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Exploring the potential for parameter transfer from daily to hourly time step in the HYPE model for Sweden

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ABSTRACT

Catchments with response time shorter than a day require simulations at sub-daily resolution for flood forecasting. Long-term hydrological data with sub-daily time resolution is lacking for many catchments and, thus, it is worthwhile to investigate the potential in using hydrological model parameters calibrated at a daily temporal resolution to simulate sub-daily runoff. This study investigates the potential of directly transferring the parameters from the one-day Hydrological Predictions for the Environment (HYPE) model for Sweden to a one-hour time step version. A sensitivity analysis and calibration of the one-hour model were also performed to explore the possibility of achieving improved model performance through an additive and multiplicative scaling of the parameters. Directly transferring the parameters led to a negligible loss in performance for all 147 catchments evaluated here. Scaling of the parameters did not lead to improvement for slow-responding catchments, while the increase in performance was negligible for catchments with sub-daily response time.

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1 Introduction

Basin response time can vary from hours to days depending on the basin size and the underlying mechanisms specific to the basin (Blöschl and Sivapalan 1995). Study of the hydrological processes at sub-daily temporal resolution is needed to be able to forecast runoff for small, fast-responding catchments (Ficchi *et al.* 2016). However, in many areas, longer record data with denser spatial coverage is available only for daily or coarser time intervals (e.g. Reynolds *et al.* 2017). In addition, calibrating models for large areas, accounting for variability of the parameters across space, is computationally demanding (Hundecha *et al.* 2016), especially for short time steps. Thus, transferring model parameters already calibrated at a coarse time step to be used for simulations at a finer time step might be desirable (IAHS: Trumper PUB Working Group 2007, Ostrowski *et al.* 2010). The importance of transferring information across time scales has long been recognized (Blöschl and Sivapalan 1995, Blöschl 2001) but has not been sufficiently covered in the literature (Ostrowski *et al.* 2010, Ficchi *et al.* 2016). In recent years, an increasing focus has been placed on this issue, especially after the initiative Towards reducing uncertainty in rainfall–streamflow model parameter regionalisation (TRUMPER; IAHS: Trumper PUB Working Group 2007).

Several studies have explored whether parameters calibrated at daily or coarser temporal resolutions can be used for simulation at sub-daily scales. For example, Cullmann *et al.* (2006) concluded that transferability of parameters was not recommended and in view of changes in time step,

recalibration is necessary. Littlewood and Croke (2008) also found poor model performance if no time-step dependencies, i.e. scaling of the model parameters, are considered. Wang *et al.* (2009), Ostrowski *et al.* (2010), Bastola and Murphy (2013) and Jie *et al.* (2018) found that transferring the same parameters from a coarser to a finer temporal resolution resulted in significant losses in the model performance, but improvement was achieved through using a scaling relationship. Jie *et al.* (2018) found that parameters related to the water balance and runoff routing processes were most sensitive to the temporal scale, while Ostrowski *et al.* (2010) and Kavetski *et al.* (2011) suggest that time dependencies exist for parameters related to fast-flow processes. Wang *et al.* (2009) and Ostrowski *et al.* (2010) attribute these dependencies to the influence coming from the relationship between the rainfall intensity and the duration. On the other hand, Reynolds *et al.* (2017) showed, using the Hydrologiska Byråns Vattenbalansavdelning model (HBV), that just transferring the calibrated (using a one-day time step) parameters to a sub-daily version of the model led to a negligible decrease in model performance. Similar results were found by Ficchi *et al.* (2016) using the GR4 model (in French, modèle du Génie Rural à 4 paramètres).

The potential of parameter transferability across modelling time resolutions is thus still not well understood but known to be complex (Beven 2001, Littlewood and Croke 2008). Many of the studies done are limited to specific models and areas and led to varying results on whether or not transferability is possible. Given the different assumptions with which models are built, it is likely that transferability of parameters is model

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dependent. This study explores the parameter transferability issue with focus on the Hydrological Predictions for the Environment (HYPE) model (Lindström *et al.* 2010) calibrated for Sweden (S-HYPE) (see Strömqvist *et al.* 2012).

S-HYPE is continuously being developed at the Swedish Meteorological and Hydrological Institute (SMHI: <https://hypeweb.smhi.se/model-water/>) and is currently being used for forecasting and warning purposes with a one-day time step. The one-day S-HYPE model, composed of 39 635 sub-basins with a median size of 7 km² in the version used here, is the outcome of years of calibrations by globally and locally adjusting the model parameters for the whole of Sweden, improving the land-use and soil-type descriptions for all sub-basins and the model itself. As a result, the one-day S-HYPE model has been shown to be good at representing many of the Swedish catchments (Lindström 2016). However, the runoff variability of fast-responding catchments, i.e. those with sub-daily response time, cannot adequately be represented by a daily model.

This study investigates the potential of directly transferring, using only unit conversion, the calibrated parameters from one-day S-HYPE to obtain a version with a one-hour time step. Furthermore, the performance of the model obtained by transferring the parameters is compared with the corresponding performance achieved through calibration at the hourly time step. We also investigate whether simulation at a one-hour time step improves the model performance when evaluated at the daily scale as shown by Hughes (1993) and Jeong *et al.* (2010) when applying the methodology for fast-responding catchments. Ficchi *et al.* (2016), on the other hand, did the evaluation both for slow- and fast-responding catchments and found improvements only for the latter.

The methodology applied here can be summarized as follows: a method to infer the response time of available catchments was implemented. Nine representative catchments, estimated to have a sub-daily response time, were chosen for calibration. The one-day S-HYPE model was unit-converted to an hourly time step (one-hour unit-converted S-HYPE). A global sensitivity analysis, developed by Saltelli *et al.* (2010), was performed to reduce the number of calibration parameters. Recognizing that many parameter sets, instead of one optimal set, are preferred for representing a modelled system (Beven and Binley 1992, Beven 2006), acceptable sets of parameters – those for which the model performed well for each of the calibrated catchments – were identified. The results of the one-hour unit-converted and the calibrated S-HYPE were evaluated and compared with the performance of the one-day S-HYPE for the hourly and daily averaged time steps. The evaluation was focused on sub-daily response catchments, but also done for all the available catchments within the HYPE set up for Sweden.

2 Data and model

The HYPE model and all datasets used in this study are explained below.

2.1 HYPE

The HYPE model was originally developed by Lindström *et al.* (2010). It simulates both water flow and the flow of substances and is aimed at regional applications. The landscape is divided into sub-basins, which in turn can be sub-divided into hydrological response units (HRUs) based on soil and land-use characteristics. Accordingly, most of the model parameters are coupled to either soil or land use, but there are also parameters that are general for all sub-basins. Adjustment of some key variables, most importantly precipitation and temperature, can further be done for selected parameter regions (see Lindström 2016). Rivers and lakes, including regulation thereof, are described explicitly. Since the development of HYPE it has been complemented with the possibility to make simulations with sub-daily time steps by unit conversion of time-step-dependent parameters (those with Δt in their unit, as described in the HYPE's manual). For instance, a recession parameter with a unit day⁻¹ is converted to have a unit hour⁻¹.

2.2 S-HYPE

The HYPE model version 5.4.1 was calibrated at the one-day scale for the whole of Sweden for the period 1999–2008 (Lindström 2016). The sub-basin division by Westman *et al.* (2017) was used together with the model version 5.4.1. The calibrated model used in this study is named S-HYPE 2016 2.0.1 (here referred to as one-day S-HYPE) and is currently being used by SMHI for national hydrological forecasting. The model is composed of 14 and 13 different land-use and soil types, respectively. The calibration was made manually to avoid unrealistic model parameter combinations. The Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe 1970) was used to evaluate the model performance during calibration. The daily S-HYPE model is continuously refined, with two releases per year. This involves the use of an improved database for land use, soil type, soil depth, and point sources, among other things. The modelling of regulations, diversions, canals, water uptake, and other human impacts is continuously developed. Discharge data and rating curves are updated. The HYPE model code is also further developed over time. There is thus a constant need to update the model parameters as well. To make use of the continuous improvements of the daily model, a simple way of converting parameters to a finer time resolution would therefore be valuable.

2.3 PTHBV

Precipitation and Temperature for the rainfall-runoff HBV model (PTHBV) is the Swedish gridded (4 × 4 km²) precipitation and temperature dataset with one-day temporal resolution developed by Johansson and Chen (2005). The data is obtained through interpolation of gauge data using additional information on elevation, wind speed and direction. PTHBV data is available for the whole of Sweden.

2.4 HIPRAD

The High-resolution Precipitation from gauge-adjusted weather RADar (HIPRAD) is a gridded ($2 \times 2 \text{ km}^2$) precipitation dataset with 15-minute temporal resolution developed by Berg *et al.* (2016). HIPRAD data is available for the period 2005–2018 and is based on radar data which are volume-adjusted against PTHBV within a certain time window. Berg *et al.* (2016) used a 30-day window to allow temporal redistribution according to the radar signal on a monthly time scale. In hydrological simulations, however, a shorter time window of one day has shown to generate slightly better results. A time window of one day effectively means that PTHBV is temporally disaggregated to hourly resolution by distributing the daily accumulations over the 24 hours of a day according to the radar signal. When the calibrated hourly version of S-HYPE was run for the period 2010–2018, NSE increased by an average of 0.04 for a total of 156 stations when using a one-day window compared with a 30-day window. The reason is likely that the one-day version is less sensitive to artefacts in the radar signal, that may remain even after quality control procedures.

2.5 MESAN

The Mesoscale Analysis (MESAN) dataset has a resolution of approximately 11 km, with hourly precipitation, temperature and other climate variables estimated by combining physiographic information, weather radar data, and satellite imagery with gauge observations (Häggmark *et al.* 2000). MESAN data is available for the whole of Sweden and surrounding areas.

2.6 Discharge

Hourly discharge time series from a total of 156 SMHI gauging stations were used in this study. All of the stations belonged, at least until the year 2017, to the official SMHI station network (“grundnät”) and were maintained by SMHI. They were continuously monitored, and measurement of water level and flow was performed. Water levels are typically measured every 15 minutes and converted into discharge using the rating curve. The high-resolution data can thereafter be aggregated into, for instance, hourly or daily data. The quality check has, however, traditionally been made for the daily data.

3 Method

Figure 1 shows a flowchart of the procedure used in this study, and a detailed description is given in the following subsections.

3.1 Catchment selection

Available catchments for this study were those that are part of the already-set-up one-day S-HYPE model and whose outlets match the one-hour resolution discharge gauging stations. Only stations with data available for the same period as for the forcing data in this study (i.e. 2005–2018, and with less than 20% missing data) and with a negligible (i.e. zero) degree of regulation were considered. The degree of regulation refers to the proportion of the total annual water flow that can be stored in the upstream reservoirs or lakes.

The same concept as the flow signature Flash described in Donnelly *et al.* (2016) as a measure of the daily variability of a hydrograph was chosen here for an hourly instead of a daily time step to estimate the variability of a hydrograph (here called flashiness):

$$\text{flashiness} = 1 - r_{e,f} \quad (1)$$

where $r_{e,f}$ is the Pearson’s product-moment coefficient for the autocorrelation of the hourly time series (e), which is itself shifted by one hour (f).

The variability of the hydrograph at the hourly step was assumed to be an indication of the catchment’s rainfall-runoff responsiveness; i.e. catchments with fast response were expected to have larger values of flashiness.

It was assumed that there is a positive monotonic relationship between flashiness and catchment response time. Catchments were thus sorted according to their flashiness in decreasing order and their response time was estimated successively for one catchment at a time, not necessarily testing all catchments, until we found catchments whose response time was longer than 24 hours. A flashiness threshold was chosen such that catchments with flashiness greater than that value tend to have a sub-daily response time. Here, the response time of a catchment was estimated as the average time between the maximum of isolated short-duration, high-intensity rainfall events and their corresponding peak discharge. Isolated short-duration, high-intensity rainfall events were those for which no rainfall was observed in the previous five days, that lasted for less than three hours and that led to a distinct peak discharge. The events were searched through visual inspection. The catchment response times obtained here are a rough approximation but are considered reasonable for categorizing catchments into daily and sub-daily response.

Those catchments for which the flashiness was greater than the identified threshold (i.e. those with sub-daily response) were prioritized for calibration. In addition, to minimize the likelihood of errors being carried over from upstream catchments, only catchments composed of one sub-basin in the one-day S-HYPE model set-up were considered. Finally, a total of nine catchments that represent a variety of physical characteristics, e.g. land use and soil, were selected for calibration. The remaining catchments were used for evaluation.

3.2 Model set-up

In this study, the one-day S-HYPE model was first unit-converted to a one-hour time step (referred to here as the one-hour unit-converted S-HYPE) by unit conversion of the model’s parameters that have time step dependency. The one-hour unit-converted S-HYPE model was then used as the starting point for the one-hour calibration method proposed here.

The one-day HIPRAD was used together with the MESAN temperature dataset as forcing data for simulation of the S-HYPE at the one-hour time step. The one-day aggregated versions of the hourly datasets were used to simulate the one-day S-HYPE. Simulations were evaluated with hourly discharge data from some of the gauging stations available at the SMHI. See Section 2 for a description of the data used.

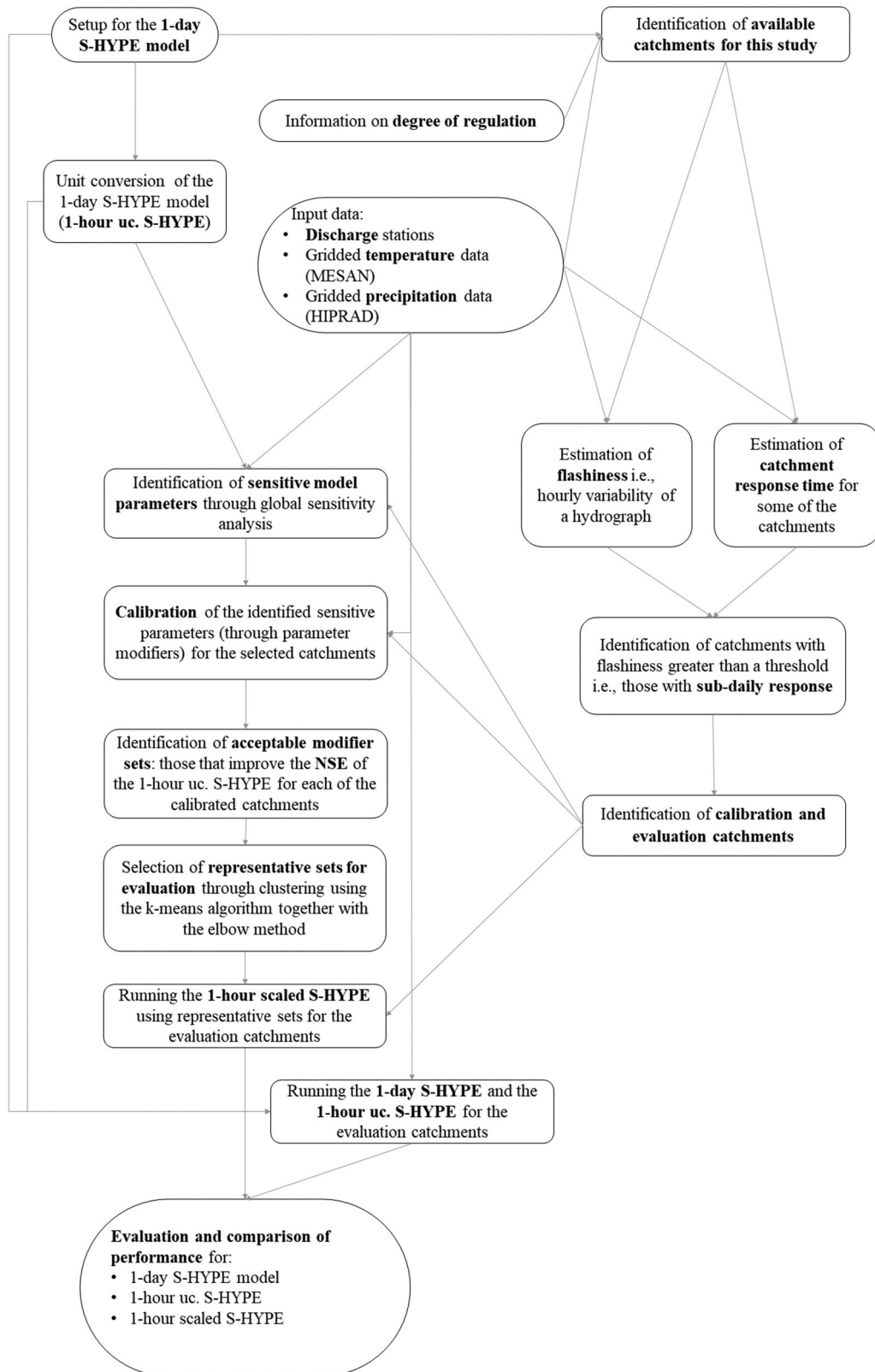


Figure 1. Flowchart for the methodology followed in this study. The main concept of each step is marked with bold text. uc.: unit-converted; S-HYPE: the HYPE (Hydrological Predictions for the Environment) model calibrated for Sweden; MESAN: The Mesoscale Analysis dataset; HIPRAD: The High-resolution Precipitation from gauge-adjusted weather RADar; NSE: The Nash-Sutcliffe Efficiency.

3.3 Calibration

We aim to establish a scaling relationship between the one-day and one-hour model parameters for S-HYPE and, therefore, the calibration was designed to search for parameter modifiers. The modifiers, which are defined as additive or multiplicative, depending on the parameter, are applied to the unit-converted parameters of the one-day model to estimate the corresponding parameters of the one-hour model. Equations (2) and (3) represent, respectively, a multiplicative (m_m) and additive (m_a) modifier:

$$\theta_{\text{hour}} = m_m \cdot \theta_{\text{day}} + \theta_{\text{day}} \quad (2)$$

$$\theta_{\text{hour}} = m_a + \theta_{\text{day}} \quad (3)$$

where θ denotes the parameter value.

Calibration was performed to find different sets of modifiers that lead to improvement over the one-hour unit-converted S-HYPE using the performance measure described in Section 3.3.1 for all calibrated catchments. To search for one modifier per parameter was convenient to reduce the number of parameters to calibrate given that each land-use and soil-type parameter is composed of 14 and 13 different sub-parameters, respectively. Thus, it was assumed that all sub-parameters within a land-use- or soil-type-dependent parameter have the same modifier value. We consider this assumption to be reasonable as calibrated parameters of the daily model are based not only on calibration but also on physical characteristics of the soil and land use.

For calibration, we aimed to consider all the model parameters that are important in controlling the catchment response while keeping their number to a minimum. Thus, to choose which parameters to calibrate, a sensitivity analysis (see Section 3.3.2) was first performed on all parameters considered sensitive selected using the authors' experience in calibrating the model. Parameters associated with negligible sensitivity were excluded from the calibration.

For both sensitivity analysis and calibration, five years (2005–2009) were used as the model spin-up period. The remaining nine years of available data (2010–2018) were used for evaluation. Five years was used as the spin-up period because for the evaluation catchments the whole S-HYPE model set-up was run and one of the lakes in S-HYPE has a residence time of about five years. To be able to compare the results, the same spin-up and evaluation periods were used for both calibration and sensitivity analysis.

The quasi-random sample technique, developed by Saltelli *et al.* (2010), was used for the calibration, as it needs fewer sampling sets than a purely random technique because it samples the space more efficiently through the use of low-discrepancy sequences. A total of 210 000 modifier sets were sampled.

Based on a clustering technique, representative sets of modifiers were chosen from a group of acceptable sets (see Section 3.3.3) and their performance was evaluated for all the

evaluation catchments (i.e. all available catchments in this study excluding those used for calibration).

3.3.1 Performance measure

The NSE was used as the performance measure in this study as it is sensitive to high flows, which is of interest for a flood forecasting system. In addition, since the one-day S-HYPE was calibrated with NSE, using the same measure for the calibration of the one-hour model is expected to facilitate evaluating the hourly against the daily model performance.

3.3.2 Identification of sensitive parameters for calibration

The variance-based global sensitivity analysis (GSA) method with quasi-random sample, developed by Saltelli *et al.* (2010), was used here (see also Ratto *et al.* 2001, Saltelli, 2002a, Saisana *et al.* 2005). Within this method, parameters that are at first considered important are included in the analysis. Consequently, a number of simulations, depending on the number of parameters considered, are done to explore the effect of the parameters' interaction on the model's output uncertainty. From these interactions, the total sensitivity index (S_T), a measure of the contribution of an individual parameter (including its interactions) to the model's output variance, can be estimated. The smaller (i.e. close to zero) the S_T is the less important the parameter is for driving the model's output uncertainty. There is no hard and fast rule on setting a cut-off value S_T that is low enough so that a parameter can be fixed. Some studies argue that 0.05 might be not stringent enough for simple models (Zhang *et al.* 2015) while 0.01 might be found to be conservative (Tang *et al.* 2007). To be on the conservative side, we choose to use a cut-off equal to 0.01 for the average S_T across catchments (as explained below).

The GSA was implemented here for each of the nine catchments selected for calibration using the SALib Python library (Herman and Usher 2017). The estimation of S_T is expected to be influenced by the sampling range chosen (Saltelli 2002b). The sampling ranges for some of the parameter modifiers considered in the GSA were initially chosen based on the range suggested by Hundedcha *et al.* (2016), and an initial guess was used for others. Parameters were then slightly modified after inspection of an initial GSA test. For example, the range was reduced if too-extreme values of a parameter always led to very poor performance. If, on the other hand, the shape of a parameter's posterior distribution had a maximum at any of the edges of the sampling range, the range was increased.

Besides using the NSE as a performance measure for the calibration (see Section 3.3.1) it was also used as a measure of variability in the model output for the sensitivity analysis. The NSE is a common measure used for sensitivity analysis studies (see Song *et al.* 2015 for a review). Finally, S_T was estimated here for each of the chosen parameters and for each catchment. Then, the average S_T across catchments ($\overline{S_T}$) was estimated. Those parameters with negligible $\overline{S_T}$ ($\overline{S_T} \leq 0.01$) were excluded from the calibration.

3.3.3 Acceptable and best representative modifier sets

The NSE was estimated for each catchment and each modifier set. Only those sets that improve the NSE of the one-hour unit-converted S-HYPE for each of the calibrated catchments were considered acceptable. The criterion for acceptable parameter modifier sets guarantees that any retained parameter set will lead to an improved performance (for each of the calibrated catchments) when compared to the unit-converted model. Thus, retained sets are expected to represent a scaling relationship for transferring the S-HYPE parameters calibrated at a daily temporal resolution to hourly resolution.

The average of the NSE for all nine calibrated catchments ($\overline{NSE}$), was estimated for each of the acceptable modifier sets.

To save computational cost and time, not all acceptable sets are evaluated here; rather, evaluation was done only for the representative ones. Representative sets were selected through clustering of the acceptable modifier sets into different groups based on the parameter modifier values using the k-means algorithm (Lloyd 2006). The k-means algorithm has the advantage that it is relatively simple to implement due to its low complexity (in comparison with other clustering methods) leading to fast computations. The k-means algorithm is commonly used for clustering in sensitivity analysis (see e.g. Zahmatkesh *et al.* 2015, Aytaç 2020). The number of representative clusters was set using the elbow method. The elbow method is a technique commonly used with the k-means clustering method to choose the optimal number of clusters. It measures the quality of the clustering by calculating separability, i.e. of the modifier sets, as the total within-cluster sum of squares (WCSS). The optimal number of clusters is the one for which adding another cluster does not lead to a large change in the total WCSS. Thus, by using the k-means algorithm in combination with the elbow method, each cluster is expected to represent similar modifier sets. The set associated with the best ($\overline{NSE}$) for each cluster was chosen for inspection and evaluation.

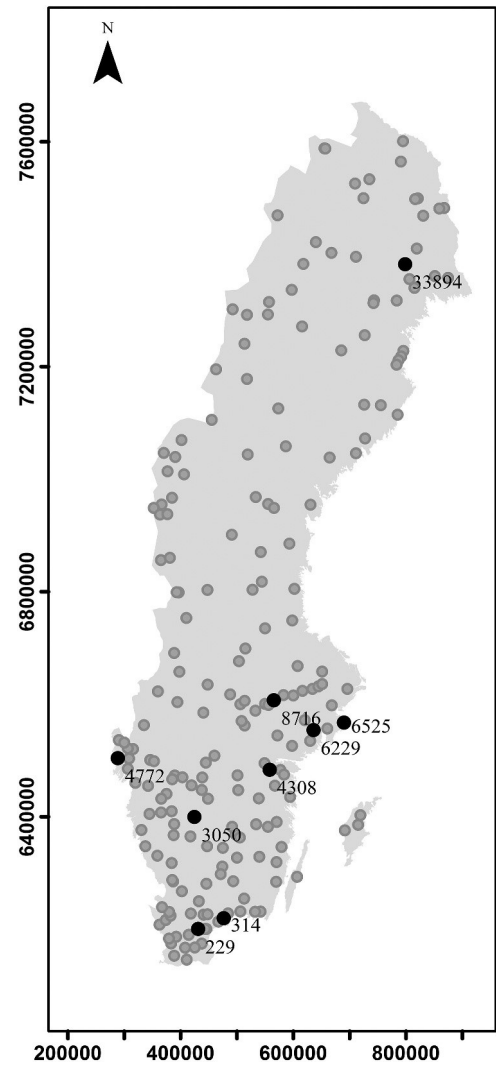


Figure 3. Location of calibration and evaluation catchments within Sweden (black and grey dots, respectively). The S-HYPE ID number for calibrated catchments is shown at the lower right of each dot. The SWEREF 99 TM projection was used.

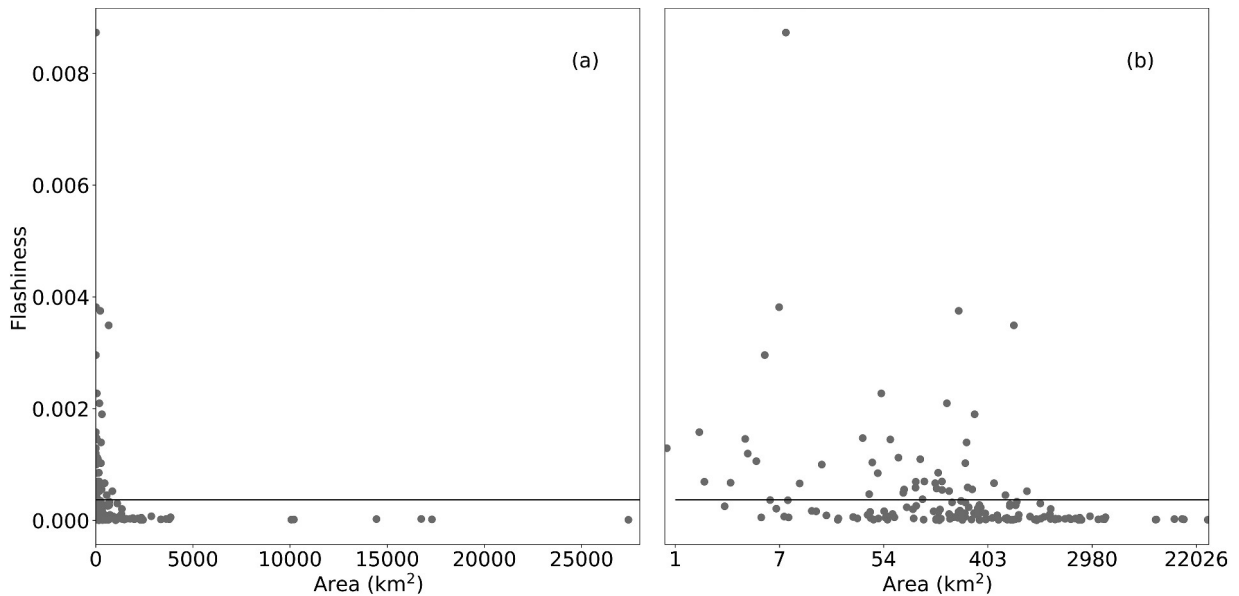


Figure 2. Flashiness values for the available catchments in this study, with catchment size given on (a) a linear scale and (b) a logarithmic scale. The horizontal line shows the threshold flashiness (0.00037) for separating catchments with sub-daily and higher response time.

Table 1. Characteristics of the calibrated catchments sorted according to flashiness.

No.	S-HYPE ID	Station name	Area (km ²)	Slope	Soil*	Land-use*	Flashiness (–)
1	4772	Krokbräcke	8.34	7.44	Thin soils and bare rock	Coniferous forest	0.0087
2	4308	Rytttarbacken	7.33	3.12	Clay	Farmland	0.0038
3	229	Sätaröd	1.59	4.06	Till	Coniferous forest	0.0016
4	8716	Berg	36.47	3.04	Till	Coniferous forest	0.0015
5	3050	Hulubäcken	3.82	0.82	Peat	Wetlands	0.0015
6	6229	Acksjön Nedre	0.85	3.93	Thin soils and bare rock	Coniferous forest	0.0013
7	6525	Stormyra	4.02	4.73	Thin soils and bare rock	Coniferous forest	0.0012
8	314	Hålabäck	4.74	5.31	Till	Deciduous forest	0.0011
9	33 894	Vuoddasbäcken	41.29	4.35	Till	Coniferous forest	0.0005

*Predominant type. S-HYPE: the HYPE (Hydrological Predictions for the Environment) model calibrated for Sweden.

Table 2. Description of the parameters and the sampling range for the parameter modifiers chosen for the sensitivity analysis.

No.	Parameter name*	Unit	Parameter dependency	Process	Description	Modifier's sampling range	
						Min	Max
1	rivvel	$m s^{-1}$	General	River	Celerity of flood in watercourse (rivvel > 0)	-0.5	1.6
2	rrcs3	$\Delta t^{-1} \%^{-1}$	General	Runoff	Recession coefficient for slope dependence (upper layer)	-0.95	4.0
3	cevp	$mm^{\circ}C^{-1} \Delta t^{-1}$	Land use	Potential evaporation (PET)	Controls the rate of potential evapotranspiration	-0.2	0.75
4	cmlt	$mm^{\circ}C^{-1} \Delta t^{-1}$	Land use	Snowmelt	Melting parameter for snow	-0.3	0.5
5	srrcs	Δt^{-1}	Land use	Surface runoff	Recession coefficient for surface runoff (fraction), is set to 1 for lake and river classes with floodplains	-0.95	2.0
6	ttmp	$^{\circ}C$	Land use	Snowmelt, snowfall and potential evaporation (PET)	Threshold temperature for snowmelt, snow density and evapotranspiration	-0.50	0.95
7	mperc1	$mm \Delta t^{-1}$	Soil type	Percolation	Maximum percolation capacity from soil layer 1 to soil layer 2	-0.2	6.0
8	mperc2	$mm \Delta t^{-1}$	Soil type	Percolation	Maximum percolation capacity from soil layer 2 to soil layer 3	-0.95	3.0
9	rrcs1	Δt^{-1}	Soil type	Runoff	Recession coefficient for uppermost soil layer	-0.2	2.5
10	rrcs2	Δt^{-1}	Soil type	Runoff	Recession coefficient for lowest soil layer	-0.8	3.0
11	srrate**	-	Soil type	Surface runoff	Fraction for surface runoff	-0.95	1.7
12	trrcs	Δt^{-1}	Soil type	Tile runoff	Recession coefficient for tile drains	-0.95	0.95
13	wcfc1	-	Soil type	Soil water content	Fraction of soil available for evapotranspiration but not for runoff, for uppermost soil layer	-0.95	3.0
14	macrate**	-	Soil type	Macropore	Fraction for macro-pore flow	-0.95	0.95
15	mactrinf	$mm \Delta t^{-1}$	Soil type	Macropore and surface runoff	Threshold for macro-pore flow	-0.7	4.0
16	mactrsm***	-	Soil type	Macropore and surface runoff	Threshold soil water for macro-pore flow and surface runoff (fraction of wcwp + wcfc in uppermost layer)	-0.5	0.6

* The modifier is additive for ttimp and multiplicative for the rest of the parameters.

** Following the limiting values that this parameter can take (between 0 and 1), modified sub-parameters smaller than 0 were replaced with 0.005 and values larger than 1 with 0.995.

*** Following the limiting values that this parameter can take, modified sub-parameters smaller than 0 were replaced with 0.0005.

Table 3. Total effect sensitivity index S_T per parameter and catchment. Catchments are sorted according to the average S_T . A description for each of the parameters can be found in Table 2.

[illegible]

4 Results and discussion

4.1 Catchment selection

There were a total of 156 available catchments that fulfilled the requirement for this study, whose areas vary from 0.85 to 27 400 km². The flashiness was estimated for each of the available

catchments (Fig. 2). A flashiness equal to 0.00037, obtained using the method described in Section 3.1, was found to be a good threshold to limit those with sub-daily response. All catchments with flashiness above the threshold had relatively small area (between 0.85 and 850 km²). However, not all small catchments had a sub-daily response. These results are

Table 4. Description of the parameters selected for calibration and the sampling range for their modifiers. Parameters are sorted according to the average $\bar{S}_T$.

No.	Parameter name*	Unit	Parameter dependency	Process	Description	$\bar{S}_T$	Modifier sets sampling range	
							Min	Max
1	cevp	mm °C ⁻¹ Δt ⁻¹	Land use	Evapotranspiration	Controls the rate of potential evapotranspiration	0.48	-0.2	0.75
2	cmlt	mm °C ⁻¹ Δt ⁻¹	Land use	Snowmelt	Melting parameter for snow	0.30	-0.3	0.5
3	ttmp	°C	Land use	Snowmelt, or snowfall and potential evaporation (PET)	Recession coefficient for slope dependence (upper layer)	0.28	-0.50	0.95
4	wcfc1	-	Soil type	Water content	Fraction of soil available for evapotranspiration but not for runoff, for uppermost soil layer	0.12	-0.95	3.0
5	rrcs1	Δt ⁻¹	Soil type	Runoff	Recession coefficient for uppermost soil layer	0.07	-0.2	2.5
6	mactrinf	mm Δt ⁻¹	Soil type	Macropore and surface runoff	Threshold for macro-pore flow (max infiltration)	0.03	-0.7	4.0
7	rivel	m s ⁻¹	General	River	Celerity of flood in watercourse (rivel > 0)	0.03	-0.5	1.6
8	srrate**	-	Soil type	Surface runoff	Fraction for surface runoff	0.02	-0.95	1.7
9	rrcs2	Δt ⁻¹	Soil type	Runoff	Recession coefficient for lowest soil layer	0.02	-0.8	3.0

* The modifier is additive only for ttmp and multiplicative for the rest of parameters.

** Following the limiting values that this parameter can take, modified sub-parameters smaller than 0 were replaced with 0.005 and values larger than 1 with 0.995.

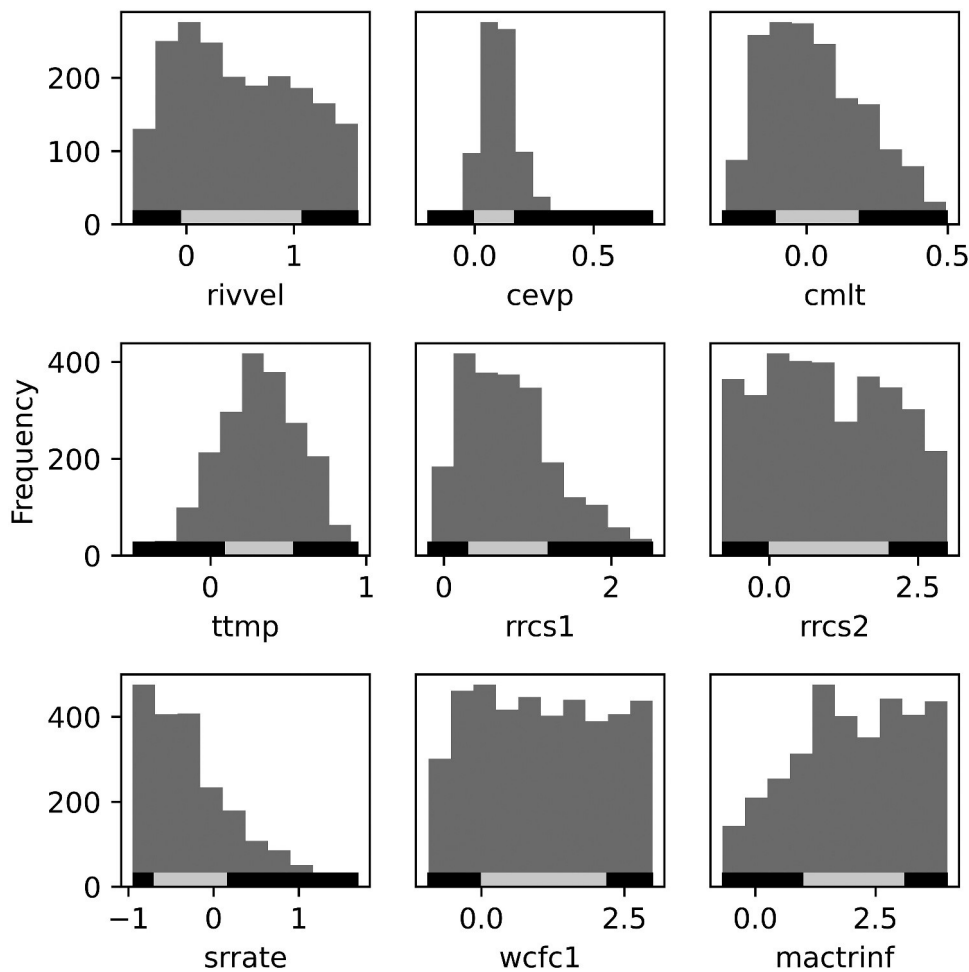


Figure 4. Frequency distribution of the parameter modifiers for all sets considered acceptable. Horizontal black and light grey lines on the x-axis show, respectively, the initial sampling range and the reduced range produced by considering only the modifier sets for which each of the modifiers fell within the 20th to 80th percentile. A description for each of the parameters can be found in Table 2.

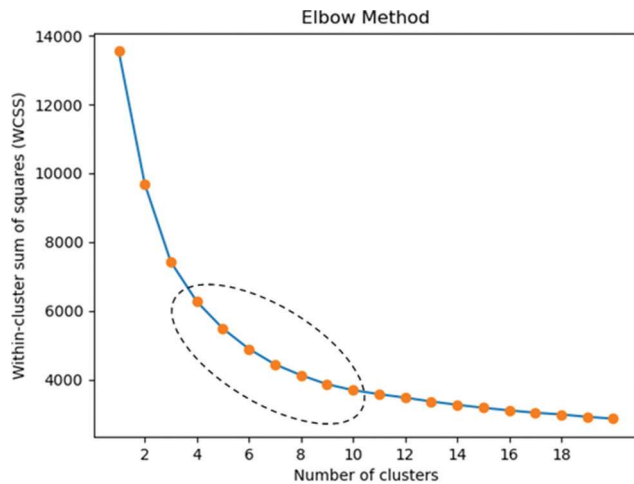


Figure 5. Elbow plot of clusters. The dashed ellipse encompasses the number of clusters where the inflection occurs (between four and 10 clusters).

expected, as basin response time depends not only on their size but also on the catchments' geology and soils (Blöschl and Sivapalan 1995, Merz *et al.* 2009).

Nine catchments (shown in Fig. 3 and Table 1) were selected for calibration by assessing whether they belong to the group of catchments with sub-daily response time and the other criteria described in Section 3.1 were fulfilled. The rest of the available catchments, i.e. 147 catchments, were used for evaluation. The majority of the catchments used for calibration are located in Southern Sweden and may not be fully representative of the whole country, but the southern part is the most densely populated, and therefore the region where high-resolution model results and flood forecast are of greatest interest.

4.2 Calibration

4.2.1 Identification of sensitive parameters for calibration

A total of 16 parameters were initially considered to be important in controlling the major hydrological processes in the model. Most of the parameters (10) were soil-type dependent (Table 2). A wide but plausible sampling range was assumed at first and later reduced after an initial GSA test. For example, too-extreme values for the *cevp* parameter always led to very poor performance, thus the range was reduced to a more feasible one.

The total sensitivity index (S_T) per parameter and for each of the calibrated catchments as well as the average for all catchments is shown in Table 3. Five parameters had S_T equal to zero and therefore have no impact on the model output uncertainty. Nine parameters (those with S_T greater than 0.01 in Table 3) were chosen for calibration (see Table 4).

4.2.2 Acceptable and best representative modifier sets

A total of 1984 out of 210 000 sets of parameter modifiers (approximately 1%) were considered acceptable (i.e. these sets improved the performance for each of the calibrated catchments). The posterior frequency distributions of the accepted modifier values are shown in Fig. 4. The range of the distribution can further be reduced by considering only the modifier sets for which each of the modifiers fall within the 20th to 80th percentile of its own group of acceptable values (see Fig. 4). The parameters found acceptable in this study and their corresponding likelihood can be used to scale the daily model to an hourly version for prediction in the calibrated catchments (Beven 2006, 2012) as in Fuentes-Andino *et al.* (2017). If the results for the evaluation catchments are also satisfactory, it can be used for the entire model domain.

The optimal number of clusters identified using the k-means clustering technique together with the elbow method lies between four and 10 clusters (Fig. 5). Here it was decided to use 10 clusters, i.e. the number of clusters for which the smallest change in the total WCSS is gained by adding one more. The modifier values for each of the ten best representative modifier sets (one per cluster) are shown in Table 5. It can be seen that modifiers can take many different values (see also the variation in their distributions in Fig. 4) but lead to equally good performance (that they are assessed based on NSE). This is expected as different parameter sets can be equally good in reproducing the model's outcome (Beven and Binley 1992, Beven 2006).

Performances of the one-day, the one-hour unit-converted and the one-hour scaled S-HYPE (shown for 10 different representative modifier sets) are compared in Fig. 6. Figure 7 is similar to Fig. 6 but shows the one-day averaged outputs of the one-hour models. The comparisons are done for three different sub-groups: the nine calibrated catchments, 34 catchments with sub-daily response time (flashiness greater than 0.00037), and all 147 evaluation catchments.

All sub-groups in Fig. 6 show similar results for the first two box plots (dark grey): the loss in performance when only

Table 5. Representative best modifier sets found through calibration. Sets are sorted according to the average Nash-Sutcliffe Efficiency (NSE) for all calibrated catchments. Maximum and minimum values per parameter are shaded. A description for each of the parameters can be found in Table 2.

Modifier set	Parameters									NSE
	rivvel	cevp	cmlt	ttmp	rrcs1	rrcs2	srrate	wcfc1	macrinf	
1	1.300	0.071	−0.096	0.098	0.696	−0.610	−0.856	1.000	1.680	0.724
2	0.123	0.072	0.038	0.270	1.268	0.276	−0.737	1.963	0.916	0.724
3	0.879	0.103	0.014	0.268	0.632	0.018	−0.664	1.714	1.359	0.724
4	0.681	0.096	0.150	0.467	0.979	0.191	−0.627	1.664	2.699	0.724
5	1.300	0.071	−0.096	0.098	0.696	−0.610	−0.856	1.000	3.701	0.723
6	0.968	0.165	0.013	0.305	0.862	−0.319	−0.835	−0.197	−0.548	0.723
7	0.630	0.081	−0.087	0.056	1.205	2.050	−0.692	2.432	1.893	0.721
8	1.458	0.120	−0.072	0.102	0.980	2.408	−0.869	0.880	1.890	0.721
9	0.258	0.134	0.111	0.407	1.352	1.981	−0.175	1.293	2.956	0.721
10	0.382	0.193	0.015	0.222	1.702	2.183	−0.846	0.690	2.835	0.719

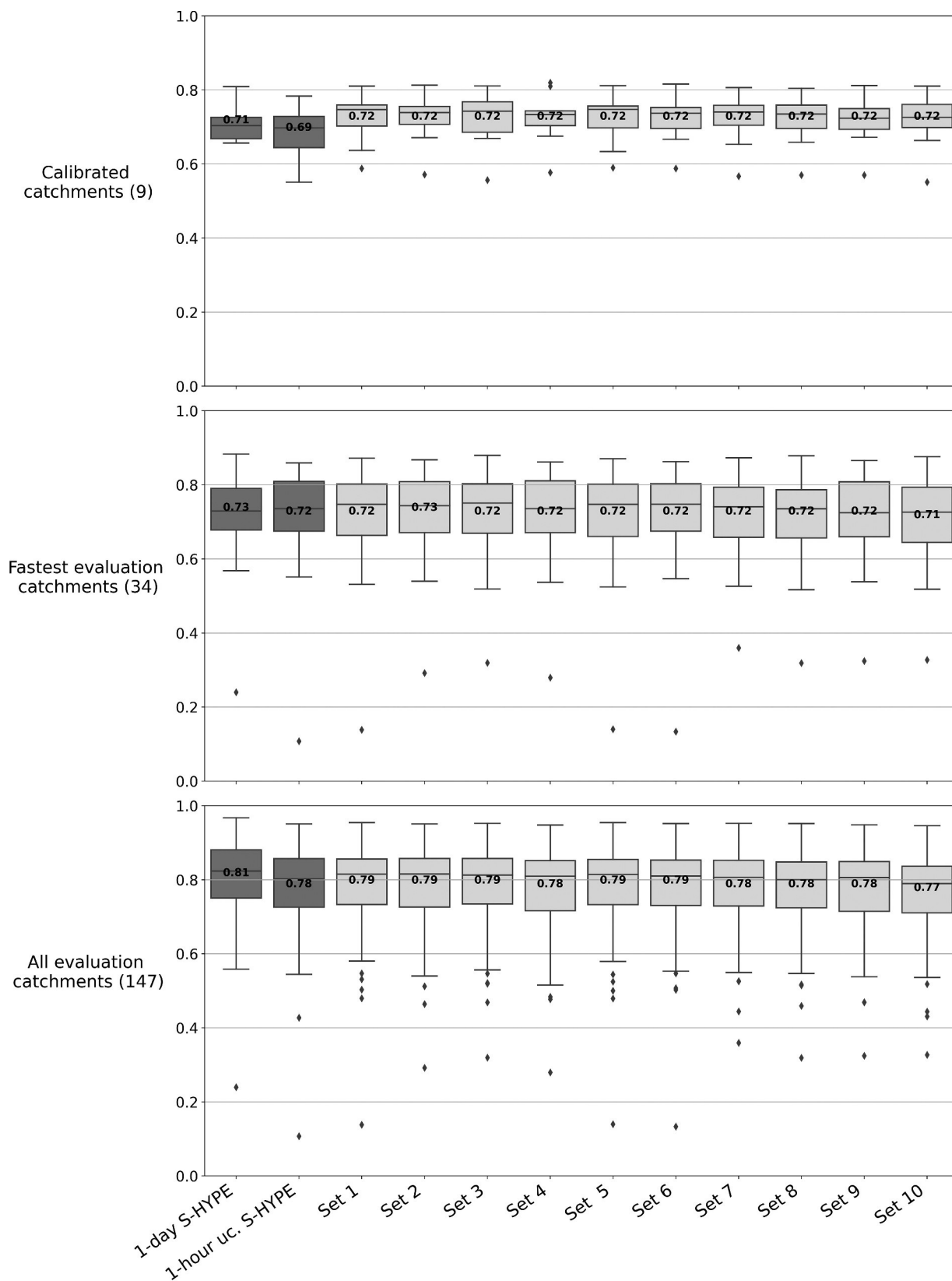


Figure 6. Box plot of the Nash-Sutcliffe Efficiency (NSE) for only calibrated, fast (sub-daily response) and all evaluation catchments. Each sub-plot shows the box plot for the one-day and one-hour unit-converted S-HYPE and the best sets of modifiers found through model calibration (1–10). The mean value is labelled while the box plot shows the median value. uc.: unit-converted; S-HYPE: the HYPE (Hydrological Predictions for the Environment) model calibrated for Sweden.

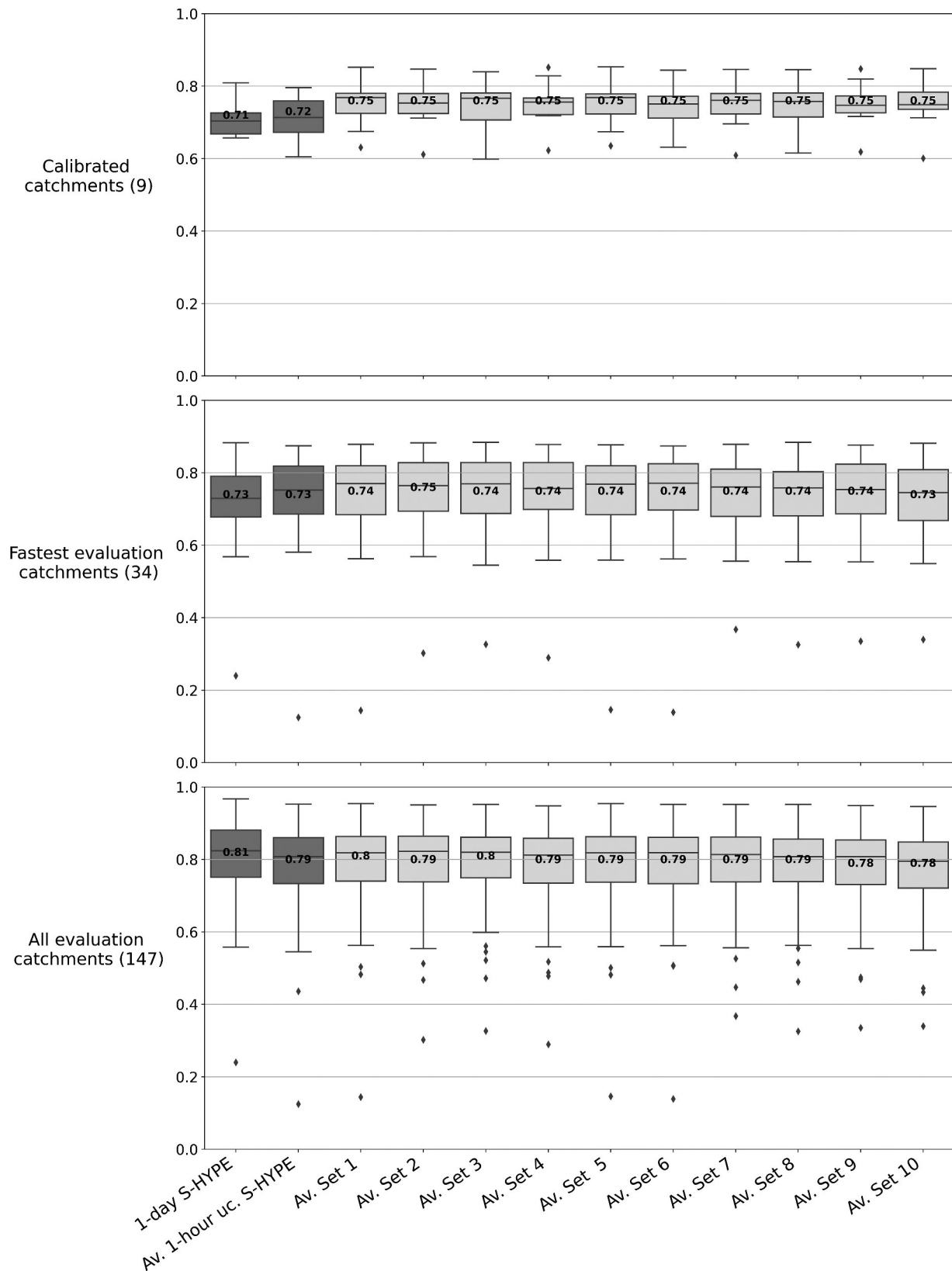


Figure 7. Box plot of the Nash-Sutcliffe Efficiency (NSE) for only calibrated, fast (sub-daily) and all evaluation catchments. Each sub-plot shows the box plot for the one-day S-HYPE, for the daily average outputs of the one-hour unit-converted S-HYPE and for the best modifier sets (1–10). The mean value is labelled while the box plot shows the median value. Av.: averaged; uc.: unit-converted; S-HYPE: the HYPE (Hydrological Predictions for the Environment) model calibrated for Sweden.

transferring the parameters from the one-day to the one-hour model is relatively small. $\overline{NSE}$ decreased by 0.02, 0.01, and 0.03, respectively, in the calibrated catchments, evaluation catchments with sub-daily response time, and all evaluation catchments. Some similar previous studies have found a significant loss in model performance when transferring model parameters from coarser to finer time steps using different models (Cullmann *et al.* 2006, Littlewood and Croke 2008, Ostrowski *et al.* 2010, Bastola and Murphy 2013, Jie *et al.* 2018). Our results are more in line with the results of Reynolds *et al.* (2017) and Ficchi *et al.* (2016), who found the loss in performance when transferring parameters across time scales using the HBV and GR4 models, respectively, to be negligible. The reason for the negligible loss in performance may be that most of the parameters in HYPE are related to catchment properties.

Through calibration we were able to find a small number of acceptable modifier sets, which slightly increased the model performance for catchments with sub-daily response time (top sub-plot in Fig. 6). The improvement in terms of NSE obtained for the nine calibrated catchments is small, especially considering that the calibration here was made by tuning nine of the parameters of the one-hour unit-converted model, thus ensuring a good performance in these basins. Given the uncertainties in all models and data, the improvements of the model after calibration are negligible. There were no clear improvements for fast-responding evaluation catchments (middle sub-plot in Fig. 6). In addition, when catchments with slower response time are included, the performance of the one-hour model in reproducing the average daily values was slightly worse than the corresponding performance of the one-day model (bottom sub-plot in Fig. 6).

In general, the gain in performance obtained through calibration is slightly better when evaluating the results at the daily scale (i.e. comparison of Figs 6 and 7). Larger improvements were reported by Ficchi *et al.* (2016) and Jie *et al.* (2018). The improvement was slightly better for fast-responding catchments, as in Ficchi *et al.* (2016).

The one-hour model built by unit-converting and scaling parameters from the one-day model resulted in small to negligible improvement over the one-day model for fast-responding catchments, while the performance was slightly worse for slow-responding catchments. This can be seen for both, the hourly model simulation (Fig. 6) and the daily average of the 1-hour model simulation (Fig. 7). The deterioration in performance for slow-responding catchments can be attributed partly to the focus placed in this work on calibrating catchments with sub-daily response time.

The lack of improvement in model performance achieved through the calibration exercise to estimate modifiers to scale the model parameters might be due to the simplicity of the scaling approach formulated in this work. Time scalability of parameters might depend on catchment characteristics that are not considered here. There might also be limitations in representing additional complexities that come with shorter time steps in the model structure (Hughes 1993, Ficchi *et al.* 2016), making it difficult to achieve improvement of model performance at shorter time scales. Furthermore, the rainfall and runoff data with shorter time resolution might be

associated with larger noise (Yu *et al.* 1997.), thus leading to deterioration of the model performance at shorter time steps.

Rescaling model parameters calibrated at one time scale to another may not always be straightforward, as some of the hydrological processes may vary in a complex way at different time scales. A more elaborate non-linear relationship between the model parameters at different time scales may better capture the relationship and reduce the uncertainty. This may be tested in a future work, including the possibility of transferring parameters to even finer time scales.

5 Conclusions

In this study, we tested whether transferability of parameters from the HYPE model calibrated at a daily time step for Sweden (S-HYPE) to the same model set-up operating at an hourly time step was possible without a considerable loss of model performance. We further tested, through a calibration exercise, whether a simple approach to scaling of the model parameters could improve the performance of the hourly model over just transferring them across time scales. Finally, we tested whether the average daily output of the hourly model performs better than the daily model at a daily time step. The work was motivated by the need to have a simple yet practical framework to obtain a model that captures the fine-scale variability of discharge in fast-responding catchments, where otherwise important events, like short-lived flow peaks, would be missed. Such a modelling capability is crucial for flood forecasting in small and fast-responding catchments.

In this study the following findings were made:

- Only unit-converting the S-HYPE model parameters from daily to hourly time step led to a negligible loss of performance in terms of NSE for all 147 catchments, both fast- and slow-responding ones. Thus, when hourly data is available, parameters of the S-HYPE model calibrated at the daily time step can be unit-converted and used at the hourly resolution without much loss in performance.
- Calibration of S-HYPE at the hourly time step by assuming a simple scaling approach led to a small to negligible improvement for catchments with sub-daily response time. However, the performance of the daily model could not be surpassed by any of the hourly models for slow-responding catchments.
- The negligible improvement of the model performance achieved by using a scaling approach might suggest the need for a more complex scaling method than the additive and multiplicative approaches used here. Performance at an hourly time step might also be affected by noise in higher time resolution input and evaluation data or because the model structure is more fit to simulate at a daily or longer time step.
- The gain of using an hourly model became slightly better in terms of NSE when the output was averaged over a day.

The results shown here and the conclusions drawn relate to the calibration and evaluation methodology used in this work. A more complex scaling method or a more elaborate calibration

strategy, for instance through increasing the number of calibration catchments and considering a unique modifier per each parameter, may improve the performance that can be achieved through calibration. This can be tested in a future study.

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