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Global hydrological parameter estimates to local applications: Influence of forcing and catchment properties

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ABSTRACT

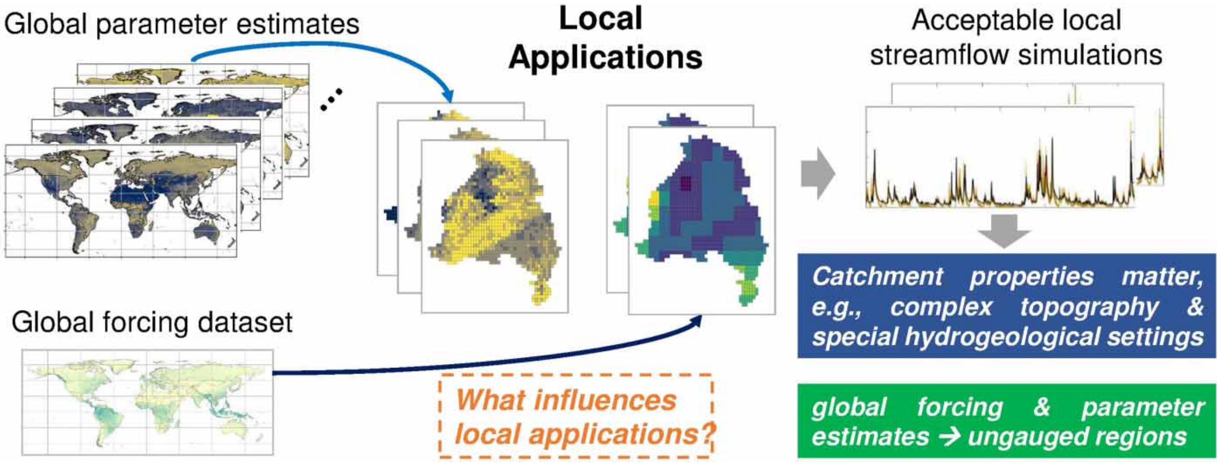
Data scarcity in many areas around the world represents a major problem for hydrological model calibrations. Global parameter estimates and global forcing can provide possibilities to access hydrological responses in ungauged regions. In this study, we applied HBV global parameter estimates considering uncertainty in the Upper Neckar and Upper Danube catchments, Germany, to answer what are the influencing factors and how good are their local applications. We tested simulations with precipitation in spatial resolutions from 0.05 to 0.2° and with local/global sources. Results show that the general performance is acceptable to good (Kling-Gupta efficiency, KGE: 0.51–0.79) in both catchments using local or global precipitation. The influence of spatial resolutions is insignificant while using local precipitation slightly increases performance in both catchments. Catchment properties such as complex topography and special karst subsurface may lead to a deterioration of performance by 0.2 of median KGE in the Upper Danube compared with the Upper Neckar catchment. The median correlation coefficient, runoff ratio and relative error suggest that using global parameter estimates can reproduce seasonality and long-term water balance in our studied region. Our study highlights the potential of using global parameter estimates and global forcing in ungauged areas.

Key words: global parameter estimates, global precipitation, hydrodynamics, hydrological signatures, spatial resolution

HIGHLIGHTS

- Global parameter estimates with global forcing can produce acceptable local discharge simulations in our study area.
- Catchment properties have more impacts on local applications than sources and spatial resolutions of forcing when applying global parameter estimates.
- Our study highlights the potential of using global forcing to understand hydrological behavior and water balance at a monthly scale in ungauged areas.

GRAPHICAL ABSTRACT



1. INTRODUCTION

The traditional calibration of a lumped hydrological model requires observed streamflow time series and meteorological forcing. However, many regions around the globe lack streamflow observational networks (Hannah *et al.* 2011), which form the so-called ungauged catchments. On the contrary, there is a high availability of climatic data all over the world due to the continuous monitoring network such as using remote sensing techniques (Sood & Smakhtin 2015). Hydrological regionalization approaches can transfer parameters calibrated in gauged catchments to ungauged regions (Sivapalan *et al.* 2003; Hrachowitz *et al.* 2013; Beck *et al.* 2016). Using regionalized parameters and global available climatic forcing allows for estimating water balance for the ungauged catchments.

Hydrological regionalization currently includes three types of approaches: (a) regression-based, using different climatic and physiographic predictors (Livneh & Lettenmaier 2013), (b) similarity-based, using spatial proximity and similar catchment settings (Nijssen *et al.* 2001; Merz & Blöschl 2004) and (c) signature-based using hydrological signatures (Yadav *et al.* 2007; Kapangaziwiri *et al.* 2012). Recently, regionalization approaches have been used to derive hydrological model parameters for all land surfaces. For instance, Arheimer *et al.* (2020) emphasized the potential of regionalized parameters of the HYPE model, which was evaluated well in a high number of catchments with a median monthly KGE of 0.4. Beck *et al.* (2020) derived globally distributed HBV model parameters in a high spatial resolution (0.05°) using a regression-based approach. It was evaluated with a large number of catchments all over the world and a median daily KGE of 0.46 was achieved. These studies show the possibility of obtaining satisfactory discharge simulations using global parameter sets, providing a provoking way for discharge predictions and water balance quantifications in ungauged catchments.

The application of global parameter estimates on a local scale can be influenced by many factors. Among those, the catchment physical and climatic properties influence the general performance. Beck *et al.* (2020) reported higher KGE values for applying the regionalized parameters in temperate and cold climates, while lower performance was found in arid climates (Beck *et al.* 2016; Arheimer *et al.* 2020). Larger catchments tend to have better water balances (Poncelet *et al.* 2017; Beck *et al.* 2020; Liu *et al.* 2020). Choosing different forcing data sets may also impact hydrological simulations using the global parameter estimates. Even though ground observations of input variables like precipitation are the most accurate forcing data (Sood & Smakhtin 2015) assuming a dense gauge network for the local application, global data sets have also been successfully applied in many studies (Guo *et al.* 2018; Senent-Aparicio *et al.* 2018; Wu *et al.* 2018). Hence, these global data sets enable discharge simulations in ungauged catchments. One issue about the global data sets is their quality (Maidment *et al.* 2013), which may lead to large bias and uncertainty. Biemans *et al.* (2009) reported an average uncertainty of the annual and seasonal precipitation mean of 30% by assessing seven global precipitation data sets in 294 catchments. This precipitation-induced uncertainty even increased when using the data sets for the simulation of discharge. Besides the advantage of large land coverage of global data that can be used in data-sparse regions, there is a need to quantify the influence of forcing data on model performance and the uncertainty associated with it. Moreover, not only the type of forcing data, but also its spatial resolution may influence the model performance. There is no consensus on whether a finer spatial representation of the model or forcing can result in better model performance in hydrological models (Lobligeois *et al.* 2014). Some studies showed that a finer spatial resolution led to an improved model performance (Boyle *et al.* 2001; Liang *et al.* 2004), while other studies could not detect a significant influence of the spatial resolution (Refsgaard & Knudsen 1996; Tran *et al.* 2018). The influence of spatial resolution of forcing data on model performance is very important for the application of global data sets since they have a rather coarse resolution. The sensitivity of model performance on spatial resolutions of model forcing can therefore indicate the applicability of these global data sets and whether finer forcing data should be preferred. Hence, whether and to which extent the spatial resolution of force has an influence needs more investigation.

In this study, we elaborate on the applicability of global parameter estimates to local catchments. We take the global parameter sets of the HBV model (Beck *et al.* 2020) as an example and apply them to two neighboring catchments in Southern Germany. Three spatial resolutions of forcing data (0.05, 0.1 and 0.2°) and two sources (local and global) are tested with a model resolution of 0.05°. We evaluate the results using different performance criteria and flow signatures. That way, we want to answer (i) How the source and spatial resolution of forcing data influence discharge simulations? (ii) Which catchment properties may largely affect the application of global parameter estimates to local regions? and (iii) Will global forcing data be able to produce acceptable discharge simulations? This work will provide insight into using global parameter sets and global forcing data for hydrological simulations in ungauged catchments.

2. MATERIALS AND METHODS

2.1. Study site

The study site consists of the Upper Neckar and the Upper Danube catchments located in southern Germany (Figure 1). The two catchments lie within the same region to reduce uncertainties induced by other factors, e.g. climatic conditions. We choose a similar catchment area (ca. 12,700 km^2 for the Upper Neckar catchment and ca. 11,300 km^2 for the Upper Danube catchment) to reduce uncertainties induced by different catchment sizes since in larger catchments errors in the forcing data can cancel each other out (Beck *et al.* 2020). The elevation in the Upper Neckar catchment ranges from 122 to 1,022 m a.s.l. (above sea level), while the Upper Danube catchment is characterized by higher elevations ranging from 417 to 2,587 m a.s.l. due to the proximity to the Alps.

The Upper Neckar and Upper Danube catchments have a mean temperature of 8.8 and 7.5 °C, and a mean annual precipitation of 918 and 1,008 mm based on the areal mean, respectively. Both catchments exhibit different coverages of karst. Especially in the Swabian Alps, there are large areas of karst that mostly lie in the Upper Danube catchment. Even though karst can be found in both catchments, there are indications that the Upper Danube catchment has a higher level

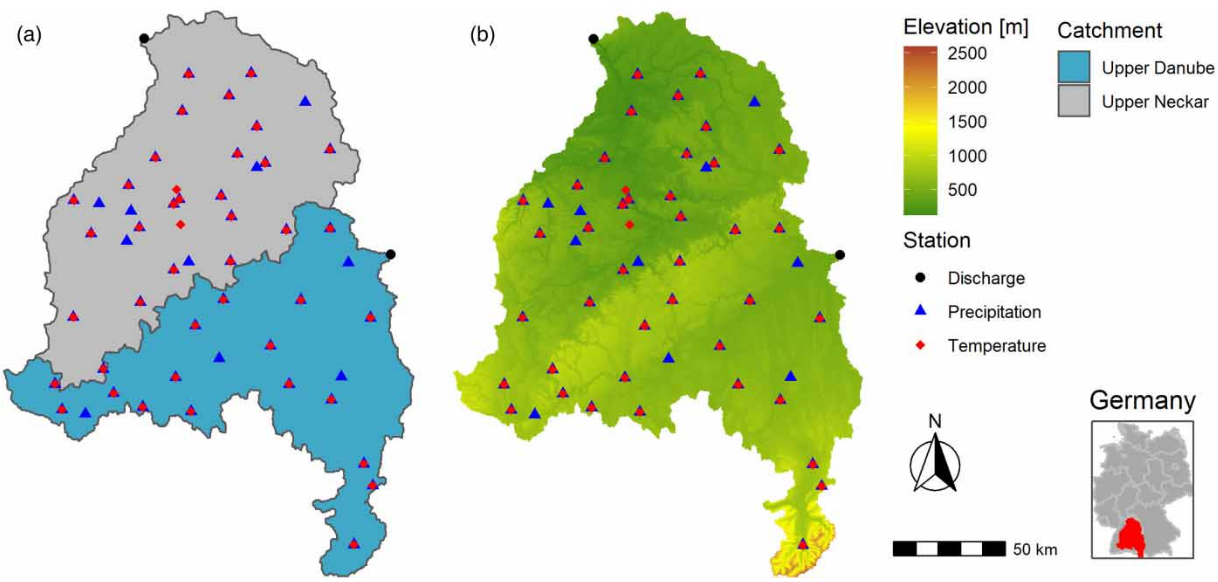


Figure 1 | Catchments (a) and topography (b) in the study area and the location of meteorological stations (for precipitation and temperature) and discharge gauging stations.

of karstification. Another special characteristic, sinkhole, can be found along the Upper Danube river. These differences regarding the geology and the topography of both catchments can be reasons leading to different model performances as well as the uncertainty using global parameter estimates.

2.2. Data

We collected streamflow observations and global and local forcing data for model simulations and information about geology and topography to show catchment properties (Table 1). We used the time period 1980–1995 for model simulations since it has the highest data availability, which results in 50 and 41 stations for precipitation and temperature, respectively. We chose the Multi-Source Weighted-Ensemble Precipitation (MSWEP V2) data set (Beck *et al.* 2019) as the global precipitation data. It has a high spatial resolution of 0.1°. Compared with other global precipitation data sets, it can represent spatial patterns in a more realistic way and is, therefore, able to provide more accurate precipitation amounts and frequencies also in mountainous areas (Beck *et al.* 2019; Xu *et al.* 2019). The earlier version has been applied in many study contexts like the simulation of soil moisture and evaporation (Martens *et al.* 2017) and lake dynamics (Satgé *et al.* 2017). By aggregation, we derived global precipitation in the spatial resolution of 0.2°.

2.3. Local precipitation interpolation

We use the external drift kriging to derive spatially distributed local precipitation and mean, minimum and maximum temperature based on point observations. The external drift kriging uses an additional variable to consider the non-stationarity for the mean of the variable of interest. This can improve the representation of spatial structures (Fohrer *et al.* 2016). It is commonly used for interpolating precipitation and temperature data on a catchment scale (Grayson & Blöschl 2001; Das *et al.* 2008; Kumar *et al.* 2010). Elevation was used as an external drift since there is a high correlation between elevation with precipitation and temperature. The daily mean precipitation was interpolated on grids with the resolutions of 0.05, 0.1 and 0.2° (~5.5, 11.1 and 22.2 km at the equator), while the daily temperature data was only interpolated on grids with the resolution 0.05° to highlight the influence of precipitation.

2.4. Hydrological model and setup

We use the HBV model (Bergström & Forsman 1973) for discharge simulations. It uses 12 parameters (|Beck *et al.* 2020) to include a snow routine to describe snow accumulation and melt, a soil moisture routine to represent evapotranspiration and recharge, and a runoff routine to model groundwater storages and outflow. The potential evapotranspiration is estimated using the Hargreaves equation (Hargreaves 1994). The regionalized parameters for the HBV model were obtained from Beck *et al.* (2020) because of its good global performance. The parameters are spatially distributed with a resolution of 0.05°. In this study, 10 different parameter maps covering the entire land surface were created by using a 10-fold cross-validation. They allow addressing the uncertainty associated with parameters. A more detailed description can be found in Beck *et al.* (2020).

In this study, a fully gridded implementation of the HBV model in *Python* which runs at daily time steps was used. Five model setups are used to test the influence of spatial resolution and sources of forcing data, i.e. spatial resolutions of 0.05,

Table 1 | Overview and description of data sources

Category	Data set	Details	Reference
Streamflow	GRDC	Global Runoff Data Centre: Observed discharge; discharge at the outlet of both catchments	GRDC (2020)
Forcing	ECA&D	European Climate Assessment & Data set: Local precipitation (50 stations) and temperature data (41 stations) with daily mean, minimum and maximum values; originates from DWD (Deutscher Wetterdienst) meteorological stations	Klein Tank *et al.* (2002)
	MSWEP V2	Global precipitation data (0.1°); 0.2° produced by aggregation	Beck *et al.* (2019)
Catchment property	WOKAM	World karst aquifer map	Chen *et al.* (2017)
	IHME1500	International Hydrogeological Map of Europe with the scale 1:1,500,000	Duscher *et al.* (2015)
	SRMT V2.1	Digital elevation model	USGS (2006)

0.1 and 0.2° for the local interpolated precipitation data and spatial resolutions of 0.1 and 0.2° for the global precipitation data. The parameter set remains the same for these five model setups. Five additional years were used as the warm-up period. Finally, the simulated discharge in the grid cells within a catchment was summed up to get its total discharge.

2.5. Model evaluation

We use several metrics and hydrological signatures to evaluate model simulations, including the general performance of discharge simulations, the reproduction of hydrological responses by model simulations, and long-term water balances. Table 2 summarizes all the metrics and signatures.

Table 2 | Performance metrics and hydrological signatures

Metric & signature	Equation	Description	Reference
Kling-Gupta efficiency (KGE [–])	$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2}$; $\alpha = \frac{\sigma_s}{\sigma_o}$; $\beta = \frac{\mu_s}{\mu_o}$	Describes the model performance. KGE ranges from $-\infty$ to 1, with optimum at 1. α, β and r indicates variability, bias and linear correlation, respectively	Gupta *et al.* (2009)
Baseflow index (I_{BF} [–])	$I_{\mathrm{BF}} = \frac{V_{\mathrm{B}}}{V}$	Characterizes the proportion of baseflow of the total discharge	Sawicz *et al.* (2011)
R-B Flashness index ($I_{\mathrm{f-RB}}$ [–])	$I_{\mathrm{f-RB}} = \frac{\sum_{t=1}^{n} \lvert Q_t - Q_{t-1} \rvert}{\sum_{t=1}^{n} Q_t}$	Describes the frequency and rapidness of changes in discharge over a given time	Baker *et al.* (2004)
Inter-annual correlation coefficient (r_{yr} [–])	$r_{\mathrm{yr}} = \mathrm{corrcoef}(\overline{Q_{\mathrm{s,yr}}}, \overline{Q_{\mathrm{o,yr}}})$	Describes the linear correlation between observed and simulated annual average discharge	–
Intra-annual correlation coefficient (r_{ym} [–])	$r_{\mathrm{ym}} = \mathrm{corrcoef}(\overline{Q_{\mathrm{s,ym}}}, \overline{Q_{\mathrm{o,ym}}})$	Describes the linear correlation between observed and simulated long-term monthly mean discharge (mean of specific month over a period)	–
Runoff ratio (R_{QP} [–])	$R_{\mathrm{QP}} = \frac{q}{P}$	Characterizes the separation of precipitation to discharge and evapotranspiration	Yadav *et al.* (2007)
Relative error of long-term mean discharge (ϵ_{r} [–])	$\epsilon_{\mathrm{r}} = \frac{\overline{Q_{\mathrm{s,all}}} - \overline{Q_{\mathrm{o,all}}}}{\overline{Q_{\mathrm{o,all}}}}$	Characterizes relative error of the long-term water balance	–
Rainfall index (I_{δ} [–])	$I_{\delta} = \frac{\sum_{t=1}^{T} \delta_t * P_t}{\sum_{t=1}^{T} P_t}$	Characterizes spatial variability of precipitation in a catchment	Smith *et al.* (2004)
Location index (I_{L} [–])	$I_{\mathrm{L}} = \frac{\sum_{t=1}^{T} I_{\mathrm{pcp}}(t) * P_t}{\sum_{t=1}^{T} P_t}$	Characterizes the variability of the precipitation fields	Smith *et al.* (2004)
Mean interquartile range (M_{IQR} [–])	$M_{\mathrm{IQR}} = \frac{\sum_{t=1}^{T} \mathrm{IQR}_t^{\mathrm{std}}}{T}$	Characterizes the uncertainty associated with different parameter sets	–
Mean standard deviation (M_{sd} [–])	$M_{\mathrm{IQR}} = \frac{\sum_{t=1}^{T} \sigma_t^{\mathrm{std}}}{T}$	Characterizes the uncertainty associated with different parameter sets	–
Mean variance (M_{var} [–])	$M_{\mathrm{IQR}} = \frac{\sum_{t=1}^{T} \sigma_t^{2^{\mathrm{std}}}}{T}$	Characterizes the uncertainty associated with different parameter sets	–

Note: (μ_{o}, σ_{o}) and (μ_{s}, σ_{s}): mean and standard deviation of observations and simulations, respectively; V_{B} and V: volumes of baseflow and total discharge, respectively [m^3]. Q_t: discharge at time t [m^3/s]; ($\overline{Q_{\mathrm{s,yr}}}$, $\overline{Q_{\mathrm{o,yr}}}$), ($\overline{Q_{\mathrm{s,ym}}}$, $\overline{Q_{\mathrm{o,ym}}}$), and ($\overline{Q_{\mathrm{s,all}}}$, $\overline{Q_{\mathrm{o,all}}}$): mean of simulated and observed annual, long-term monthly, and entire discharge, respectively [m^3/s]; q: long-term areal mean discharge [mm]; P: long-term areal mean precipitation [mm]; P_t: daily precipitation at time step t [mm]; δ_t: standard deviation of precipitation at one time step [–]; $I_{\mathrm{pcp}}(t)$: rainfall centroid ratio at one time step [–]; $\mathrm{IQR}_t^{\mathrm{std}}$, σ_t^{std} and $\sigma_t^{2^{\mathrm{std}}}$: interquartile range, standard deviation and variance of standardized discharge per catchment based on all parameter sets at one time step, respectively [–].

3. RESULTS

3.1. Daily hydrodynamics

Through visualizing the daily hydrographs (Figure 2), we can see that the model using the global parameterization with local and global precipitation forcing can both reproduce the dynamics and timing of events in the Upper Neckar and Upper Danube catchments, especially in the Upper Neckar catchment (Figure 2(a)). For both catchments, differences between discharge simulations using the global and local forcing are not significant, where the uncertainty bounds are mostly overlapped. Only for certain events are differences in the simulated discharges visible. For instance, at the end of 1981, a higher discharge in the Upper Danube catchment is simulated with the local precipitation data. There is no significant influence of the spatial resolution or forcing sources (global or local) on the simulated discharge for our studied catchments. However, there are large differences in discharge simulations between the two catchments. Generally, the low flow in the Upper Danube catchment is underestimated throughout the year and events in winter are clearly overestimated at the daily resolution. In the Upper Neckar catchment, the observed discharge can be better reproduced by the simulations. Most events in both Summer and Winter can be well captured, indicating a generally good fit.

The performance metrics calculated with the daily simulations (Figure 3) show a similar pattern as the hydrograph. Simulations using forcing with different spatial resolutions and sources for a studied catchment exhibit small differences. Concerning the general performance measured by KGE, using local precipitation improves the model performance by only 1.7% in the Upper Neckar catchment and by 9% in the Upper Danube catchment. The performance regarding variability (α), bias (β) and correlation (r) also has small differences for a catchment between cases using different spatial resolutions and global/local forcing. Comparing the two catchments, the median KGE for the Upper Neckar catchment is 0.78 (local forcing) and 0.77 (global forcing), which is over 40% higher than that in the Upper Danube catchment. While the performance regarding bias and correlation is slightly better (the absolute difference is within 0.1) in the Upper Neckar catchment than in the Upper Danube catchment, the variability performance is better simulated by 20–27% in the Upper Neckar catchment

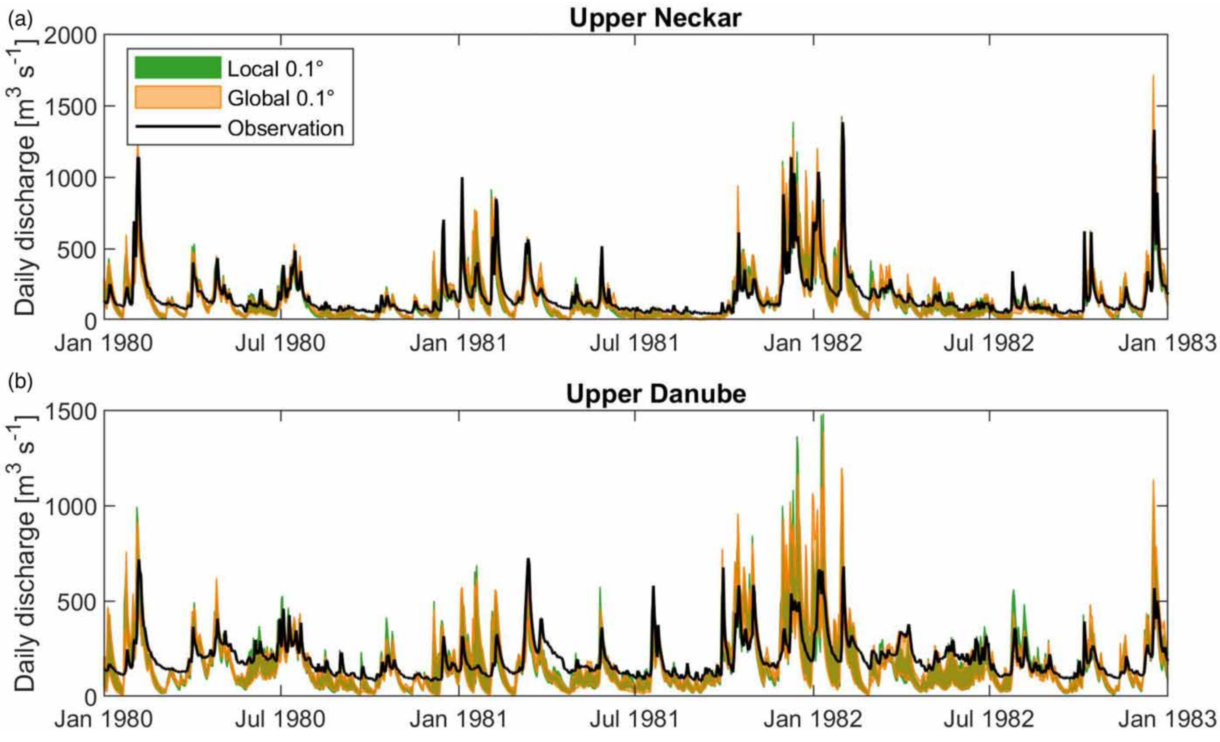


Figure 2 | Observed and simulated discharge based on the local and global precipitation data with the spatial resolution of 0.1° in the Upper Neckar (a) and Upper Danube (b) catchments. Three-year discharge time-series (1980–1983) are used to show details, while the complete time series is provided in Supplementary Figure S1. The simulated uncertainty bound is obtained using the 10 different global parameterizations. Since simulations with precipitation in different spatial resolutions do not lead to noticeable differences in the hydrographs, the simulation with precipitation in the spatial resolution of 0.1° is used for visualization.

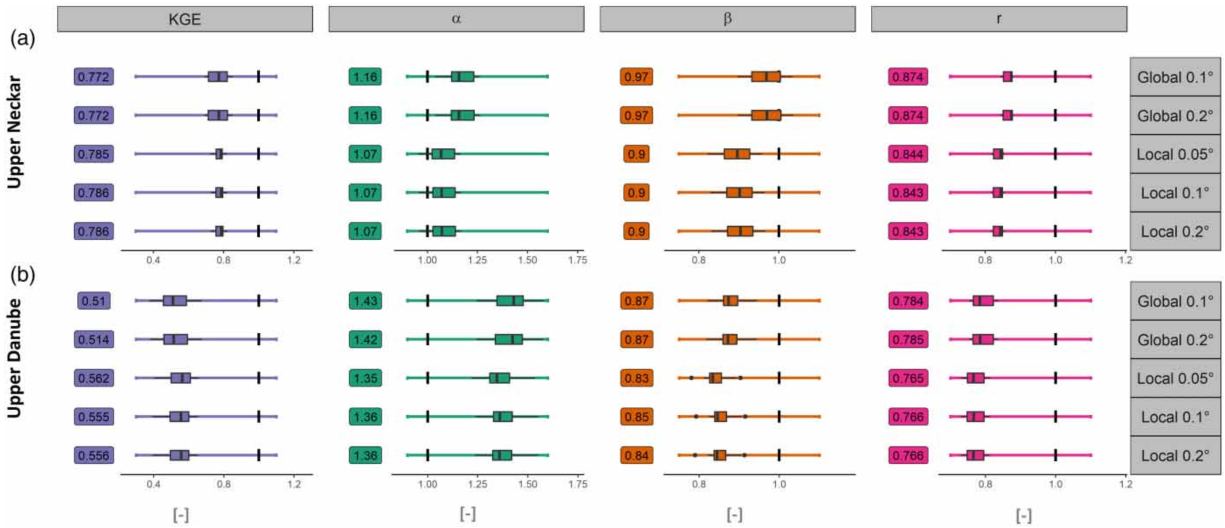


Figure 3 | Model performance at daily resolution measured by KGE and its components for the simulated discharge in the (a) Upper Neckar and (b) Upper Danube catchments. The box plots show the performance with 10 global parameterizations.

than in the Upper Danube catchment. Overall, the global parameterization performs much better in the Upper Neckar catchment than in the Upper Danube catchment for the overall fit indicated by KGE and its three components.

3.2. Monthly and seasonal hydrodynamics

Compared with the overall performance (KGE) calculated by the daily simulations, we can see a difference in the median KGE values calculated by the monthly mean discharge between using the global and local precipitation to drive the model (Figure 4), but no significant difference is observed between different spatial resolutions for each forcing source (global or local). The median KGE values increase by 0.05 and 0.08 for the Upper Neckar and Upper Danube catchments, respectively, when using the local forcing. The performance regarding correlation has slight differences between simulations using local or global forcing and at different spatial resolutions, while the variability is better represented using the local

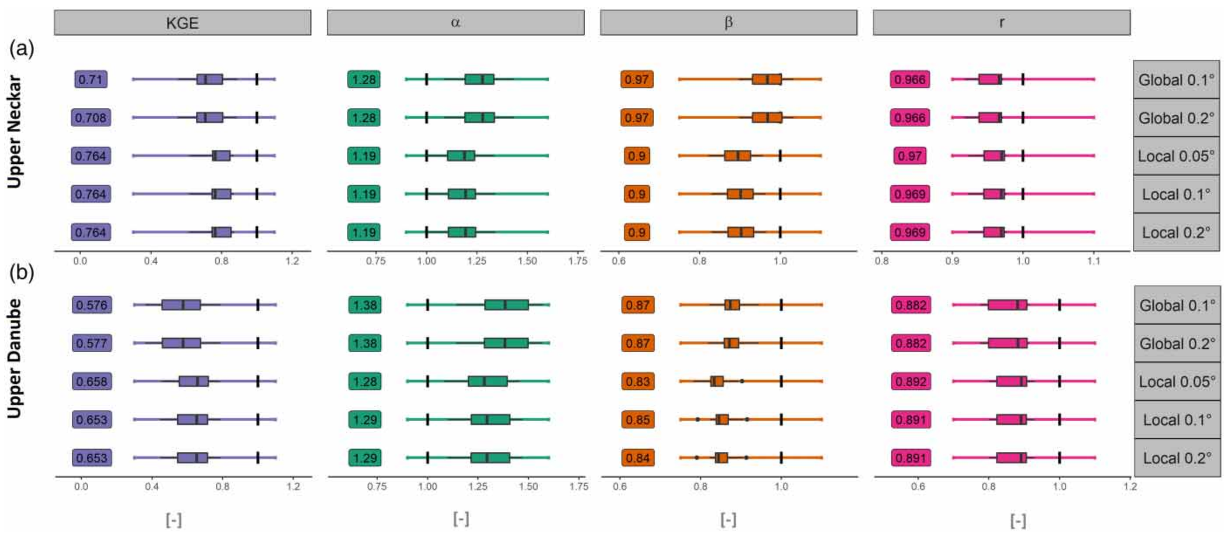


Figure 4 | Model performance at monthly resolution measured by KGE and its components for the simulated discharge in the (a) Upper Neckar and (b) Upper Danube catchments. The box plots show the performance with 10 global parameterizations. The monthly discharge is calculated by the mean of discharge of a natural month.

precipitation but the performance concerning bias decreases. Except for these differences, both the Upper Neckar and the Upper Danube catchments have good performance for bias and correlation at a monthly scale. Similar to the daily resolution, the overall performance KGE and its three components at monthly resolution are better in the Upper Neckar catchment, where KGE, variability α, bias β and correlation r all have improvement of 0.1 in their respective metric values compared with the Upper Danube catchment.

The difference in the uncertainty bounds between simulations using global and local forcing is relatively small, especially in the Upper Neckar catchment (Figure 5(a)). It indicates we can obtain a similar simulation using MSWEP V2 global precipitation compared with the local forcing that is usually hard to get (the spatially distributed data). The general monthly dynamics can be well captured in both catchments (Figure 5(a) and 5(c)). In particular, high monthly mean discharge (such as from December to March) mostly fall within the simulation uncertainty bound in both catchments. However, low monthly mean discharge, particularly in August and September, is underestimated by simulations in both catchments. From the long-term monthly mean discharge (Figure 5(b) and 5(d)), we can see the intra-annual variability of discharge can be reproduced in both catchments, even though the underestimation is shown in the Summer months. Therefore, using global parameterization and the MSWEP V2 precipitation can reproduce the monthly dynamics and seasonality.

3.3. Hydrological signatures

For the hydrological signatures based on daily discharge simulations (Figure 6), the base flow index (I_{BF}) is underestimated and the flashness index ($I_{f\text{-}RB}$) is overestimated in both catchments for all simulations. A slightly better I_{BF} is simulated using the local precipitation while changing spatial resolutions does not lead to a distinct difference in I_{BF}. The difference exists between the two catchments; I_{BF} is less underestimated (ca. 30% underestimation) in the Upper Neckar catchment than that (ca. 40% underestimation) in the Upper Danube catchment. A similar pattern is observed for the flashness index ($I_{f\text{-}RB}$) as well. There is a small difference for simulated $I_{f\text{-}RB}$ compared with discharge simulations using local and global forcing, but the simulated $I_{f\text{-}RB}$ hardly differs regarding simulations with different spatial resolutions. The simulated $I_{f\text{-}RB}$ performs much better in the Upper Neckar catchment (ca. 10% overestimation), while it has a large overestimation

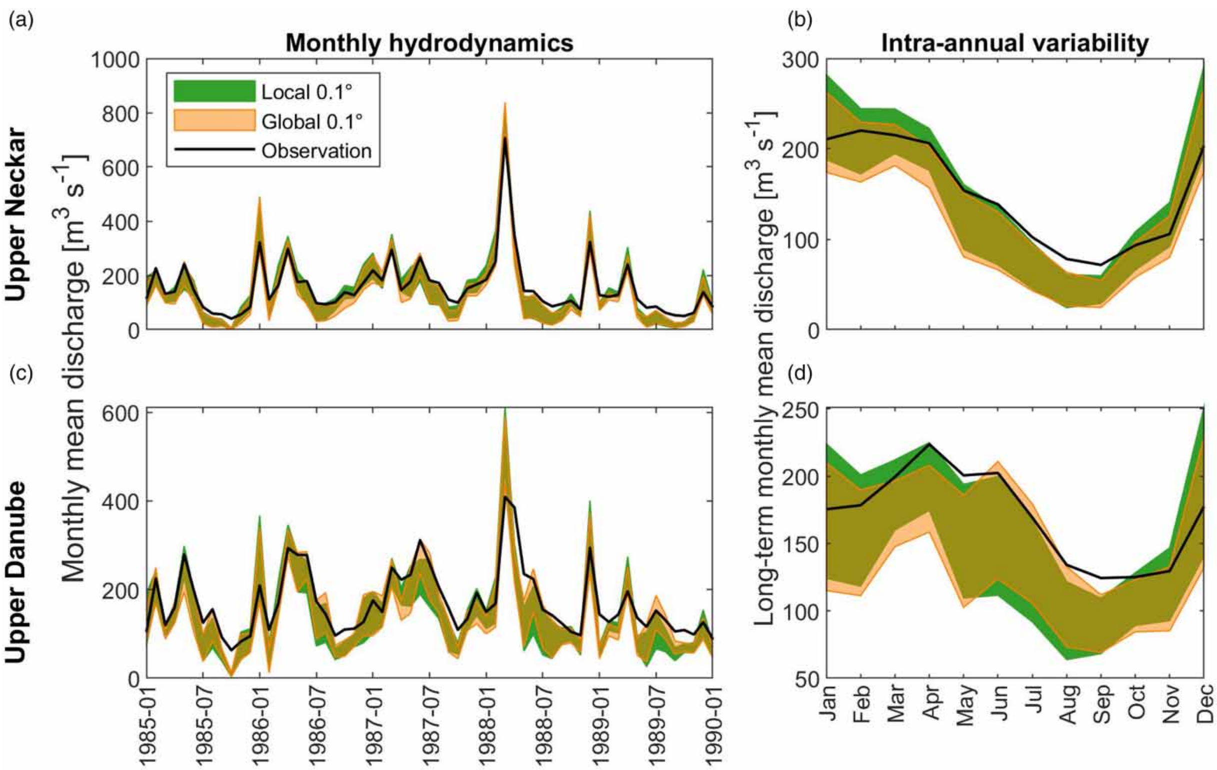


Figure 5 | The observed and simulated monthly mean discharge (a and c) to show the monthly dynamics and the long-term monthly mean discharge to show the intra-annual variability (b and d) for the Upper Neckar and Upper Danube catchments, respectively.

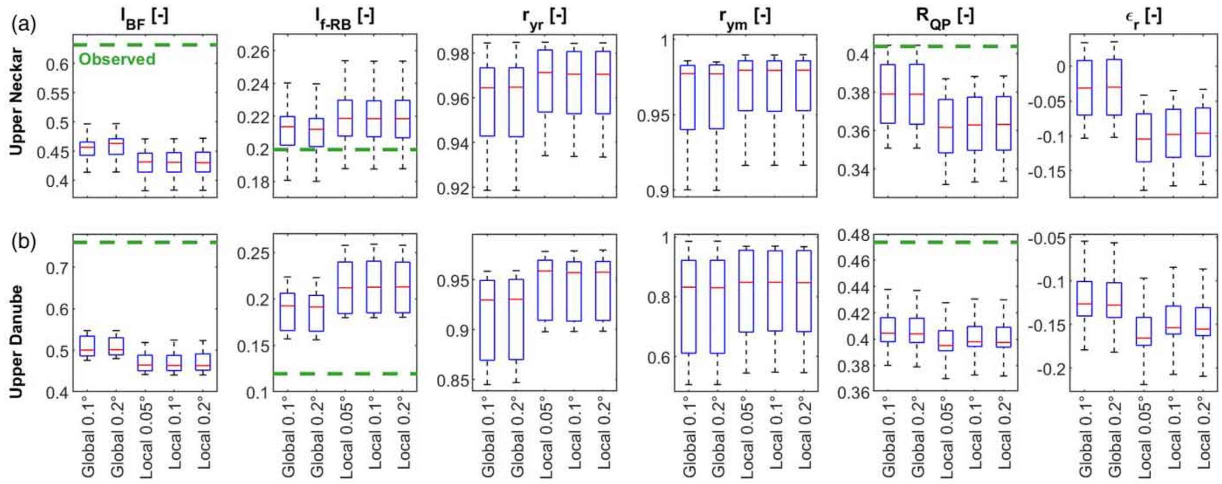


Figure 6 | Hydrological signatures based on different time scales (daily: I_{BF}, $I_{f\text{-}RB}$; annual: r_{yr}, r_{ym}; long-term: R_{QP}, ϵ_r) in the (a) Upper Neckar and (b) Upper Danube catchments using 10 global parameterizations.

(>60%) in the Upper Danube catchment. Therefore, deriving from daily simulations, the forcing source (local or global) has a small influence and the spatial resolution has a barely invisible influence on hydrological signatures. Global parameterizations due to different catchment properties lead to a large difference in the hydrological signatures between the two studied catchments.

For the hydrological signatures based on the annual and long-term average of discharge simulations, they are better simulated compared with those derived from daily simulations. The median correlation coefficients calculated by the annual mean time-series (r_{yr}, indicating inter-annual variability) are around 0.97 and 0.95, and the median correlation coefficients calculated by the long-term monthly averages (r_{ym}, indicating intra-annual variability) are 0.97 and 0.82 for the Upper Neckar and Upper Danube catchments, respectively. No significant difference can be seen between different spatial resolutions and only a very small difference can be detected between simulations using local or global forcing in both catchments. The runoff ratio is underestimated in both catchments. However, the underestimation is much smaller, ca. 7 and 15% underestimations in the Upper Neckar and Upper Danube catchments, respectively, compared with hydrological signatures derived from daily simulations (such as baseflow index). Demonstrated by the relative error regarding the long-term water balance (ϵ_r), the long-term average discharge is underestimated by 4–10% in the Upper Neckar catchment and 13–15% in the Upper Danube catchment. Therefore, it can be seen that hydrological signatures derived from the annual or long-term average are simulated quite well in both catchments even though the Upper Neckar catchment has a better performance. This demonstrates that seasonality, annual and long-term water balance can be captured using the global parameterization and the global forcing (MSWEP V2) in our studied catchments.

A high dependency of precipitation patterns on catchments can be seen in Figure 7, quantified by the rainfall index (I_δ, Figure 7(a)) and location index (I_L, Figure 7(b)). They both show a higher variability of precipitation in the Upper Danube catchment compared with the Upper Neckar catchment. We can also see that the spatial pattern of precipitation calculated by local precipitation observations (Figure 7(a)) can not be well represented by global precipitation for the Upper Danube catchment. However, the global precipitation in the spatial resolution of 0.1° is better for capturing the spatial pattern compared with the spatial resolution of 0.2° in the Upper Danube catchment.

3.4. Uncertainty of discharge simulations

All three metrics (M_{IQR}, M_{sd} and M_{var}) show the same behavior for different simulations (Figure 8). Using the 10 different parameter sets, there is a higher uncertainty associated with the discharge simulation in the Upper Danube catchment compared with the Upper Neckar catchment. The uncertainty approximately doubles in the Upper Danube catchment, which is also consistent with the lower KGE values in Figure 3(b). The larger simulation uncertainty in the Upper Danube catchment could be explained by its more complex topography that leads to a complex spatial precipitation pattern and its more intensive karst area that leads to difficulties for model parameters to capture the special flow characteristics. Within both

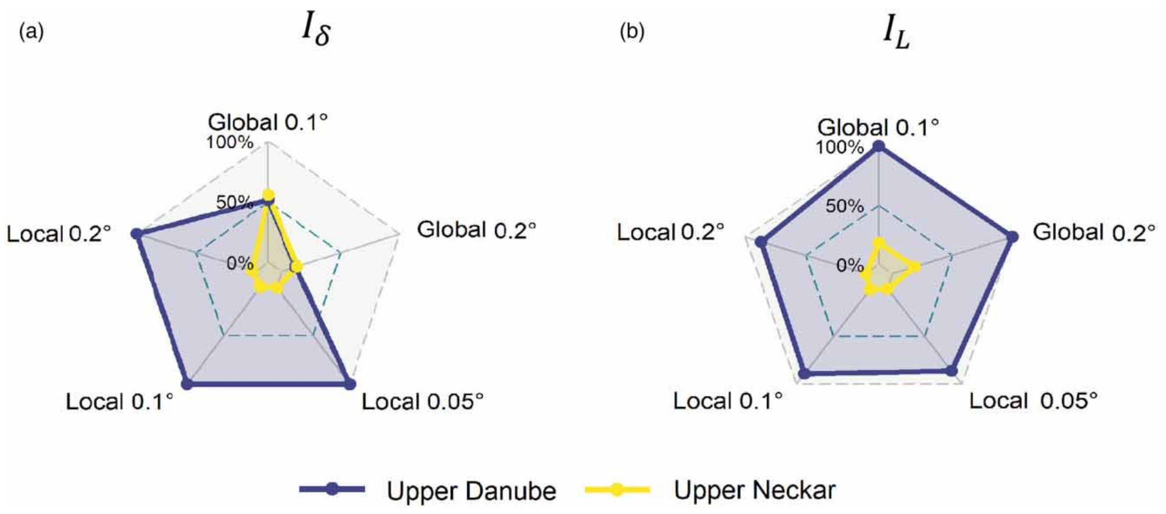


Figure 7 | Comparisons of global and local precipitation in different spatial resolutions using the rainfall index, I_δ, (a), location index, I_L, (b), where the values are expressed on a scale from 0 to 100%, 0% describes the minimum and 100% the maximum value of the particular performance metric. The rescaling for the I_L and I_δ is applied on the whole performance metric independent of catchments.

catchments, there is a very minor difference in the uncertainty of discharge simulations with changing spatial resolutions. Meanwhile, all metrics show that simulations using global precipitation have a higher uncertainty compared with simulations using local precipitation. However, the difference is small (1–4%). This can also be seen in the box plots in Figure 3 (represented by the width of the boxes, and the interquartile range). It should be noticed that for the KGE in the Upper Neckar catchment (Figure 3(a)) the interquartile ranges differ between simulations using local and global precipitation, while the trend is barely noticeable in the Upper Danube catchment. This indicates that for catchments with good global parameterizations, using global precipitation can introduce additional uncertainty in discharge simulations but maintain the generally good performance. For catchments with less good global parameterizations, the added uncertainty due to using this global forcing is rather small since the total uncertainty may be dominated by model parameterizations.

4. DISCUSSION

4.1. Influence of forcing data

Simulations using precipitation with different spatial resolutions do not show large discrepancies, indicating an insignificant influence of the spatial resolution of forcing input in our study area. This can be explained by the small spatial deviations of precipitation with different spatial resolutions (Figure 9(a)). Additionally, minor changes in the uncertainty in discharge simulations emphasize the negligible influence of the tested spatial resolutions. This coincides with the results of previous studies on the influence of a finer spatial representation of models (Lobligeois *et al.* 2014; Tran *et al.* 2018). Dankers *et al.* (2007) reported an increased performance of discharge simulations with a finer spatial resolution for the Berg gauging station in our region, while similar model performance was shown with coarser spatial resolutions for other gauging stations. Lobligeois *et al.* (2014) suggested that the fit of the simulated discharge is strongly dependent on the catchment. Another reason could be the ability of catchments to dampen the spatial variability of precipitation due to their geological settings such as karst, especially in the Upper Danube catchment. It can be seen from the quite low observed streamflow elasticities in both catchments (0.67 and 0.91 for the Upper Danube and Upper Neckar catchments, respectively). The coarser spatial resolution of the model is sufficient for discharge simulations in both catchments because no significant influence of the model spatial resolution can be observed. This emphasizes the potential of the discharge simulation in ungauged areas with global parameters since coarser spatial resolutions are easier to obtain and most global data sets have a rather coarse resolution.

Simulations using the local precipitation are slightly better compared with simulations with global precipitation. This is expected with a common assumption that local spatially interpolated precipitation can better capture the spatial variability of precipitation (Sood & Smakhtin 2015; Sirisena *et al.* 2018). Contrary to this, Guo *et al.* (2018) reported that discharge simulations based on global precipitation outperformed the local interpolated precipitation since poor gauging density is

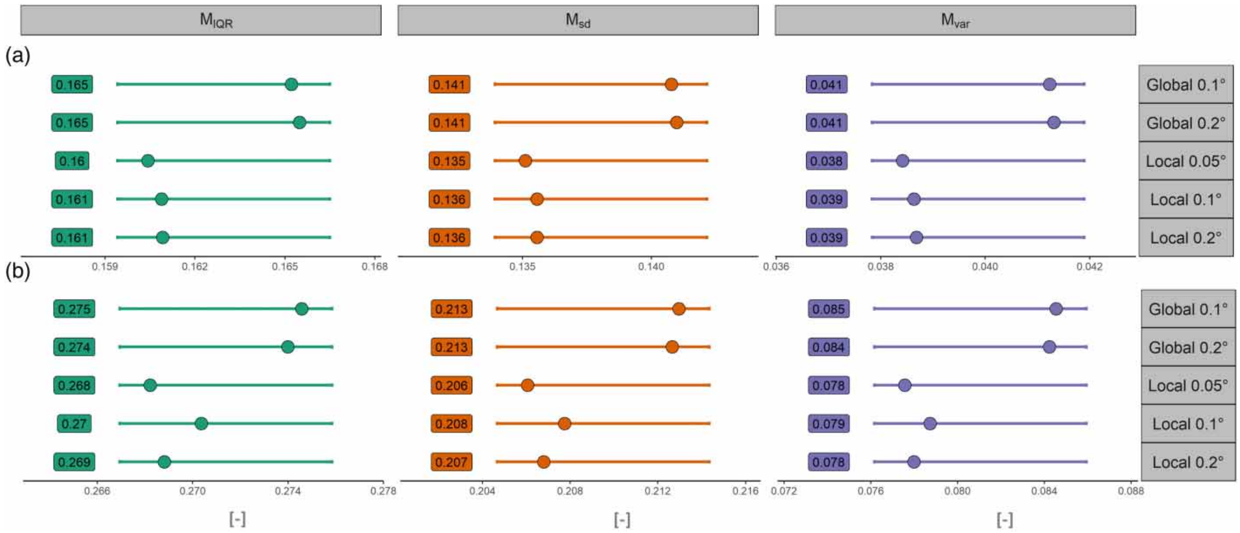


Figure 8 | Measurement of uncertainty in the discharge simulation in the (a) Upper Neckar and (b) Upper Danube catchments induced by 10 global parameterizations.

unable to provide grid interpolated precipitation with sufficient quality. It is noted that both local and global precipitation can be affected by topography due to spatial interpolation (Biemans *et al.* 2009; Schreiner-McGraw & Ajami 2020). Generally, the MSWEP V2 precipitation has a good agreement with the interpolated rain gauge data. Only grids at the edge of the catchment and in the high elevations, such as in the south part of the Upper Danube catchment, have large deviations (Figure 9(b)). This can be explained by larger errors of global precipitation in areas with a higher spatial variability (Biemans *et al.* 2009; Wu *et al.* 2018) due to a complex topography. Insignificant differences between discharge simulations using local and global precipitation, particularly the good performance in the Upper Neckar catchment, emphasizes the great potential of using the MSWEP V2 precipitation for local applications (Senent-Aparicio *et al.* 2018; Wu *et al.* 2018). It provides a large opportunity for discharge simulations in ungauged areas. At the same time, the results identify the forcing data as an influencing factor on the application of a global parametrization that needs to be taken into account, especially in catchments with a complex topography.

4.2. Influence of catchment properties

The distinct difference in model simulations between these two neighboring catchments may suggest that model performance using global parameter estimates strongly depends on catchment properties. According to the rainfall index and the location index, the Upper Danube catchment shows a higher variability of precipitation compared with the Upper Neckar catchment (Figure 7). While the Upper Danube catchment exhibits a spatially complex topography, especially in the south close to the Alps and in the Swabian Alb, the Upper Neckar catchment has a rather simple topography characterized by lower elevations. Higher elevations heavily influence the precipitation pattern and result in higher spatial variability (Ly *et al.* 2013). Mountainous areas with a complex topography generally lead to a more difficult simulation of the hydrological response (Rahman *et al.* 2013), where snow processes are crucial (Weber *et al.* 2010). Another factor could be geological settings. The Upper Danube catchment has 38% (1,179 km^2) more continuous carbonate rocks (Goldscheider *et al.* 2020) than the Upper Neckar catchment. The majority of Swabian alb lies within the Upper Danube catchment, forming a complex karst system (Villinger 1977; Hötzl 1996). The occurrence of the Danube Sinkhole may also largely impact discharge simulations in the Upper Danube catchment. It highlights the importance of inter-catchment groundwater flow (Fan 2019; Liu *et al.* 2020). Liu *et al.* (2021) showed that combining karstic and non-karstic processes can better simulate water balances. Therefore, future studies should consider special karst groundwater processes in the Upper Danube catchment to improve hydrological simulations and predictions. However, caution should be taken when comparing the influence of a fewer number of catchment properties on the model performance because recent study indicated that replacing a catchment

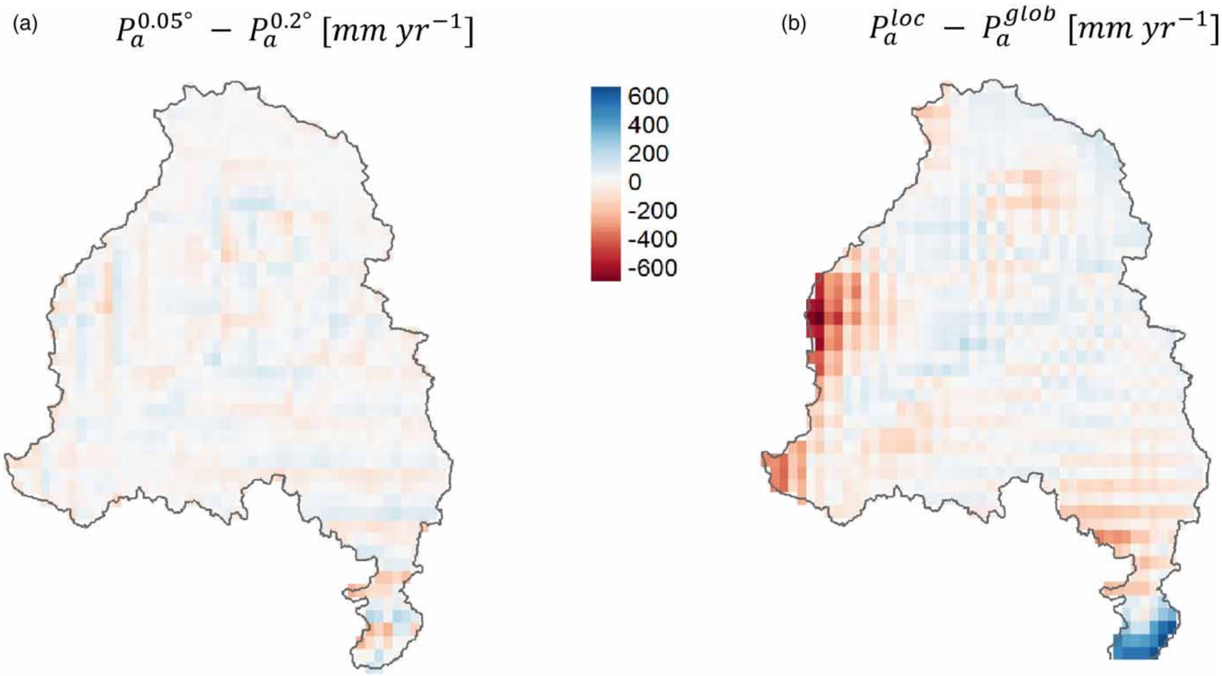


Figure 9 | Deviation of precipitation between two spatial resolutions, 0.05° and 0.2°, (a); deviation of precipitation between the local and global sources (b), where the spatial resolution of 0.1° is used.

property in parameter prediction has not resulted in model performance degradation to establish a relationship between model parameters and catchment properties (Merz *et al.* 2020).

4.3. Transferability and limitation

Using the global parameter estimates with global precipitation at daily resolution can provide acceptable performance, especially in the Upper Neckar catchment with a simple topography. When focusing on monthly, annual and long-term water balance, it can capture the monthly and seasonal hydrodynamics and the performance in the Upper Danube catchment is enhanced, too. The hydrological signatures derived from the monthly to long-term averages also suggest that the HBV global parameter estimates with the MSWEP V2 precipitation can reproduce the system responds well. Therefore, the global parameter estimates and global forcing are able to provide an easily accessible way to quantify water balance at monthly and even larger temporal resolutions. This highlights the value of using such information for understanding hydrological behaviors and water balance in the ungauged regions.

We showed a good transferability of global parameter estimates and global forcing to the local applications, especially for monthly dynamics and water balance, despite using two neighboring catchments in the humid regions. However, the transferability of this good experience to arid regions may be challenging considering the generally poor streamflow simulation in arid regions (Lin 2001). In addition, care should be taken for the different levels of parameter identifiability while transferring the global parameter in order to minimize the errors emerging from insensitive parameters. Regionally dominant catchment properties can also influence success in global parameter transfer (Singh *et al.* 2014). However, such errors introduced by the regionally dominant catchment property would be bounded in the uncertainty range of global parameterization. Complexity in catchment topography and geology should be paid more attention.

Some limitations of our analysis should be noted. We only tested with two catchments of similar size and which lie within the same climate zone considering good data availability. However, the catchment size can alter the influence of the spatial resolution on larger catchments (Lobligeois *et al.* 2014). The climatic condition within the catchment also plays an important role in the general applicability of regionalized parameters since the humidity has a strong influence on the model performance (Beck *et al.* 2020). Regionalized parameters tend to result in higher model performance in more humid catchments like the Upper Danube and Upper Neckar catchments compared with arid areas. Additionally, the influence of forcing data which was tested with one global data set represents a limitation since global forcing data sets can vary heavily in their quality (Maidment *et al.* 2013). Hence, caution should be made when transferring the good results with the MSWEP V2 data set in this study to other global forcing data sets. Rather the applicability of a specific global data set should be confirmed by studies and tailored to the investigated catchments, e.g., usage of global data set with the ability to represent spatial complexity in mountainous catchments. The fully distributed HBV model that was used in this study is only one possibility for discharge prediction, while global parameter estimates from other hydrological models can be applied for such purposes. Hence, the structural uncertainty resulting from the HBV model that is incorporated in the results cannot be accounted for and quantified. Multi-model ensembles for simulating the discharge may account for these uncertainties and have been successfully applied in the past (Butts *et al.* 2004; Georgakakos *et al.* 2004).

When applying global parameter estimates and global forcing for discharge simulation to new local applications, one should keep in mind that (i) influence of climate, catchment size and property, and forcing data can compromise; (ii) the sufficient performance of global forcing data is strongly dependent on the specific data set, and therefore, a data set should be chosen which has proven to be applicable for such purpose and (iii) uncertainty introduced in these results due to the model structure can be different when choosing different hydrological models. Nevertheless, the findings reported here lay the foundation for further research on this topic to answer the remaining open questions when applying global parameter estimates to local applications for discharge simulation.

5. CONCLUSIONS

Local observational climatic and streamflow networks are not available in many regions around the world. Global hydrological parameter estimates and global forcing provide possibilities to investigate the hydrological responses of a system even at ungauged catchments. In this study, we chose two neighboring catchments (the Upper Neckar and Upper Danube catchments), where we have reliable climatic forcing and streamflow measurements, to discuss what affects the local applications using global parameter estimates and global forcing, and whether simulations are sufficient for water balance analysis at different temporal scales. We find that (i) changing the spatial resolution of forcing only has a very minor influence on our simulations for the tested spatial resolutions (0.05°–0.2°) in our studied catchments. Using a local interpolated precipitation performs better than using the global forcing (MSWEP V2). However, the difference is not large with a small decrease in the median KGE (~0.02 and ~0.05) in the Upper Neckar and Upper Danube catchment based on daily resolution, respectively (~0.05 and ~0.07 based on monthly resolution); the simulations are all acceptable to good (especially in the Upper Neckar catchment) using both local and global precipitation. (ii) Catchment properties largely affect the application of global parameter estimates. The complex topography indicated by large spatial variation of elevations and special geological settings such as the strong karstification in the Upper Danube catchment lead to decreased model performance compared with the Upper Neckar catchment, particularly at the daily scale. (iii) Simulations using the HBV global parameter estimates and global forcing (MSWEP V2) can reproduce monthly and seasonal hydrodynamics. The long-term water balance and system behaviors measured by hydrological signatures based on monthly to long-term simulations can also be captured quite well in both catchments. Our study highlights the potential for applying global parameter estimates at the local scale and promotes the usage of global parameter estimates and global precipitation (MSWEP V2) for understanding hydrological behaviors, particularly the monthly hydrodynamics, seasonality and long-term water balance, in the ungauged catchments. When simulating streamflow using global parameter estimates and global forcing data sets, more attention should be paid to catchment properties including the complexity of topography that largely influences precipitation patterns and special subsurface features like the karst occurrence and the complexity of subsurface. Furthermore, inter-comparisons between different regionalization approaches may provide some uncertainty estimation for streamflow simulations for ungauged catchments. Future studies taking more catchments with various catchment properties and climates may provide more general insights into how can global parameter estimates and forcing be appropriately applied at the local scale.

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AUTHOR CONTRIBUTION

Y.L. conceptualized the study. J.S. performed model simulations. J.S. and Y.L. analyzed the results and wrote the paper. T.A. wrote part of the discussion. A.H. provided supervision and advice throughout developing this manuscript. All authors contributed to the revision of the manuscript.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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