicable to a model with MPR as shown for mHM. Further analyses with other model structures are envisaged as MPR has been further developed as a model-agnostic tool (Schweppe et al., 2022) and has already been applied to various models (Boussetta et al., 2021; Coxon et al., 2019; Mizukami et al., 2017; Samaniego et al., 2017). Such a model-agnostic MPR tool will further allow us to analyze the sensitivity of selecting different transfer functions linking global parameters and geophysical characteristics as well as the choice of upscaling operators linking fine-scale hydrologic parameters to those at coarser modeling scales. In this context, our study on diagnosing the global parameter sensitivity—though in mHM—can be considered a benchmark for a further possible comparative study where similar sensitivity analysis can be conducted to understand the space-time variability of modeled fluxes and storages in other modeling concepts employing the MPR scheme.

7. Main Outcomes and Conclusions

The temporal sensitivity analysis of 14 mHM parameters on four hydrological states and fluxes in 102 German catchments has at least partially confirmed the initial hypotheses. The major outcomes of this study are:

The number of relevant parameters varies among the hydrological state and fluxes. While the corresponding model parameters highly control actual evapotranspiration, several parameters from different hydrological components control recharge and runoff (e.g., soil substrate, subsurface, snow, and evapotranspiration parameters). Soil moisture is regulated by an infiltration and evapotranspiration parameter with seasonal varying patterns.

The temporal variability in parameter sensitivity is related to the intra-annual variability of the corresponding process. Thus, our results support the first hypothesis. Therefore, snow and evapotranspiration parameters show the highest variability in sensitivity in time. The major temporal variability in parameter dominance was detected for the snow parameter.

Due to the MPR method and one consistent parameter set for the entire study region, the parameter dominance patterns are also consistent in space with respect to the dominance of the corresponding processes as

hypothesized. The spatial variability of parameter sensitivities for runoff could be explained by the differences in the process magnitudes and their relevance on the integrated value of runoff.

Also the third hypothesis is supported by our analysis. The comparison of temporal and spatial variability reveals that the degree of variability depends on the model parameter and the corresponding hydrological component. Overall, the sensitivity patterns are consistent in space and time with our expectations and our understanding of dominant processes.

The most remarkable sensitivity patterns are identified in relation to the magnitude of the hydrological variable. Magnitude-controlled sensitivity patterns are detected for some model parameters for each hydrological target variable. Therefore, the fourth hypothesis is partly supported by this study. Infiltration and evapotranspiration parameters dominate low recharge, while soil texture and percolation parameters are dominant on high recharge. With regard to SM, wet conditions are controlled by infiltration and dry conditions by evapotranspiration parameters. Therefore, different phases of the hydrograph are controlled in the model by different parameters, states, and fluxes. For future analysis of other models, we recommend considering the relationship between the sensitivities of model parameters and the magnitude of their corresponding hydrological components.

An improved understanding of model parameter control in mHM as demonstrated in this study, is a step toward more accuracy in process representation that can benefit more efficient parameter identification and model calibration.

Data Availability Statement

For the discharge data, we refer to the different authorities as listed in the acknowledgements. The source code of the mHM is publicly available at <https://doi.org/10.5281/zenodo.4575390>.

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