The multiscale Routing Model mRM v1.0: simple river routing at resolutions from 1 to 50 km

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Abstract. Routing streamflow through a river network is a fundamental requirement to verify lateral water fluxes simulated by hydrologic and land surface models. River routing is performed at diverse resolutions ranging from few kilometers to around 1°. The presented multiscale Routing Model mRM calculates streamflow at diverse spatial and temporal resolutions. mRM solves the kinematic wave equation using a finite difference scheme. An adaptive time stepping scheme fulfilling a

5 numerical stability criteria is introduced in this study and compared against the original parametrization of mRM that has been developed within the mesoscale Hydrologic Model (mHM). mRM requires a high-resolution river network, which is upscaled internally to the desired spatial resolution. The user can change the spatial resolution by simply changing one number in the configuration file without any further adjustments of the input data. The performance of mRM is investigated on two datasets: a high-resolution German dataset and a slightly lower resolution European dataset. The adaptive time step scheme within

10 mRM shows a remarkable scalability compared to its predecessor. Median Kling-Gupta efficiencies change less than 3 percent when the model parametrization is transferred from 3 to 48 km resolution. mRM also exhibits seamless scalability in time, providing identical results when forced with hourly and daily runoff. The streamflow calculated over the Danube catchment by the Regional Climate Model REMO coupled to mRM is comparable at 25 and 50 km resolution. The mRM source code is freely available and highly modular facilitating an easy internal coupling in existing Earth System Models.

1 Introduction

Streamflow provides an integrated signal of lateral hydrologic fluxes at the land surface over a catchment area. Streamflow observations are routinely used within hydrologic modeling to perform model characterization or calibration/validation (Beven, 2012). Comparisons between simulated and observed streamflow are typically conducted using measures focusing on daily values (Nash and Sutcliffe, 1970; Gupta et al., 2009). Similarly to hydrologic models (HM), land-surface models (LSM) also

20 represent the terrestrial hydrologic cycle. They additionally include the terrestrial energy budget and biogeochemical cycles, such as the carbon cycle, to provide the exchange fluxes of the land-surface with the atmosphere in, for example, Regional Circulation Models (RCM) or Earth System Models (ESM). Streamflow is estimated in ESMs to provide fresh water input of the land surface into the ocean (Sein et al., 2015). Streamflow observations are also used in land surface models in the context

of climate studies to validate the hydrologic cycle at daily (a.o., Marx et al., 2018; Thober et al., 2018; Samaniego et al., 2018), monthly (a.o., Hagemann et al., 2009; Li et al., 2015; Zhang et al., 2016) or even annual time scales (a.o., Zhou et al., 2012).

Hydrologic models and land surface models (LSM) are historically run at different spatial resolutions. Hydrologic models (HM) are, for instance, applied at scales of few kilometers and less, even in continental-scale applications (Wood et al., 2011;

5 Marx et al., 2018; Thober et al., 2018; Samaniego et al., 2018), whereas LSMs are applied at resolutions of tens of kilometers and more within climate change studies (Van der Linden and Mitchell, 2009; Taylor et al., 2012). However, a substantial increase in model resolution has been achieved for Regional Circulation Models (RCM) in the past years and these are run nowadays at different resolutions down to the convection-permitting scale of a few kilometers (Jacob et al., 2014). Applying RCMs at diverse resolutions implies that the same LSM (i.e., the same representation of water, energy, and biogeochemical

10 processes) is used on diverse resolutions. This imposes a challenge on the LSM parametrizations to be able to represent all included processes at the different resolutions (Wood et al., 1998; Haddeland et al., 2002; Boone et al., 2004). One goal of this study is to make streamflow observations accessible to LSMs independent of their modeling resolution.

River routing is the process of predicting the hydrograph evolution as runoff moves through a river network. It can be described at different levels of complexity. The general governing equation of this phenomena are the uni-dimensional Saint-

15 Venant equations (de Saint-Venant, 1871). Models using the Saint-Venant equations are referred to as hydraulic models that are especially suited if backwater effects occur such as in flat regions or river deltas (Paiva et al., 2011; Miguez Macho and Fan, 2012; Paiva et al., 2013; Yamazaki et al., 2013). These models exploit remote sensing to derive model parameters and setup (Neal et al., 2012; Beighley et al., 2009). If rivers are steep enough and relatively shallow, simplification of the Saint-Venant equations such as the kinematic wave equation are sufficient (Lohmann et al., 1996; Hagemann and Dümenil, 1997;

20 Todini, 2007). They require less information about river topography and only account for wave advection and attenuation. These models are not applicable for large river basins with extensive floodplains such as the Amazonas and Niger because they cannot account for floodplain inundation (Neal et al., 2012; Getirana et al., 2012; Pontes et al., 2017), which causes a negatively skewed hydrograph (Collischonn et al., 2017). It is worth noting that the impact of floodplain processes dominates the differences between a hydrodynamic model and kinematic wave models (Paiva et al., 2013).

25 A common approach to achieve scale-independent streamflow is to perform the river routing calculations on a fixed spatial and temporal resolution, regardless of the resolution of the hydrologic or land surface model providing the input runoff flux. Global routing schemes, for example, often use fixed 0.5° or 1.0° resolutions to produce river discharge of large river basins globally (Hagemann and Dümenil, 1997; Pappenberger et al., 2009; Hagemann et al., 2009; Oki et al., 1999). Within hydrologic models, high-resolution routing algorithms at fixed scales of 5 to 16 km are used (David et al., 2011; Kumar et al., 2013b, a).

30 Only few studies have explicitly investigated the spatial scaling capabilities of existing routing approaches by introducing sub-grid and between-grid heterogeneities (Li et al., 2013).

The main objective of the multiscale Routing Model mRM presented in this study is to provide a simple, both in model complexity and applicability, river routing of hydrologic and land surface model outputs at various spatial resolutions ranging from the kilometer scale to large scales at 50 km or more in a seamless way (Samaniego et al., 2017b). The stand-alone model

35 allows the user to adjust freely the spatial resolution by simply changing a single number in a configuration file without any

further modifications of the input data. The resolution of routing should thereby not influence the obtained streamflow, otherwise model re-calibrations at each resolution would be necessary. mRM also keeps the computational demand to a minimum, one major advantage of a scalable modeling system (Kumar et al., 2013a).

The analysis of the scaling capabilities of the multiscale Routing Model mRM is shown at 622 catchments in Europe ranging in size from about $100\,\mathrm{km}^2$ to $100\,000\,\mathrm{km}^2$ and spatial resolutions from 1 to 48 km (section 3.2). The river network has to be provided only at the highest spatial resolution supported by the available data, for example a digital elevation map. This high-resolution river network is then internally upscaled to the resolution specified by the user in a configuration file. The upscaling accounts for the correct representation of the catchment area/stream network without any further data requirement (section 2.4). A parameter sensitivity analysis is presented at all of the 622 catchments, which highlights the little influence of the model parameter of mRM (section 3.1). The multiscale Routing Model mRM is coupled internally to the mesoscale Hydrologic Model mHM (Samaniego et al., 2010; Kumar et al., 2013b) and the improvement of mRM over the original routing parametrization in mHM is demonstrated (section 3.3). The overall focus of mRM is to provide a simple routing tool that can be coupled to any land-surface and hydrologic model across several spatial resolutions, and giving them access to streamflow observations. mRM is applied as a stand-alone post-processor to the output of the REMO Regional Climate model over the Danube catchment for demonstration (section 3.4).

2 Description of the multiscale Routing Model mRM

2.1 Finite Difference Approximation of Kinematic Wave Equation

The multiscale Routing Model mRM uses the kinematic wave equation, first analyzed by Lighthill and Whitham (1955), to describe the water flow within a stream as

$$\frac{\partial Q}{\partial t} + c\frac{\partial Q}{\partial x} = 0, \tag{1}$$

where Q ($\mathrm{m^3\,s^{-1}}$) is streamflow, x (m) the space dimension, t (s) the time dimension, and c ($\mathrm{m\,s^{-1}}$) the celerity. The kinematic wave equation is a simplification of the Saint-Venant equations (Chow et al., 1988). The derivation is based on the assumption that the continuity equation is sufficient to describe the movement of flood waves. In detail, a constant river bed slope and time-invariant celerity c have to be assumed (Lighthill and Whitham, 1955). Kinematic waves account for the advection of water but not for complex fluvial processes such as flood wave attenuation, backwater effects, and floodplain inundation. However, it is widely used because advection is the governing fluvial process as long as backwater and floodplain inundation effects can be neglected (Paiva et al., 2013). mRM employs the classical finite difference weighted approximation on a four points scheme to solve equation (1). Details about the derivation can be found in Chow et al. (1988) and Todini (2007). It is summarized shortly in the following.

The partial derivatives within equation (1) are represented as finite differences between four values, that means on two locations at two points in time:

$$\frac{\partial Q}{\partial t} \approx \frac{\epsilon(Q(x_j, t_{i+1}) - Q(x_j, t_i)) + (1 - \epsilon)(Q(x_{j+1}, t_{i+1}) - Q(x_{j+1}, t_i))}{\Delta t},$$

$$\frac{\partial Q}{\partial x} \approx \frac{\varphi(Q(x_{j+1}, t_{i+1}) - Q(x_j, t_{i+1})) + (1 - \varphi)(Q(x_{j+1}, t_i) - Q(x_j, t_i))}{\Delta x}, \tag{2}$$

5 where j denotes the spatial location (i.e., reach id) and i denotes the timestep. ϵ is a space-weighting factor and φ is a time-weighting factor. mRM uses a rectangular grid to represent the river network with a river reach in the model connecting two center grid locations. Different spatial locations are separated by Δx and time steps by Δt. The two weighting factors, ϵ and φ, can be chosen between 0 and 1, but the numerical solution becomes unstable for $\epsilon > 0.5$ (Cunge, 1969). The numerical diffusion depends linearly on ϵ (Cunge, 1969), with 0 implying full numerical diffusion and 0.5 no numerical diffusion, respectively.

10 Setting φ to 0.5, which represents a time-centered scheme, and substituting equation (3) into equation (1) results in the classical linear equation:

$$Q(x_{j+1}, t_{i+1}) = C_1 Q(x_j, t_{i+1}) + C_2 Q(x_j, t_i) + C_3 Q(x_{j+1}, t_i), \tag{3}$$

with the coefficients C_1, C_2 and C_3 being:

$$C_1 = \frac{-2\Delta x \epsilon + c\Delta t}{2\Delta x(1 - \epsilon) + c\Delta t},$$

15 $$C_2 = \frac{2\Delta x \epsilon + c\Delta t}{2\Delta x(1 - \epsilon) + c\Delta t}, \tag{4}$$

$$C_3 = \frac{2\Delta x(1 - \epsilon) - c\Delta t}{2\Delta x(1 - \epsilon) + c\Delta t}.$$

The coefficients C_1, C_2 and C_3 add up to one. The spatial resolution at which equation 3 is applied is called "routing" resolution in the following.

2.2 Stream Celerity Parametrization based on Terrain Slope

20 Two parametrizations of equation (5) are available in mRM: firstly the regionalized Muskingum-Cunge (rMC) parametrization with a fixed time step as implemented in the mesoscale Hydrologic Model mHM presented in Samaniego et al. (2010) and Kumar et al. (2013b), and secondly the newly developed parametrization using spatially varying celerities in combination with an adaptive time step (aTS). A short summary of the former is presented in the Appendix A and is referred to as rMC in the following. The latter is described in detail in this and the next section and is referred to as aTS scheme.

25 The aTS calculates stream celerity as a function of terrain slope using a simple relationship:

$$c_i = \gamma \sqrt{s_i}, \tag{5}$$

where c_i, s_i and γ are celerity, terrain slope and a free model parameter, respectively, and i is the grid cell index. Equation 5 was proposed by Miller et al. (1994) for evaluating the accuracy of atmospheric GCMs against streamflow observations. They used $\gamma = 49$ with a topography at 5' resolution (ca. 10 km at the equator). Coe (2000) used the same formulation also at 5'

resolution but set $\gamma = 113$. $\gamma = c_0/\sqrt{s_0}$ is the ratio of a minimum celerity c_0 over the square root of a reference slope s_0. The latter should depend on the resolution of the input data so that the aTS model parameter γ should theoretically also depend on the resolution of the underlying terrain data, i.e., the Digital Elevation Model (DEM). Because both parameters, c_0 and s_0, are unknown, aTS uses only the combined model parameter γ. It is set to range between 0.1 and 30 in this study because values

5 above 30 led to unrealistic celerities with the two DEMs of 100 m and 500 m resolution used (see below). The parametrization used here (equation 5) is an alternative to Manning's equation (Manning, 1891; Chow et al., 1988), which is more physically based than equation 5, but additionally requires information of river cross sections and Manning's roughness coefficient, which need to be parametrized if observations are not available. Manning's equation thus typically requires more parameters than the equation 5. The latter is used in aTS because of its simplicity and the sufficiently high model performance (see Section 3.1).

10 The celerity relationship (equation 5) is applied at the resolution of the Digital Elevation Model (DEM), from which terrain slope is derived. Ideally, channel slope instead of terrain slope should be used in equation 5, but it is not as available as terrain slope. Applying equation 5 at the resolution of the DEM provides a compromise because a high-resolution DEM provides a close approximation of channel slope. A median absolute deviation (MAD) filter (Sachs, 1999) is applied to the high resolution slope data along the path of the main river with a threshold value of 2.25 to correct for outliers. Large slope

15 outliers happen easily in DEMs, for example, when the river flows in a valley and one grid cell represents the valley while the next grid cell represents the hill top. A minimum river bed slope of 0.1% is further assumed. The celerities are then upscaled to the routing resolution, i.e., the resolution at which the kinematic wave equation is solved (equation 3). The upscaling is by averaging with the harmonic mean, the correct averaging operator for celerities (or speed). This follows the Multiscale Parameter Regionalization (MPR) approach (Samaniego et al., 2010; Kumar et al., 2013b), which relates model parameters to

20 physiographic characteristics at the highest resolution possible. The upscaling considers also only those high-resolution grid cells that align with the path of the main river because aTS only considers the flow in the main river reach, assuming that travel times in the main reach dominate the routing process in tributaries. Alternative models such as MOSART (Li et al., 2013) also consider flow in tributaries and head waters.

2.3 Adaptive Time Step (aTS) Implementation

25 The aTS scheme uses an adaptive time step to calculate the linear coefficients in equation (5). The basic idea is that the time step should be such that water has not been transported further than Δx during a single step. This condition is generally known as Courant-Friedrich-Lewy criterium, which is a necessary condition for numerical stability of finite difference schemes (Courant et al., 1928). The condition can be expressed as:

$$C_r = \frac{c\Delta t}{\Delta x} \leq C_{max} = 1, \tag{6}$$

30 where C_{max} is the Courant number. aTS uses a Courant number of 1 (Bates et al., 2010). The Courant condition couples the applied spatial resolution with the integration time step of the finite difference scheme. Celerities c_i are typically in the order of a few m s^{-1}, calculated using equation 5 and averaged harmonically along the river path. Spatial grids are in the range of a few kilometers to around 100 km in the case of regional to continental applications. The time step Δt is chosen such that it

does not deviate too much from the Courant number C_{max} (equation 6) to keep computational demand to a minimum. This implies that Δt ranges from a few minutes for high-resolution grids to a few hours for continental scale applications.

In detail, aTS chooses Δt from a set of prescribed values such that $c_i \Delta t / \Delta x$ is close to but less than 1 for all celerities c_i. The prescribed values range from one minute to one day, namely: 1 min, 2 min, 3 min, 4 min, 5 min, 6 min, 10 min, 12 min, 15 min, 20 min, 30 min, 1 h, 2 h, 3 h, 4 h, 6 h, 8 h, 12 h, and 1 day. The choice of these values is motivated from the fact that these represent multiples or dividers of hourly and daily time steps. These time steps allow in principle model applications from 100 m to 100 km, for typical celerities around $1.5\,\mathrm{m\,s^{-1}}$.

Note that the chosen time step depends only on the spatial resolution and is independent of the time resolution of the provided forcing. For example, applying aTS at 12 km resolution using a celerity of $c = 1.5\,\mathrm{m\,s^{-1}}$ gives $\Delta x/c$ of 2.2 hours and, hence, a time step of two hours will be chosen. If aTS is forced with hourly input, it will aggregate the input over two consecutive time steps prior to the routing. The calculated streamflow is then distributed to the previous two time steps because these represent the mean flow over this period. If aTS is forced with daily input, it will use internally 12 iterations of 2-hour time steps to route the water through the river network. In this case, aTS will also return the average of the calculated 12 streamflow values at each reach.

2.4 Data Requirements and Model Setup
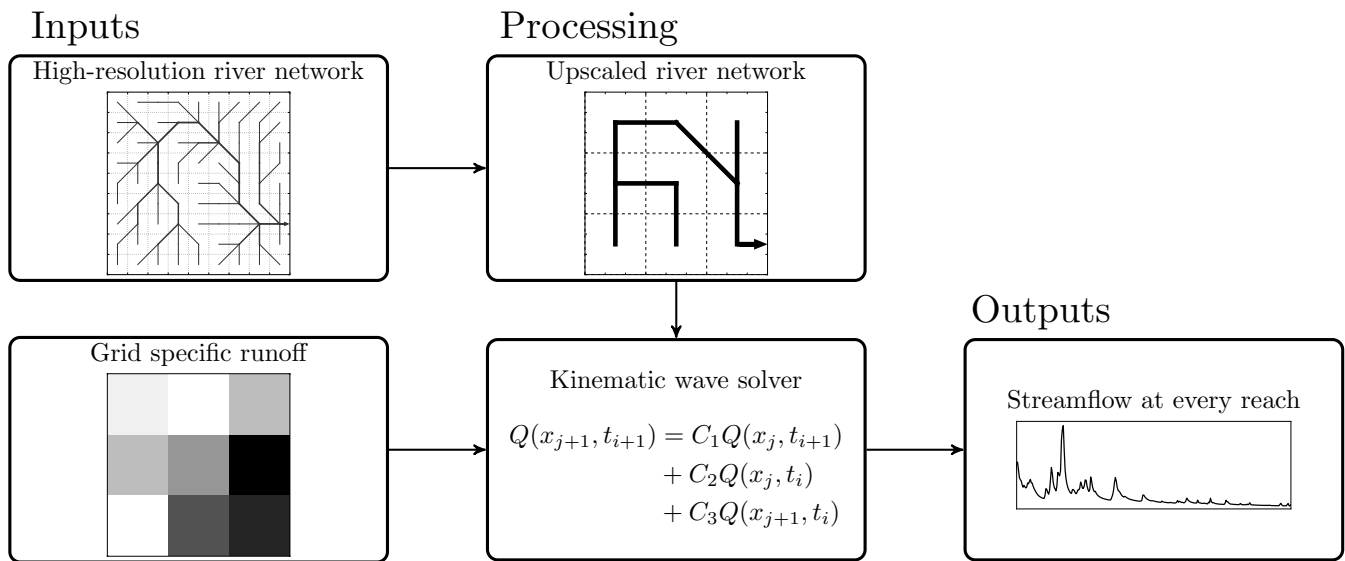
Figure 1. Flowchart of the processing steps required to run the multiscale Routing Model mRM: left, input: static high-resolution information about the routing network and dynamic runoff field; middle, internal mRM processing: aggregation of static and dynamic data to the routing resolution given by the user and execution of routing at this resolution; right, output: calculated streamflow at prescribed gauge.

Three different input variables are required to run the multiscale Routing Model mRM. First, mRM requires information about the river network. mRM uses a rectangular grid to represent the river network over a domain (Yamazaki et al., 2011). Water can only be transported from a specific grid cell to one of the eight neighboring cells following the steepest slope direction (D8 method, O'Calaghan and Mark, 1984). This procedure has to be carried at the highest possible resolution supported by the

5   available dataset. For example, a high-resolution 100 m digital elevation model (DEM) can be used to calculate flow directions following the D8 method (Figure 1 top left). It is worth mentioning that DEMs typically have to be adjusted to align with existing river networks using additional information about river locations (Döll and Lehner, 2002). High-resolution datasets such as HydroSHEDS (Lehner et al., 2006) can be used alternatively. Once the high-resolution flow direction is obtained following the nomenclature of 1 – east to 128 – north east clockwise, it is internally upscaled in mRM (Figure 1 center top)

10   to the routing resolution specified by the user, employing the method of Döll and Lehner (2002). This upscaling technique has already been implemented in Samaniego et al. (2010). The flow direction at a low resolution grid cell (3×3 grid in Figure 1) is equal to the flow direction of the underlying high resolution grid cell with the highest flow accumulation. If this high resolution grid cell is not along an edge of the low resolution grid cell, then the low resolution grid cell is an outflow of the domain.

Second, the gridded runoff fields have to be provided in Network Common Data Form (NetCDF). Units of the forcing can

15   be either $\mathrm{mm\,h^{-1}}$ or $\mathrm{kg\,m^{-2}\,s^{-1}}$ to facilitate applications to hydrologic models as well as land surface models. The spatial resolution of the runoff field is required to be a multiple of the resolution of the flow direction field. The most common use case is that streamflow is calculated at the resolution of the runoff and mRM will upscale the river network to the resolution as described before. However, mRM puts no constraints on model resolution and simulations at higher or lower resolutions can be conducted as long as it is a multiple of both, the runoff grid and the grid of the flow directions. In this case, runoff will be

20   up-/down-scaled employing weighted area fractions, which guarantees mass conservation.

Third, observed river streamflow can be provided to mRM at multiple locations within the river network. These locations have to be specified within the high-resolution river network and are then located on the upscaled river network internally within mRM. However, users should be cautious when selecting the model resolution so that the streams represented by the gauging data are still resolved within the upscaled river network. Thus, the upscaled flow accumulation in each grid cell is given in an

25   output NetCDF file, which allows comparison to the drainage area of a given gauge. Observed discharge data is not required for mRM when applied, for example, at ungauged locations. It is, however, mandatory when performing model optimization. Different error measures such as Nash-Shutcliffe efficiency (Nash and Sutcliffe, 1970) and Kling-Gupta efficiency (Gupta et al., 2009) can be calculated directly in mRM to inform the user about model performance.

A test basin is provided alongside the model code to illustrate the different data required to run the model and their formatting.

30   The model code also contains pre-processing scripts to calculate the flow direction from a given DEM, or flow accumulation from given flow directions.

2.5   Experimental Setup

A total of 622 stream gauges are used in this study to assess the performance and scaling capabilities of mRM (Figure 2). These contain 368 basins in the German dataset (Figure 2a) and 254 basins in the European dataset (Figure 2b). Input for mRM
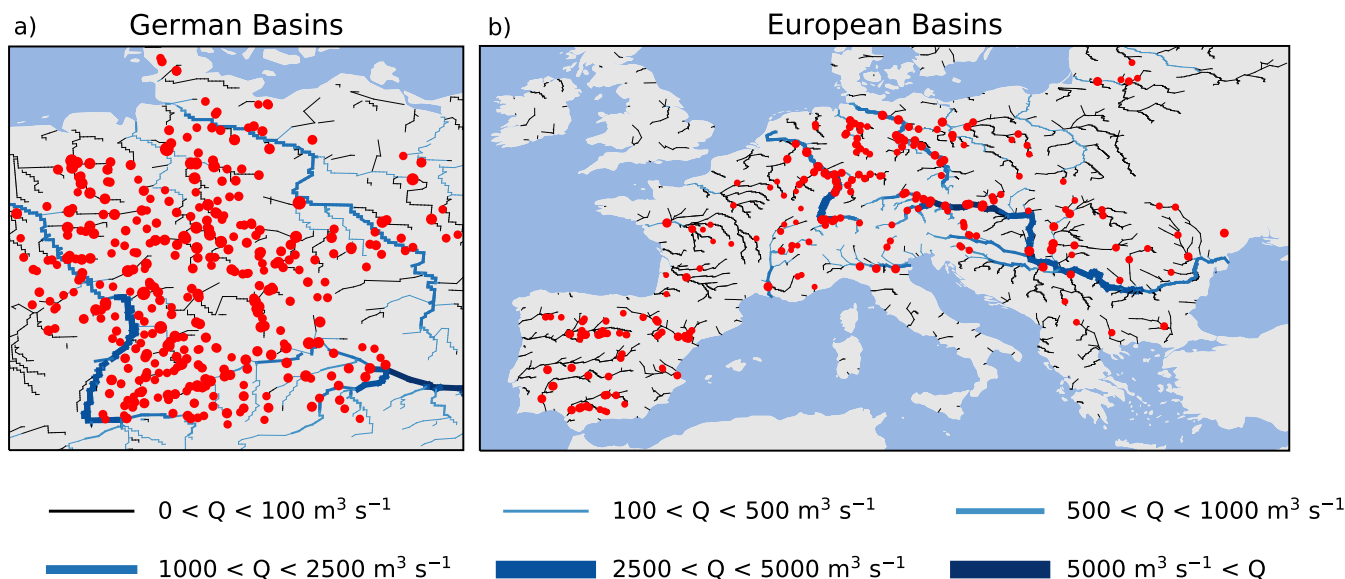
Figure 2. Discharge gauges used for the evaluation of the multiscale Routing Model mRM: a) 368 gauges in the German dataset, b) 254 gauges in the European dataset. In the background, the results of a pan-European simulation using the multiscale Routing Model mRM and the mesoscale Hydrologic Model mHM at a 5 km resolution is shown. The simulated streamflow Q is depicted for the 5th Aug 2002.

is derived from simulations carried out with the mesoscale Hydrologic Model mHM (Samaniego et al., 2010; Kumar et al., 2013b). Two different model setups for mHM are used in this study. The setup for the German dataset is identical to Samaniego et al. (2013) and Zink et al. (2016) with details given in Zink et al. (2017). The flow direction and accumulation are derived from a 100 m DEM. The setup for the European dataset was used in Thober et al. (2015) with details given in Rakovec et al.

5   (2016). The DEM used to derive the river network has a 500 m resolution in this case. Runoff simulated by mHM was stored at hourly and daily resolution NetCDF files for both sets of basins. mHM simulations for German dataset are provided at 4 km resolution while European simulations are provided at 24 km spatial resolution. The difference originates from the available meteorological forcing datasets, which are derived from station data of the German weather service at 4 km resolution (Zink et al., 2017) while E-OBS data at 24 km resolution (Haylock et al., 2008) was used for the European dataset. To study the

10 spatial scalability of mRM, streamflow is routed at different spatial resolutions, which are 1 km, 2 km, 4 km, 8 km, and 16 km for the German dataset and 3 km, 6 km, 12 km, 24 km, and 48 km for the European dataset. The selected resolutions cover a range of hydrologic applications from small to large scale modeling studies (Wood et al., 2011; Samaniego et al., 2017a) as well as scales of 0.5° used in climate studies (Taylor et al., 2012). Input runoff on 4 km for the German dataset and on 24 km for the European dataset is rescaled internally in mRM to the desired routing resolution that is provided in a configuration file.

15   The mesoscale Hydrologic Model mHM coupled to mRM using the regionalized Muskingum-Cunge (rMC) and adaptive time step (aTS) parametrization were calibrated at all catchments to provide a realistic representation of the hydrologic cycle. Details about model calibration can be found in Samaniego et al. (2010); Kumar et al. (2013b); Rakovec et al. (2016), and Zink

et al. (2017). The calibrations of both mHM and mRM parameters are carried out using the Shuffled Complex Evolution (SCE) algorithm (Duan et al., 1992). SCE is coupled internally to both models and SCE parameters (e.g., number of complexes) can be specified by users in a namelist.

The Kling-Gupta efficiency (KGE) is selected as a metric for evaluating model performance (Gupta et al., 2009). KGE is
5 composed of three measures that relate simulated and observed streamflow. These are the ratio of simulated and observed mean values, the ratio of simulated and observed standard deviations, and the Pearson correlation coefficient. In comparison to the Nash-Sutcliffe efficiency (NSE, Nash and Sutcliffe, 1970), KGE provides a more balanced metric that is less sensitive to high streamflow values than NSE.

The model calibration and evaluation employs daily values of observed streamflow, which was obtained from the Global
10 Runoff Data Centre (GRDC) for the period from 1950 to 2010. Although mRM is run internally at higher temporal resolutions, the simulated streamflow is eventually aggregated to daily values for comparison against observations. Daily observed values are chosen here because they allow to investigate the hydrologic cycle in greater detail compared to monthly values, commonly used with land surface models (e.g., Hagemann et al., 2009; Zhang et al., 2016).

3 Results

15 ### 3.1 General Model Performance and Parameter Sensitivities

The adaptive time step parameterization (aTS) in mRM has one parameter modulating the relationship between terrain slope and streamflow celerity (γ in equation 5). There is also an adjustable coefficient for the space weighting in the finite difference solver (ϵ in equation 3). The sensitivity of aTS to ϵ and γ is explored here. The performance of simulated streamflow of aTS appears to be very high in general and exhibits limited impact to changes of ϵ and γ.

20 The density function peaks around ΔKGE = 0 for the space-weighting factor ϵ. The ΔKGE estimated across all basins are within the interval -0.03 to 0.01. All changes in KGE below a magnitude of 0.01 are considered negligible, in alignment with previous literature, corresponding roughly to an error level in stream flow of $1\,\mathrm{mm\,d^{-1}}$ (Kollat et al., 2012). Some large basins in the European dataset show up to 0.03 higher KGE values using $\epsilon = 0$ compared to $\epsilon = 0.5$. Note that the numerical diffusion of this finite difference solver (equation 5) depends linearly on ϵ (Cunge, 1969). An ϵ value of 0 corresponds to full numeric
25 diffusion, whereas a value of 0.5 to no diffusion. The numerical diffusion is often chosen to correspond to the actual physical diffusion of the river by adjusting the value of ϵ (Todini, 2007; Beighley et al., 2009). aTS is using a space-weighting factor $\epsilon =$ 0 because this value provides slightly better estimates than a value of 0.5, but the impact of this factor is overall negligible.

The density function of ΔKGE is skewed when comparing the performances between optimized γ values at each gauging station and resolution with a constant value of 15 for all stations (Figure 3b). A value of 15 is chosen because it provides
30 the best compromise solution of the obtained optimized values (Figure 3d). It can be expected that optimized parameters give higher performances than a fixed value. The performance increments with optimized parameters were, however, less than 0.01 in more than 37% of the basins while only about 42% of the basins exhibited ΔKGE values of 0.01 to 0.05. This means that performance increments with optimized γ values were below 0.05 in 79% of the basins (Figure 3b).
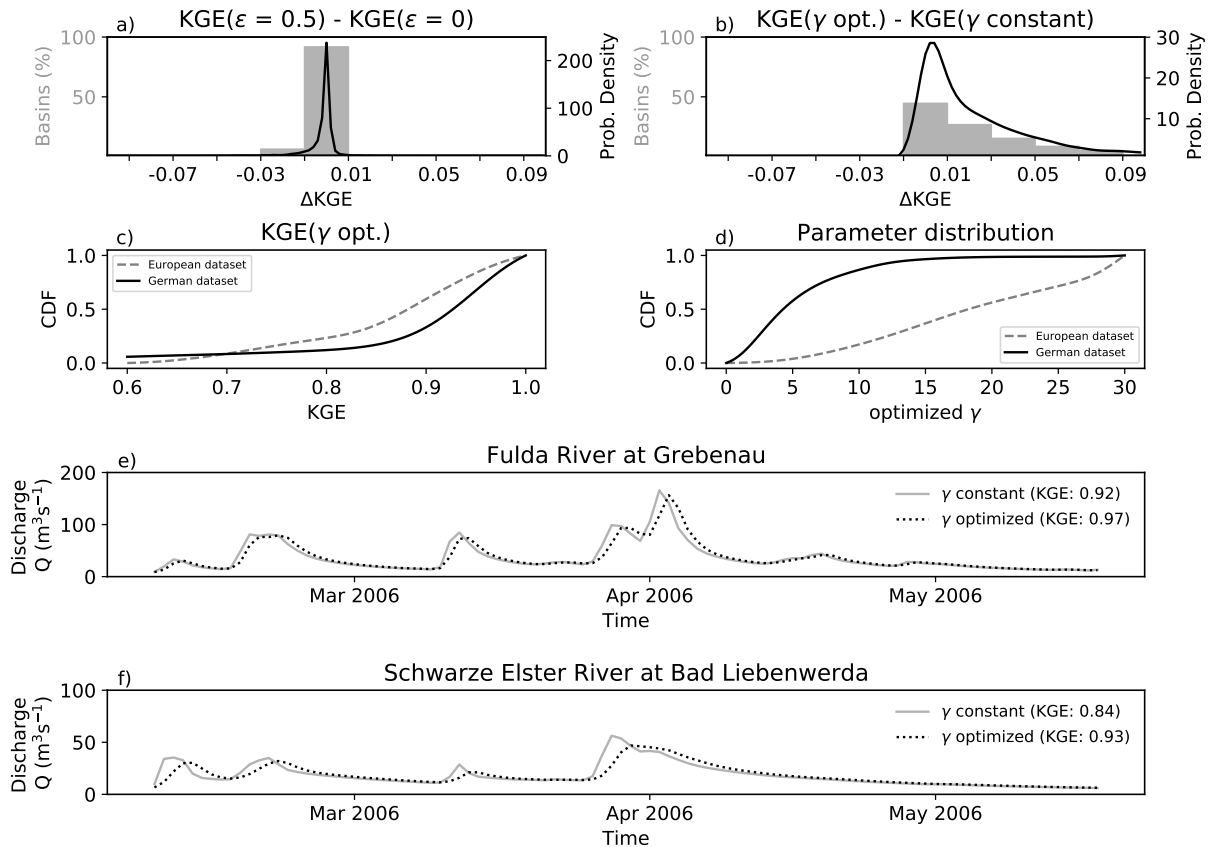
Figure 3. Differences in KGE between no numeric diffusion ($\epsilon = 0.5$) and full numeric diffusion ($\epsilon = 0.$) for the combined European and German datasets (panel a), and differences in KGE between model runs with optimized parameter values at each gauge and one constant parameter for all gauges (panel b). Probability density functions (PDF) are shown as black lines. The integrals of the PDFs over intervals of 0.02 (e.g., -0.01 to 0.01) are shown as gray bars normalized with respect to all basins. Panel c: Cumulative distribution functions (cdfs) of Kling-Gupta Efficiencies (KGE) for the European and German datasets separately based on optimized parameters γ. Panel d: CDF of optimized γ for the two datasets. The underlying data shown in panels a-d is pooled for all catchments and all resolutions. Panels e) and f) show the hydrographs for two catchments at 4 km resolution for a parameter value of $\gamma = 15$ (solid gray line) and the optimized value (dashed black line).

Overall, the KGE values for the European and German dataset are very high with only 4% of the basins exhibiting a KGE value less than 0.6 (Figure 3c). The median KGE values are 0.89 and 0.94 for the European and German dataset, respectively. KGE values are, however, highly dependent on the used hydrologic model (i.e., mHM) and the quality of the input data. The hydrologic model determines the partitioning of precipitation into evapotranspiration and runoff as well as the temporal

dynamics of generated runoff. It thus affects all three components of KGE: the bias, the variance and the correlation. The routing model, on the other hand, is not able to change the long-term water balance and is thus not affecting the bias term of the KGE. The routing model is, however, able to change the dynamics of simulated streamflow and thus greatly affect the variance term of KGE. The distribution of the optimized parameter values is very different for the German and the European datasets

5   with median values of 4 and 21, respectively (Figure 3d). These differences originate from the resolution of the underlying digital elevation model (DEM) and hence the slopes used in equation 5. The slope data for the German dataset is available at a 100 m resolution, while it is at 500 m resolution for the European dataset. The slopes will hence be larger and more variable at 100 m resolution compared to 500 m resolution. This implies that lower slope values (European dataset) are associated with higher γ values and higher slope values (German dataset) are associated with lower γ values, which results in similar celerities

10   for the two datasets. This highlights that the obtained parameter values are highly dependent on the underlying dataset, which has been identified as a major source of hydrologic modelling uncertainty (Livneh et al., 2015).

Hydrographs for two German river basins that exhibit ΔKGEs of 0.05 and 0.11, respectively, are shown in Figure 3e and Figure 3f. These ΔKGE values were among the highest of all basins and model resolutions considered in this study. A shift in peak flows of about one day can be spotted visually at ΔKGE values of 0.05 (Figure 3e). This difference is representative

15   for around 21% of all catchments. A difference in KGE of 0.11 implies a change in the amount and timing of peak flows (Figure 3f) and is representative for around 8% of all catchments. The overall recession dynamics are comparable regardless of the change in γ (Figure 3e and 3f). Moreover, no substantial shift in amount and timing of peak flows is observed in 79% of the catchments. It will ultimately depend on the preference of the model user if parameter calibration is applied for a specific use case.

20   **3.2   Temporal and Spatial Scalability**

The aTS scheme is run firstly with different temporally aggregated inputs and secondly on different spatial resolutions to demonstrate its scalability across time and space.

The adaptive time step procedure of aTS allows to use different input time steps. This might be the case if input runoff is provided as an aggregate over a specific period, for example as daily runoff. aTS aggregates or disaggregates any given

25   temporal resolution to the internal time step constrained by a Courant number of 1 (equation 6). Similar performances are achieved with aTS using either daily or hourly inputs across all basins in the German and European dataset at every spatial resolution (Figure 4). This is achieved because of the aggregation and disaggregation to the internal time step but it is also affected by the fact that we compare against observed daily discharge. Sub-daily differences are thus averaged out before comparison. Observed hourly discharge would contain information about sub-daily variability that could not be obtained from

30   daily inputs and, thus, hourly inputs might perform better in this case. However, observed discharge is mainly available on a daily resolution.

Evidently, aggregated input provides less variable runoff to the routing scheme, leading to less variable river discharge. Aggregation does, however, not change absolute values (bias). The ΔKGE values therefore appear due to changes in streamflow variability, which should be reduced with aggregated runoff values.
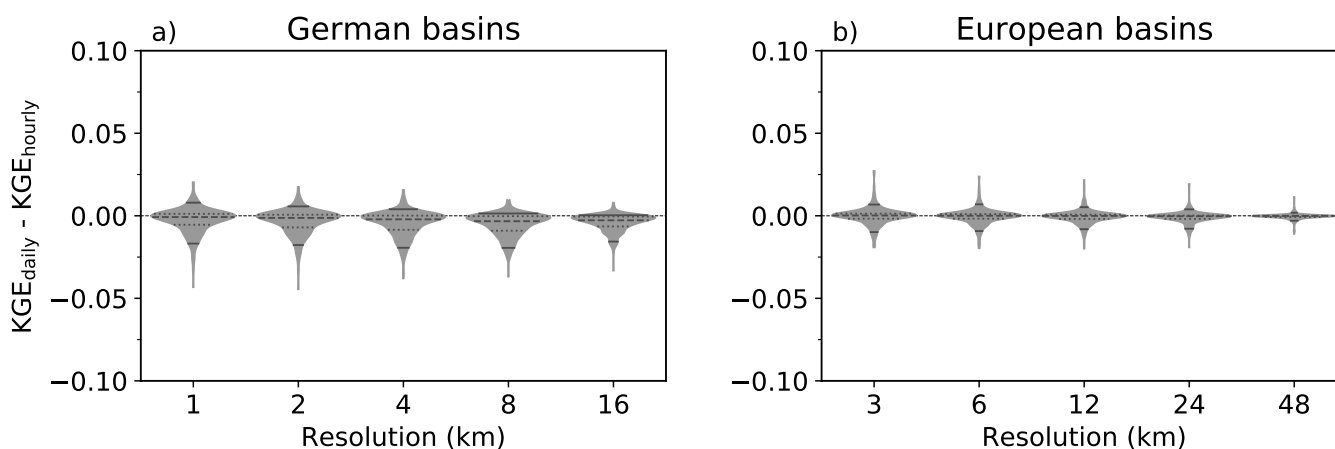
Figure 4. Probability density functions (PDF) of differences in KGE values obtained with hourly and daily input to aTS. PDFs are limited to the minimum and maximum ΔKGE values and have been normalized with respect to its width to ease the comparison. A thin dashed horizontal line is given at ΔKGE = 0 for reference. Dashed lines in the violins indicate the medians, dotted lines the 25th and 75th percentiles and solid lines the 5th and 95th percentiles.

A subtle differences exist between the ΔKGE values for the German and European dataset. The median ΔKGE values are almost zero for the European basins (Figure 4b) with very little standard deviations. Median ΔKGE values for German dataset are in contrast slightly negative around -0.005 (Figure 4a). The differences between the German and European dataset come mainly from the spatial resolution at which gridded runoff inputs for mRM were generated. Forcing for mRM was provided

5 at 4 km resolution for the German dataset, which is the lowest resolution of the meteorological input (Zink et al., 2017). The input runoff for mRM has been generated at a 24 km resolution for the European dataset, which corresponds to the resolution of the meteorological E-OBS dataset (Haylock et al., 2008). Runoff data at 4 km scale exhibit much higher spatial variability compared to the coarser 24 km runoff. The higher spatial variability of the German dataset is substantially reduced when using daily runoff compared to hourly runoff, which generates the little mismatch between using hourly and daily inputs for the

10 German dataset (Figure 4a). The equalization of variability from averaging is less pronounced in the less variable runoff fields of the European dataset.

For the spatial scaling, KGE values relative to the finest possible model resolutions (1 km for German and 3 km for European dataset) are reported (Figure 5). In other words, the reference values (observations) in the calculations of KGE are replaced by simulated streamflow obtained with optimized parameters at the highest resolution. Perfect spatial scaling is hence indicated

15 by a relative KGE value of one. Figure 5 shows the probability density functions of the relative KGE values estimated over all basins for each model resolution. The optimized parameter obtained at the highest spatial resolution for each basin is transferred for the aTS and the rMC parametrization to the model runs at the coarser spatial resolutions.

Results shown in Figure 5 clearly demonstrate a remarkable spatial scalability of aTS in comparison to the original rMC parametrization (Appendix A). The lowest median relative KGE of 0.977, which represents a change of less than 3 percent,
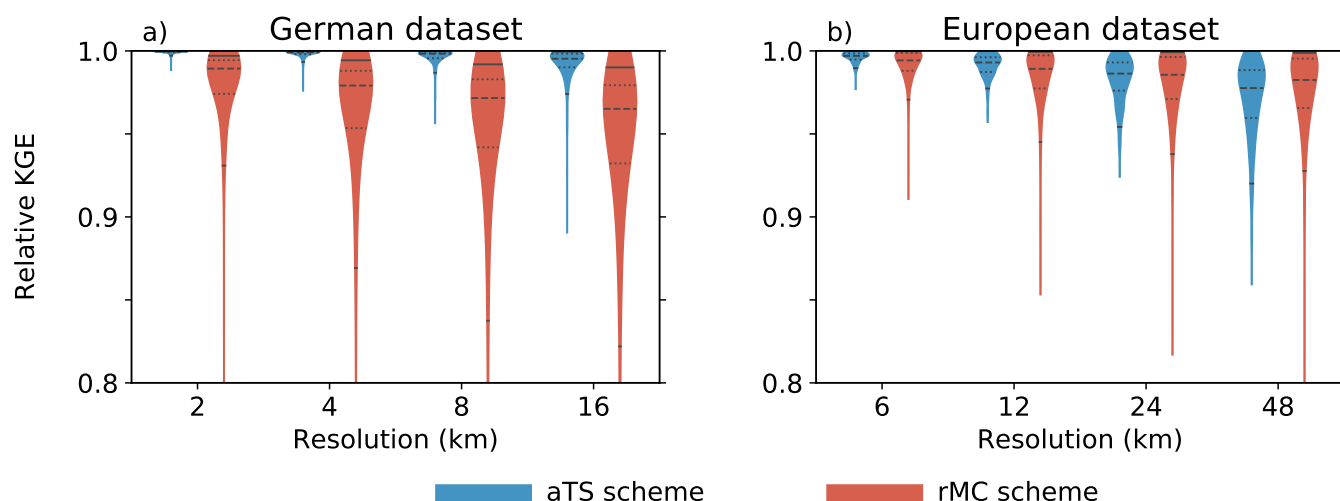
Figure 5. Probability density functions (PDF) of relative KGE values for adaptive time step scheme (aTS) (dark gray violins) and the regionalized Muskingum-Cunge (rMC) routing scheme (light gray violins). KGE values are calculated relative to the finest possible spatial resolution, which is 1 km for the German (a) and 3 km for the European dataset (b). PDFs are limited to the minimum and maximum relative KGE values and have scaled to the same widths. Dashed lines in the violins indicate the medians, dotted lines the 25th and 75th percentiles and solid lines the 5th and 95th percentiles.

is observed at the coarsest resolution of 48 km for the European dataset. The overall lowest relative KGE is 0.85 for aTS and 0.22 for the rMC scheme. The aTS scheme shows an improved scalability because it considers the between-grid heterogeniety of celerities through the parametrization based on terrain slope (equation 5) and the numerical stability criteria (equation 6). The spatial scalability of aTS is higher for the German dataset compared to the European. This can be attributed to the spatial

5 resolution of the slope data used in the parametrization of celerity (equation 5), which is available at 100 m resolution in the German dataset compared to 500 m in the European dataset. The representation of river slopes is thus more realistic in the German dataset. Notably, a similar spatial scalability is found for both aTS and rMC parametrization if default parameters are used (not shown).

The adaptive time step scheme (aTS) shows, in summary, remarkable temporal and spatial scalability in comparison to its

10 predecessor. The adaptive time step allows for aggregated or disaggregated input (generated runoff) from any given temporal resolution.

3.3 Comparison of Adaptive Time Step Routing with Regionalized Muskingum-Cunge Parametrization

The adaptive time step scheme (aTS) is the successor of the regionalized Muskingum-Cunge (rMC) routing implemented in mHM. A detailed analysis of the differences in model performances between the two routing parametrizations is presented

15 here for the German and European dataset and selected spatial resolutions (Figure 6).
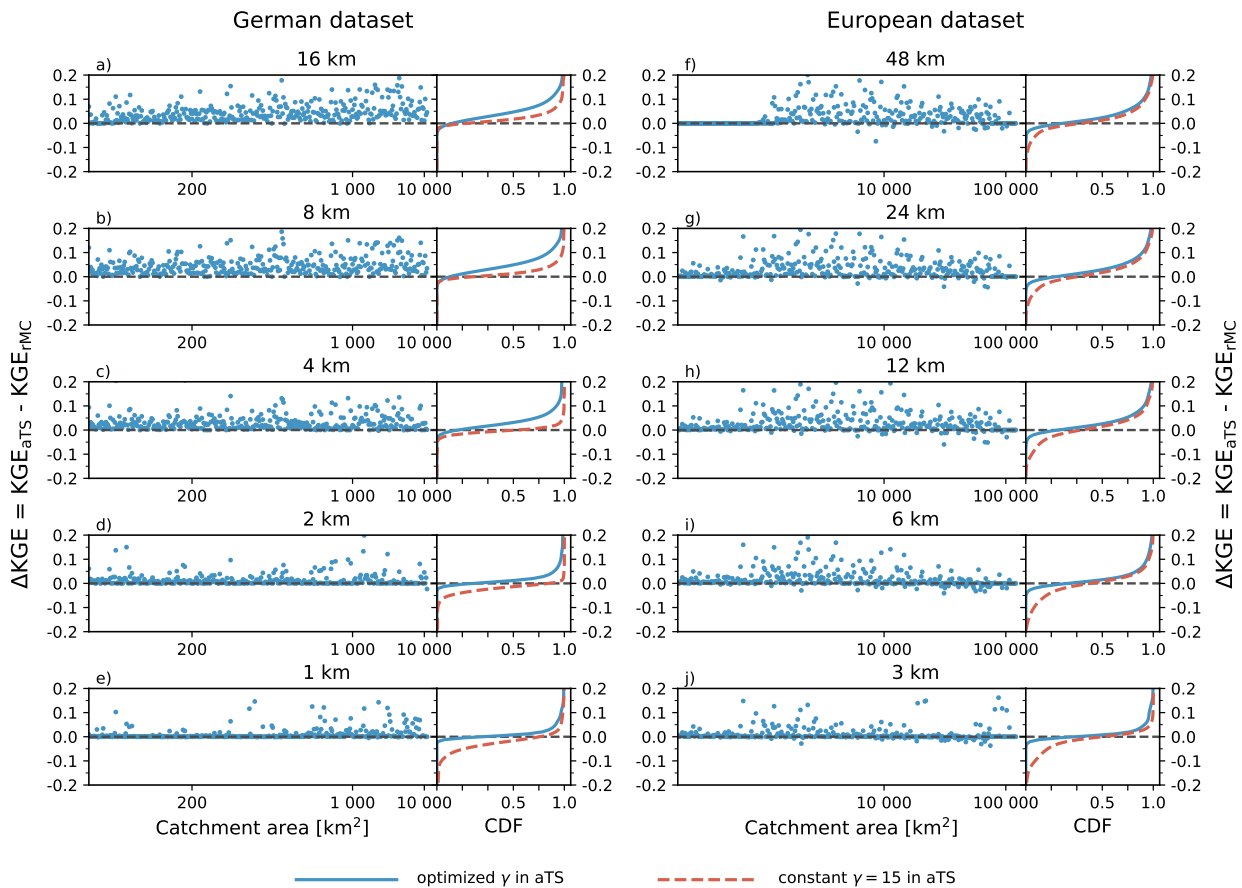
Figure 6. Differences in KGE between the multiscale Routing Model mRM using a optimized parameter γ, constant parameter value $\gamma = 15$ and the original Muskingum-Cunge routing scheme (rMC) implemented in the mesoscale Hydrologic Model mHM for the German (left column) and European dataset (right column). ΔKGE values between aTS and rMC using optimized parameter values on each basin and at each resolution are shown for the respective basins on the right of each panel, where basins are sorted according to catchment area (note the logarithmic scale). Cumulative distribution functions of ΔKGE between aTS and rMC using optimized parameter values (solid blue line) and aTS with constant parameter and rMC with optimized ones (dashed red line) are depicted on the left sides of the panels. The zeroth line (dashed black line) is added for reference.

If aTS and rMC are calibrated individually on each basin and at each resolution, then the performances are comparable across the German and European dataset (Figure 6). However, the cumulative distribution functions (cdfs) of ΔKGE values is skewed towards positive values indicating in general higher performance for aTS than rMC (Figure 6a-6j, solid blue line in right panels). This improvement is slightly higher for the German dataset compared to the European one, which can be attributed to the higher spatial resolution of the slope data in the former. ΔKGE values are closer to zero for resolutions finer than 4 km

indicating a more comparable model performance for aTS and rMC at higher spatial resolutions than at coarser ones. This is due to the fact that the original rMC routing scheme was developed at this resolution (Samaniego et al., 2010; Kumar et al., 2013b). At spatial resolution coarser than 12 km, the rMC routing strongly violates the Courant-Friedrichs-Lewy criterium (i.e., $c\Delta t/\Delta x \leq 1$) which results in poorer performance. Even re-optimizing the routing parameters could not compensate for

5 the scaling error because water is moved too fast through the river network. At these coarse resolutions, the aTS scheme is still outperforming the rMC scheme when run with a constant $\gamma = 15$ parameter for all catchments (Figure 6a-6j, dashed red line in right panels).

In summary, the adaptive time step scheme (aTS) demonstrates at least the same performances as its calibrated predecessor, the regionalized Muskingum-Cunge routing scheme (rMC). The scalability of mHM across spatial resolutions has been demon-

10 strated before, but employing a fixed spatial routing resolution for the rMC scheme (see Kumar et al., 2013a). For this purpose, the gridded runoff fields are spatially up- or down-scaled to the desired spatial resolution (e.g., 8 km runoff field disaggregated to 4 km). The aTS parametrization allows to simultaneously scale both the hydrologic and routing model. Notably, aTS requires no specific up/downscaling of runoff fields and parameters can be transferred across spatial and temporal resolutions. Both of these properties offers distinct advantages in reducing the computational costs because mRM can be directly applied at the

15 resolution of the gridded runoff input. Using a constant $\gamma = 15$ parameter for all catchments, avoiding optimisation, further reduce the computational costs but might result in slightly decreased model performances in comparison to model runs with optimized γs (ΔKGE ≈ 0.1 (95% confidence)). This is, however, still little compared to the impact that has the hydrologic model used as input to the routing scheme. Using fixed γ parameters also allows further the seamless application of aTS at ungauged basins (Rakovec et al., 2016).

20 ### 3.4 Streamflow Simulations over the Danube Catchment by applying mRM to the Regional Climate Model REMO

Regional Climate Models (RCMs) are used to dynamically downscale Global Climate Models over a specific region to obtain higher resolution information about the local climate. The evaluation of RCMs often focuses on surface fluxes and states, such as 2 m air temperature, precipitation, and evapotranspiration amongst others. River runoff, which provides an integrated signal of the water cycle over a region, is not often used as a further model diagnostic. This might be due, besides other

25 reasons, to the fact that RCMs are designed to be run at various spatial resolutions, ranging from few kilometers (e.g., Jacob et al., 2014) to tenth of kilometers (e.g., Van der Linden and Mitchell, 2009). RCM output has hence to be aggregated or disaggregated to current routing schemes with fixed routing resolutions. This is not necessary with the multiscale Routing Model mRM employing the adaptive time step parameterization (aTS) that runs seamlessly at various spatial and temporal scales (section 3.2). This eases the comparison of RCM-derived streamflow with observations as the routing model has to be

30 setup only once and can then be applied at different resolutions without adjusting the model parameter γ or the model setup. Note that mRM is not limited to regular grids if high resolution flow directions are given already on a rotated grid, for example from a rotated digital elevation model.

This section shows one exemplary application of mRM to output of the Regional Climate Model REMO (Jacob et al., 2001) over the Danube catchment. Generated runoff by REMO has been obtained from the ENSEMBLES project (Van der Linden and
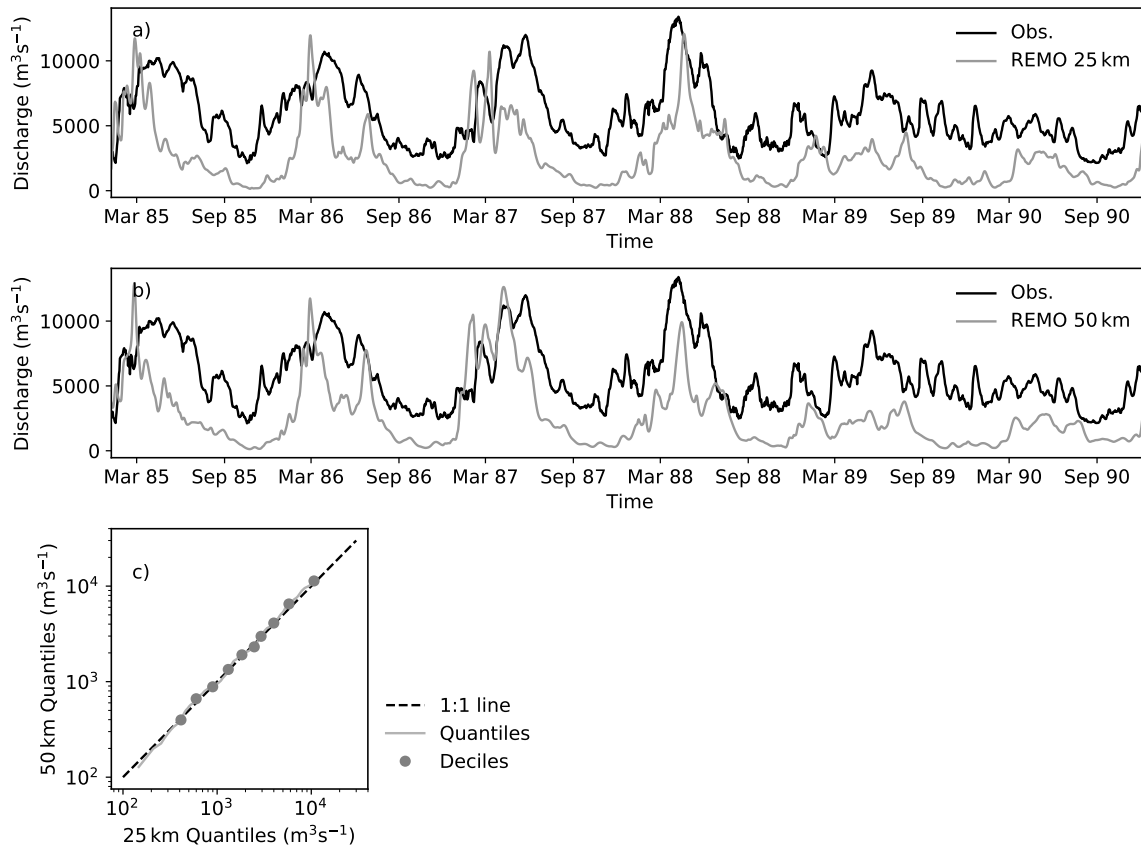
Figure 7. Hydrographs for the Danube river basin at the gauging station Ceteal-Izmail obtained by routing drainage output from the regional climate model REMO with mRM employing the adaptive time step parameterization (aTS) at 25 km (a) and 50 km (b) spatial resolutions. c) Q-Q plot of the two routed REMO outputs.

Mitchell, 2009) at 25 km and 50 km resolutions. Both resolutions were used to run mRM employing the aTS parameterization ($\gamma = 15$) over the Danube catchment (Figure 7a for 25 km and 7b for 50 km). REMO was nested into ERA-40 reanalysis in the ENSEMBLES project, which therefore allows the comparison against observed streamflow. The Danube basin is part of the European dataset used for the evaluation in previous sections. The same setup was used for routing gridded runoff fields of the REMO model and only the number indicating the routing resolution had to be changed in the mRM configuration file.

There are striking differences between the observed and simulated streamflow (Figure 7). This comes from the fact that REMO uses a simple runoff generation consisting of direct surface runoff and soil drainage. There is no groundwater description in REMO so that the only water storage is in the river itself and baseflow is therefore much too low. This highlights a common misunderstanding when using river routing with land surface models: most land surface models include only a simple

runoff generation that does not account for the temporal variability of the runoff signal such as fast flow, interflow and baseflow. Routing directly drainage fluxes leads to seasonal high flows that are much earlier than observed. Using very low celerities in the routing models might improve model-data mismatch (see Oki et al., 1999, for celerities in several routing schemes). Other runoff schemes represent different runoff components within the model code (e.g., Lohmann et al., 1996; Hagemann and

5 Dümenil, 1997; Pappenberger et al., 2009). The multiscale Routing Model mRM does not contain runoff generation because most hydrologic models already include detailed runoff generation and also land surface models start to include groundwater components nowadays (e.g., Niu et al., 2011; Clark et al., 2015). Details of these components depend strongly on model focus which should not be imposed by the river routing model (cf. section 4).

Three main conclusions can be drawn from the comparison of modeled and observed discharge: first, REMO is able to

10 capture the overall seasonal variations of runoff. There is a pronounced seasonality within the first four years in both, observation and REMO simulated streamflow, which is much reduced in the last two years (Figure 7a & b). Seasonality in the Danube catchment is dominated by spring melt, which is very little in the last two years. REMO is therefore able to simulate inter-annual variations in precipitation and surface temperature over the Danube catchment.

Second, REMO produces too little runoff on average at both resolutions. Runoff is underestimated by about 50% on both

15 25 km and 50 km resolution, whereas biases in catchment average precipitation are less than 10% compared to E-OBS (Haylock et al., 2008). Hence, the partitioning of precipitation into runoff and evapotranspiration is not correct in REMO, under the reasonable assumption that groundwater tables around the Danube river exhibit no significant trend over the simulation period. This implies that evapotranspiration is overestimated in REMO but very similarly on 25 km and on 50 km resolution.

Third, REMO exhibits statistically very similar runoff on both model resolutions, 25 km and 50 km. The quantile-quantile

20 plot (Figure 7c) shows only very little for the different deciles.

This section underlines the fact that hydrologic and land surface models have to include the processes of runoff generation and groundwater for a fair comparison of modeled and observed discharge. It also highlights the added value of investigating simulated streamflow from Regional Climate Models even with a simple runoff generation by pinpointing overestimated evapotranspiration within REMO. In particular, REMO's very good reproducibility on different spatial scales is shown. Once

25 runoff generation has been improved, the multiscale Routing Model mRM would allow to further analyze the responses of land surface models to climatic extremes (Reichstein et al., 2013) using indices and signatures of the discharge time series (Thober and Samaniego, 2014; Shafii and Tolson, 2015).

4 Comparison with Existing Routing Schemes

River routing is performed at various resolutions, depending on the application. Global streamflow simulations, using output

30 of land-surface models (LSMs) or hydrological models (HMs) for example, are typically carried out at 0.5° or 1.0° resolutions (a.o., Oki et al., 1999; Hagemann et al., 2009; Pappenberger et al., 2009; Zhang et al., 2016). However, climate models are run on ever increasing spatial scales (Jacob et al., 2014), or using even internally nested grids or zooming functionality (Zängl et al., 2014). Also, spatial resolutions of few kilometers are used within the hydrologic modeling community to obtain national

and continental estimates of hydrologic fluxes and states (David et al., 2011; Marx et al., 2018; Thober et al., 2018). Despite
the fact that diverse spatial resolutions are used to represent the hydrologic cycle, spatial resolutions of routing are mostly fixed
and cannot be changed easily. In many models, the user needs to provide the input data (e.g., flow direction, DEM, channel
information) for every resolution the model is applied on (a. o., Lohmann et al., 1998; Beighley et al., 2011; Neal et al., 2012).

5   The multiscale Routing Model mRM, on the other hand, is able to scale the river network to the desired routing resolution
internally. This allows to make full use of the information provided by the input runoff data, without uncertainties coming from
the rescaling process (e.g., from a 12 km LSM output to a 0.5° river network). It also avoids further computational demand by
scaling the generated runoff to a hyper-resolution river network, which then requires high-performance computing resources
such as in the case of the RAPID framework (David et al., 2011). This might especially be valuable if parameter estimations

10   using discharge data is to be carried out, which requires multiple model evaluations.

Current solvers describing water movement within a river network can principally be applied at different resolutions. For
example, the solution of the diffusion equation by Greens functions proposed by Lohmann et al. (1996) is valid independently
of the resolution of the river network. The CaMa-Flood model can similarly be applied to different resolutions as long as the
Courant-Friedrichs-Lewy condition is fulfilled (Yamazaki et al., 2013). aTS employs the same condition to identify an adaptive

15   time step that guarantees the numerical stability and achieves a scalability across spatial resolution. Yamazaki et al. (2009) also
developed a pre-processor for the CaMa-Flood model that explicitly allows to generate a river network at different spatial
resolutions. mRM follows the same idea but it internally includes the upscaling of the river network to the required resolution
in the model code. The user has to provide the routing network only once even if the application will focus on different
spatial resolutions. The derived river network can be stored in a restart file to further speed-up the computation. However, aTS

20   performance is dependent on the resolution of the underlying slope data (see Section 3.1 and 3.2) and it is advisable to use the
highest resolution data available. This is due to the fact that channel slope instead of terrain slope should be used in equation 5
and a high-resolution DEM provides a close approximation of channel slope.

Another reason that hampers the scalability of existing routing models is that they include not only the routing of water in
the river network but also a runoff generation mechanism, which represents a variety of other components of the hydrologic

25   cycle (Pappenberger et al., 2009). The complexity of existing runoff generation descriptions reflects the diversity of use cases
of hydrologic and land surface models. Descriptions range from simple linear models (Niu et al., 2011; Beven, 2012) to more
complex representations considering surface groundwater interactions (Maxwell and Kollet, 2008; Miguez Macho and Fan,
2012). Existing routing schemes often opt for more simple parsimonious representations. For example, routing models use
linear reservoirs for overland flow, baseflow and riverflow to delay runoff generated by the land surface (e.g., Hagemann and

30   Dümenil, 1997; Pappenberger et al., 2009; Getirana et al., 2012). mRM does not include any runoff generation because it is
beyond the scope of a river routing model to reflect the complexity of existing runoff generation processes. Notably, there
is currently ongoing research in understanding how a particular process parametrization impacts hydrologic simulations (Niu
et al., 2011; Clark et al., 2015). Runoff generation also hampers the scalability of routing models because of their highly non-
linear behavior. The Multiscale Parameter Regionalization (MPR, Samaniego et al., 2010) is one of few approaches that has

proven to provide consistent generated runoff at resolutions ranging from 2 km to 16 km for mesoscale catchments (Kumar et al., 2013b) and from 0.125° to 1° for continental scale basins (Kumar et al., 2013a).

Among the plethora of routing models presented over the past decades, only few have rigorously evaluated their spatial scalability. The "Model for Scale Adaptive River Transport" (MOSART) has been developed explicitly to achieve seamless application of river routing across scales (Li et al., 2013), similar to mRM. MOSART has been successfully coupled, for example, to the Community Land Model (CLM) to compare with global discharge data (Li et al., 2015). MOSART differs from mRM in that it solves the kinematic wave equation with Manning's equation for channel velocity (Manning, 1891) not only for the main channel but also for hillslope routing and subgrid tributaries. It thus explicitly accounts for sub-grid heterogeneity by considering all lateral travel times across hillslopes and tributaries. mRM, on the other hand, solves a kinematic wave equation with spatially varying velocities for the main channel only (equation 1 and 5). The assumption within mRM is that travel times in the main channel dominate travel times at hill slopes and tributaries and the latter are negligible. This, in turn, leads to a simpler approach with one model parameter. However, further research is needed to explicitly investigate the validity of this model assumption. It is for example possible to return to the original formulation of Miller et al. (1994), using a reference slope s_0, that should depend on the underlying digital elevation model (DEM). But two DEM resolutions, as in this study, are not enough to find a suitable formulation for the dependence of s_0 on DEM characteristics such as resolution or maximal slope. s_0 was hence lumped with the minimum celerity c_0 to give only one identifiable parameter γ.

It is worth reminding that mRM represents a simple approach towards river routing. The results in this study demonstrate that mRM employing the adaptive time step parameterization in combination with upscaled high resolution celerities (aTS) achieves almost identical daily streamflow simulations at various model resolutions in diverse German and European catchments. Recent literature has shown that a realistic representation of streamflow in river basins with extensive floodplains such as the Amazonas, Niger, and Congo require the representation of floodplain inundation processes (Getirana et al., 2012; Paiva et al., 2013; Fleischmann et al., 2016; Pontes et al., 2017). Floodplain processes are currently not considered in mRM and further research is required to include these. Paiva et al. (2013) showed that floodplain processes dominate the difference between a hydrodynamic and kinematic wave models. The approach used therein should be exploited within mRM to be applicable at different resolutions.

5 Conclusions

The adaptive time step scheme in combination with upscaled high resolution celerities (aTS) implemented in the multiscale Routing Model mRM estimates streamflow at various resolutions ranging from the hyper-resolution of 1 km to the large scale of 0.5°. Differences in Kling-Gupta efficiencies of simulated daily streamflow between various model resolutions and temporal forcings (i.e., hourly or daily runoff) are negligible with a median of 0.03 over Germany and Europe (Section 3.2). The aTS scheme shows an improved scalability over its predecessor because it considers the linkage between spatial resolution and integration timestep by virtue of the Courant criteria (equation 6) and it considers the between-grid heterogeniety of celerities through the parametrization based on high-resolution terrain slope (equation 5). mRM represents the river network internally

at the resolution of the model input, which allows seamless application to output of any hydrologic model (HM) and land surface model (LSM). It can also easily be coupled internal in the code of HMs or LSMs, providing error measures such as Nash-Shutcliffe and Kling-Gupta efficiencies for model evaluation or calibration.

mRM uses a simple kinematic wave equation to describe water flow within a river network. This representation is regarded
5   suitable as long as backwater effects and floodplain inundation processes are comparatively small. mRM does not represent runoff generation mechanisms, which are included in other routing models. Runoff generation is included in hydrologic models and nowadays often in land surface models and details of the implementation depend strongly on the application of interest. Users of river routing schemes should not be limited by the options implemented in the river routing model itself.

mRM can in principle also be used on rotated model grids commonly used for climate models if high resolution flow
10 directions are provided at the same grid. However, mRM represents the river network as a rectangular grid, allowing to apply a constant time step over the entire model domain. Future developments will focus on implementing reservoirs and natural lakes, floodplain processes, and a location dependent time stepping scheme, which will allow the use of mRM on irregular grids or in models with local refinement. The model source code along with a test case to validate succesful installation is freely available within the codebase of the mesoscale Hydrologic Model mHM at www.ufz.de/mhm.

15 *Code availability.*   The software code is available through a public git repository hosted at the Helmholtz-Centre for Environmental Research - UFZ. mRM code is hosted in a branch of the git repository of the mesoscale Hydrologic Model (mHM), that is https://git.ufz.de/mhm/mhm/tree/varying_celerity. The software version used for this paper can also be identified by the git tag "mRMv1.0". The manual of mHM contains a chapter on the installation and user guide of mRM (chapter 9). Input and output data of mRM is also included in the git repository to test succesful installation (see manual on how to run the test basin).

20 **Appendix A: Regionalized Muskingum-Cunge (rMC) routing**

The regionalized Muskingum-Cunge (rMC) parametrization implemented in the mesoscale Hydrologic Model mHM calculates the Muskingum coefficients C_1, C_2, and C_3 in equation 3 as a function of high-resolution river network properties. The coefficients C_1, C_2, and C_3 are parametrized as follows

$$C_1 = \nu_2; \; C_2 = \nu_1 - \nu_2; \; C_3 = 1 - \nu_1, \tag{A1}$$

25 where the parameters ν_1 and ν_2 are given as

$$\nu_1 = \frac{\Delta t}{\beta(1-\epsilon)+\frac{\Delta t}{2}}; \tag{A2}$$
$$\nu_2 = \frac{\frac{\Delta t}{2}-\beta\epsilon}{\beta(1-\epsilon)+\frac{\Delta t}{2}}$$

following the nomenclature of appendix A2 in Samaniego et al. (2010). This formulation is identical to equation 5 of the present study, using $\beta = \Delta x/c$ in equation A2 and substituting equation A2 into equation A1. The parameters β and ϵ are then

conceptualized as

$$\beta = \gamma_1 + \gamma_2 L + \gamma_3 S + \gamma_4 C; \tag{A3}$$
$$\epsilon = \gamma_5 \frac{S}{max(S)},$$

where L is the length of the reach, S is the slope of the reach, and C is the fraction of impervious land cover within the

5   floodplains (see table 4 in Kumar et al. (2013b)). Overall, there are five global parameters γ_1 to γ_5 in equation A3 that can be chosen by the user. The integration time step is fixed at one hour. To guarantee the numerical stability of the parameterization, the following upper and lower bounds are applied

$$0 < \epsilon \le 0.5, \tag{A4}$$
$$\frac{\Delta t}{2(1-\epsilon)} < \beta \le \frac{\Delta t}{2\epsilon}, \tag{A5}$$

10   where Δt is set to one hour.

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20   (http://ensembles-eu.metoffice.com) and the data providers in the ECA&D project (http://www.ecad.eu). We also acknowledge our data providers: the European Environment Agency, the Harmonized World Soil Database, the Global Runoff Data Centre, German Meteorological Service (DWD), the Joint Research Center of the European Commission, the Federal Institute for Geosciences and Natural Resources (BGR), the Federal Agency for Cartography and Geodesesy (BKG), and the European Water Archive. The data used within the European dataset are described in Rakovec et al. (2016) and the data used within the German dataset are described in Zink et al. (2017). Further simulation

25   data that supports findings of this study are available from the corresponding author upon request. We thank the editor Paul Dirmeyer for handling our manuscript and two anonymous reviewers for their constructive comments that helped to substantially improve our model and manuscript.

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