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Assesing the Value of High-Resolution Data and Parameters Transferability Across Temporal Scales in Hydrological Modeling: A Case Study in Northern China

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Abstract: The temporal resolution of input data and the computational time step are crucial factors affecting the accuracy of hydrological model forecasts. This study presents a four-source hydrological model tailored to the runoff characteristics of the mountainous areas in Northern China. Using this model, along with meteorological and hydrological data from seven catchments of varying sizes in Northern China, we investigated the impact of different input data resolutions and computational time steps on simulation accuracy, as well as the transferability of parameters across different time scales. The results show that: (1) The proposed model performs well across different spatial and temporal scales, with average NSE for daily and hourly flow forecasts of 0.93 and 0.85, respectively. (2) For daily streamflow simulations, there was a significant improvement in model performance when the data resolution was increased from 24 hours to 12 hours; however, beyond the 12-hour resolution, the improvement became negligible. For hourly streamflow simulations, the enhancement in overall flood process accuracy becomes insignificant when the resolution exceeds 6 hours, although higher resolutions continue to improve the precision of peak flow simulations. (3) When the computational time step is fixed (e.g., 1 hour), model parameters are transferable across different data resolutions; parameters calibrated with daily data can be used in models driven by sub-daily data. However, parameters are not transferable when the computational time step varies. Therefore, it is recommended to utilize smaller computational time step when constructing hydrological models even in the absence of high-resolution input data. This strategy ensures that the same simulation accuracy can be achieved while preserving the transferability of model parameters, thus enhancing the robustness of the model.

1 Introduction

Hydrological modeling plays a critical role in water resources management, flood forecasting, and climate impact assessments. Accurate simulation of runoff processes is essential for understanding water balance and predicting hydrological extremes. The effectiveness of a hydrological model is influenced by the scale of input data (resolution), the scale of the model's computation, and the scale of the hydrological processes being modelled (López-Moreno et al., 2013; Merheb et al., 2016).

In the past, hydrological modeling has typically relied on daily or coarser resolution data, limiting its applicability for shorter time steps required in scenarios like flash flood forecasting. Models that utilize coarse or artificially enhanced data may introduce biases when applied to finer temporal scales, as they may fail to accurately represent the variability and magnitude of key hydrological variables. However, advancements in measurement technologies, including high-frequency automated rain/streamflow gauges and phased array rain-radars, have enabled access to high-resolution rainfall and runoff datasets.

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

Despite these technological advances, the quantitative benefits of high-resolution data in enhancing hydrological model performance remain unclear. For instance, studies on the impact of rainfall data resolution on hydrological models have produced inconsistent results. Research such as Jaehak et al. (2011) suggested that finer temporal resolution significantly improves model simulations, whereas other studies (Kannan et al., 2006; Ficchì et al., 2016) found that greater data resolution does not necessarily lead to better model performance. Our previous research (Tudaji et al., 2024) in southern China showed that high-resolution data does not always have positive impact on model performance. Nevertheless, we and other related studies acknowledge that further studies across different climate zones and models are necessary to validate and extend the generality of these findings.

Moreover, there remain other unresolved issues regarding data resolution that warrant further investigation. When a certain resolution is selected for a watershed model based on current data availability (or a specific standard) and the model's parameters are calibrated accordingly, the model is essentially considered constructed. However, if the resolution of future input data differs from that used during the model's construction, it is uncertain whether the model’s forecast results will remain reliable. There is a need to explore whether the model's parameters were optimized solely to maximize simulation metrics for that particular resolution, and whether these parameters can be transferred effectively across different data resolutions. Reynolds et al. (2017) found that the model calibrated by the daily data performance almost as good as the model calibrated by data at sub-daily resolutions. However, this conclusion was reached under a fixed computational time step, and the study (including the aforementioned studies on input data resolution) also acknowledges that the generality of their conclusions to other regions and models warrants further investigation.

Similarly, another issue that arises when constructing hydrological models is the choice of the model's computational time step. The time dependence and transferability of parameters has been widely studied. (Krajewski et al. 1991; Finnerty et al. 1997; Littlewood and Croke 2008; Reynolds et al. 2017). Recent studies have provided quantitative insights into relationship of parameters at different computation time steps. Wang et al. (2009) established the relationship between the parameters and the square root of the time step; Jie et al. (2017) established transformation function between parameter values at different time steps. However, it remains uncertain whether a finer computational time step consistently leads to improved simulation accuracy when the resolutions of input and output are fixed. Moreover, the extent to which parameters can be transferred across different computational time steps without transformation and the existence of an optimal computational time step that maximizes both parameter transferability and model performance are still questions that warrant further investigation.

In light of these background, this study seeked to enhance our understanding of the value of high-resolution data and transferability of parameters across temporal scales in hydrological modeling based on 7 small-to-medium catchments in northern China, using data resolutions ranging from 1 to 24 hours. We designed two experiments focusing on the most common hydrological forecasting timescales—daily and hourly, to investigate the value of the high-resolution data on hydrological modeling. Besides, two further experiments, one with various data resolutions and another with various computation time steps, were conducted to assess the transferability of parameters under different conditions. Specifically, this study seeks to address three key questions:

(1) What is the necessary resolution of rainfall and streamflow data to provide reliable hourly and daily streamflow simulations?

(2) When the computation time step is fixed as hourly, can parameters be transferred when adopting different temporal resolutions of input data?

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

(3) When the temporal resolution of input data is fixed as daily, can parameters be transferred when adopting different computation time steps?

The rest of this paper is structured as follows: Section 2 outlines the materials and methodology, including the introduction of study catchments, the hydrological model used, and the experimental designs. Section 3 presents the results of the experiments. Section 4 explains the role of high-resolution data, discusses the transferability of parameters under different conditions, and provides insights into selecting data resolution and computation time step during the modelling. Finally, Section 5 offers concluding remarks and limitations in this study.

2 Materials and methodology

2.1 Study area and data

The Chaobai River, located in northern China and flowing through Beijing, is one of the five major rivers in the Haihe River system of China. In this study, we utilized a set of 7 various size of catchments in the upper reaches of the Chaobai River as the study area (Figure1, Table1), where data quality is relatively high and human activities (such as reservoirs or dams) have minimal impact. Among them, the Xitaizi Basin, the smallest one, is a hydrological experimental catchment. The other six study catchments are the control regions of important hydrological stations located upstream of reservoirs or lakes on the major tributaries in the upper reaches of the Chaobai River Basin.

The study area is characterized by a temperate monsoon climate, with precipitation highly seasonal and primarily concentrated in July and August, resulting in significant seasonal and interannual variations in river flow. During periods outside the rainy season, the flow is minimal, and in some cases, the river may even run dry. Therefore, we chose the 2021 flood season, which saw significant flood events and has relatively complete data, as the study period for this study.

The streamflow and rainfall data were obtained from the Rain and Hydrological Database of Beijing, curated by the Beijing Hydrological Station. When selecting the above-mentioned hydrological stations as the outlets for the study basins, the following principles were followed: (1) The station must have discharge data with a resolution finer than hourly during flood events; (2) The upstream control area of the station should be free of water control structures such as reservoirs, dams, or lakes that could significantly affect the natural progression of floods; and (3) The study catchments should cover a range of different scales, from a few square kilometers to several thousand square kilometers. The selection of rainfall data followed similar principles, ensuring that each rain gauge station provided complete rainfall data with a resolution finer than hourly throughout the entire storm runoff process. We identified 56 high-quality stations situated within the study catchments from the database. The number of rainfall gauges per catchment varied from 1 to 14, averaging 8 stations. Additionally, the rainfall gauging area—calculated as the catchment area divided by the number of stations—ranged from 3 km^2 to 373 km^2, with an average of 157 km^2. The Thiessen Polygon method (Han and Bray, 2006) was employed to generate the areal rainfall data for each sub-basin in each catchment.

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

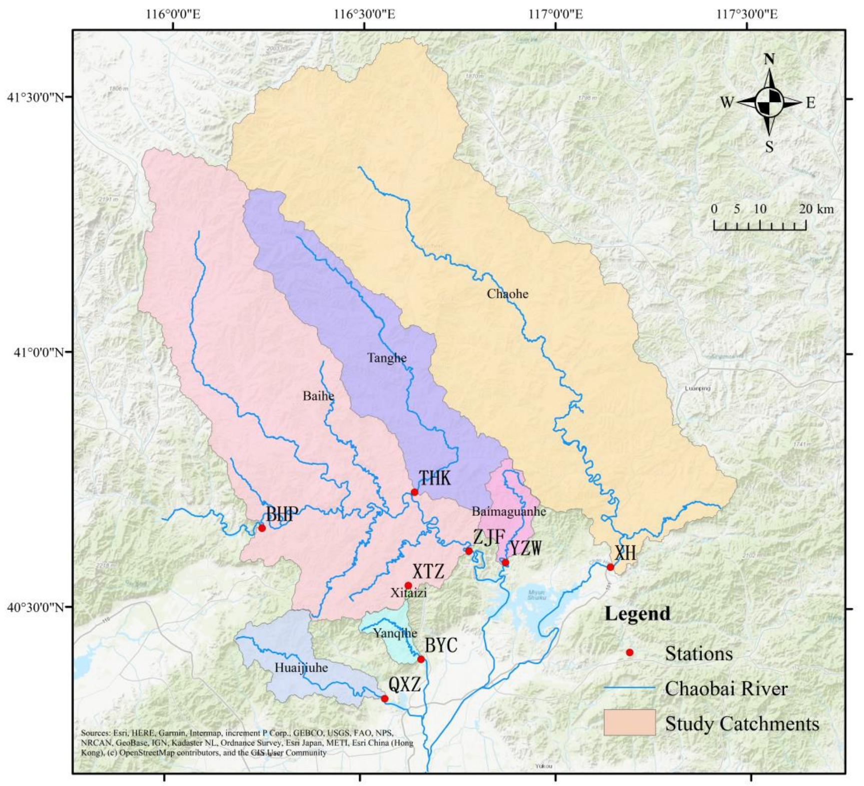

Figure 1: Geographic distribution of study catchments

Table 1. Information of study catchments and data

NO.	Basin	Hydrological Station	Abbr.	Drainage area (km^2)	Number of rainfall gauges	Rainfall gauging area (km^2)
1	Xitaizi	Xitaizi	XTZ	3.11	1	3.11
2	Yanqihe	Baiyachang	BYC	96.06	6	16.01
3	Baimaguanhe	Yaoziwa	YZW	180.04	8	22.51
4	Huaijiuhe	Qianxinzhuang	QXZ	332.85	10	33.29
5	Tanghe	Tanghekou	THK	1263.13	4	315.78
6	Baihe	Zhangjiafen	ZJF	4660.91	14	332.92
7	Chaohe	Xiahui	XH	4845.98	13	372.77

2.2 Hydrological model

The study catchments are located in a rocky mountainous region with severe weathering and high vegetation cover (Zheng et al., 2013; Yu et al., 2017). On the basis of intensive hydrological and isotopic observations from the Xitaizi experimental catchment, Zhao et al (2019) found that preferential flow in the heavily weathered granite and shallow soils makes up the majority of the stormflow. Recent studies also indicate that subsurface flow is a significant contributor to flood generation (Addisie et al., 2020; Xiao et al., 2020; Wang et al., 2022). To effectively capture the hydrological processes within the study

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

area, a four-source hydrological model was developed, designed to represent multiple hydrological pathways. The model's structural diagram (Figure 2) illustrates these pathways, where the I layer denotes the impervious layer, which occupies a small and relatively constant proportion in the study area. The W layer represents the soil moisture storage layer, which is responsible for simulating the soil moisture content. The S layer signifies the shallow subsurface layer, encompassing both the soil runoff layer and the weathered bedrock; when the S layer gets saturated, it generates surface runoff (Rs), which, along with subsurface runoff (Rss), constitutes the primary sources of stormflow. Lastly, the G layer represents the deep groundwater layer, which is the main contributor to baseflow. The equations for structure the model was listed in Appendix A.

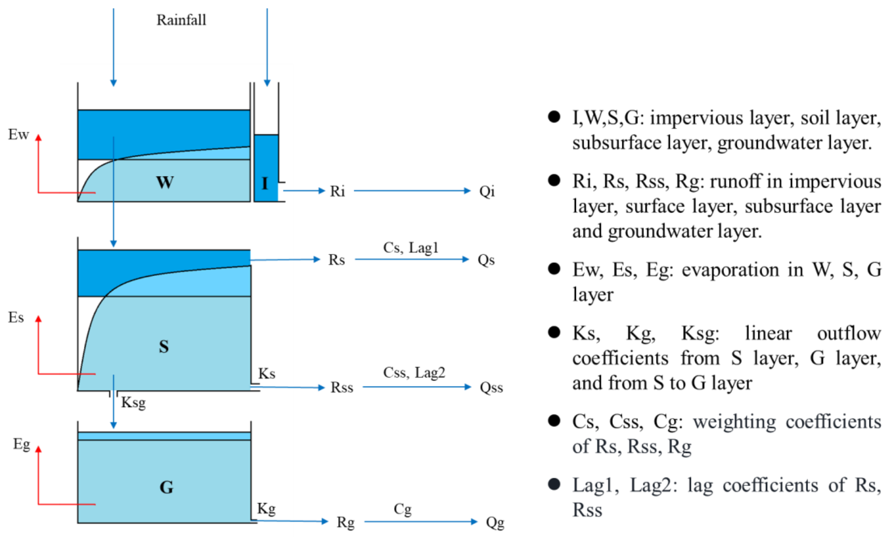

Figure 2: The structural diagram of the hydrological model

The routing process is modeled using the Muskingum method (McCarthy, 1938; Cunge, 1969), with the equation given as:

$$Q_{i+1}^{t+1} = C_1 Q_i^t + C_2 Q_i^{t+1} + C_3 Q_{i+1}^t + (C_1 + C_2) Q_L \tag{1}$$

where i is spatial index, t is temporal index, and Q_L is lateral flow.

In the Muskingum method, the three parameters C_1, C_2, C_3 must satisfy the conditions of being within the 0-1 range and their sum equaling 1. To accommodate these constraints within automatic parameter optimization algorithms, this study reparametrizes the model by optimizing the values of C_1+C_2 and C_1/(C_1+C_2), thereby determining the optimal values for the original parameters.

2.3 Experimental design for the value of high-resolution data

Daily streamflow and hourly streamflow are important modeling targets in hydrological research and practice. To test the value of rainfall and measured streamflow data at different resolutions for simulating streamflow at these two scales, we designed two specific experiments: the daily modeling test and the hourly modeling test. In this context, 'daily' and 'hourly' refer to the target time scales for the model's predictions. The flowchart of the tests was shown as Figure 3, and the details are as follows.

(1) Daily modeling test: This test was designed to investigate the impact of high-resolution rainfall data on daily streamflow simulation. The model was driven by rainfall data at various resolutions (ranging

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

from 1h to 24h) and calibrated using daily resolution streamflow data. This setup aimed to assess whether (and to what extent) sub-daily rainfall data can enhance daily streamflow simulation.

(2) Hourly modeling test: This test was designed to investigate the impact of high-resolution input and streamflow data on hourly streamflow simulation. In this test, the temporal resolutions of input rainfall data and calibration streamflow data were the same, both set as various resolutions (ranging from 1h to 24h). The model was calibrated using streamflow data with the given temporal resolution, and then the hourly streamflow simulated by the calibrated model was evaluated based on the hourly measured streamflow. This setup aimed to determine the necessary data resolution for providing reliable hourly streamflow simulation.

These experiments aimed to investigate how data resolution affects the accuracy and reliability of streamflow predictions across various temporal scales. To minimize potential impacts from varying computational time steps, the hydrological simulations were consistently set to a 1-hour time step for both tests. This standardization was maintained across all cases, with different input data resolutions used. Specifically, all input data, including rainfall, were resampled to a 1-hour resolution via prior averaging before driving the model. As a result, the model's original outputs were always produced at an hourly scale.

In the daily modeling test, rainfall data at varying temporal scales was input into the hydrological model to produce simulated hourly streamflow, which was later aggregated to the daily scale for comparison with observed daily streamflow. Model parameters were then optimized by aligning the simulation with observations using Python Surrogate Optimization Toolbox (pySOT, Eriksson et al., 2019), aiming to maximize the Nash-Sutcliffe efficiency (NSE). The optimization process, iterated via Symmetric Latin Hypercube Design (SLHD), concluded upon convergence or after reaching a 3000-iteration threshold. After 100 trials, the final parameters were selected based on maximum NSE. Additionally, after calibration, Relative Error of Peak flow (REP) was computed as a secondary performance metric. These metrics were calculated as follows:

$$NSE = 1 - \frac{\sum_{t=1}^{n} \left(Q_t^{obs} - Q_t^{sim}\right)}{\sum_{t=1}^{n} \left(Q_t^{obs} - \overline{Q^{obs}}\right)} \tag{2}$$

$$REP = \frac{Q_{sim,p} - Q_{obs,p}}{Q_{obs,p}} \tag{3}$$

where, Q_t^{obs} and Q_t^{sim} are the streamflow for the observed and simulated time series, $\overline{Q^{obs}}$ is the average value of the observed streamflow, $Q_{sim,p}$ and $Q_{obs,p}$ are the simulated and observed peak flow, respectively.

The hourly modeling test followed a similar procedure to the daily modeling test, inputting rainfall data at various temporal resolutions into the hydrological model to produce simulated hourly streamflow. This output was aggregated to match the resolution of the input data and compared with the corresponding observed data for calibration. The performance of calibrated model on simulating hourly streamflow was then assessed by calculating NSE and REP, based on the hourly simulated and observed streamflow data.

The flowchart of the experimental tests was illustrated in Figure 3, where D and H refer to daily and hourly test, x_i is each member of the time step (t.s.) set (TS), which consists of 1h, 2h, 3h, 4h, 6h, 12h and 24h. $NSE_{D,xi}$ and $REP_{D,xi}$ are the NSE of and REP of daily streamflow forced by rainfall at time step of x_i. Similarly, $NSE_{H,xi}$ and $REP_{H,xi}$ denote the NSE and REP for hourly streamflow at time step of x_i.

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

After tests, the paired two-sample t-test, a widely used statistical method to determine whether the means of two related groups of samples are significantly different (e.g., Xu et al., 2017), was adopted to test whether the performance of the hydrological model based on high-resolution data was significantly improved.

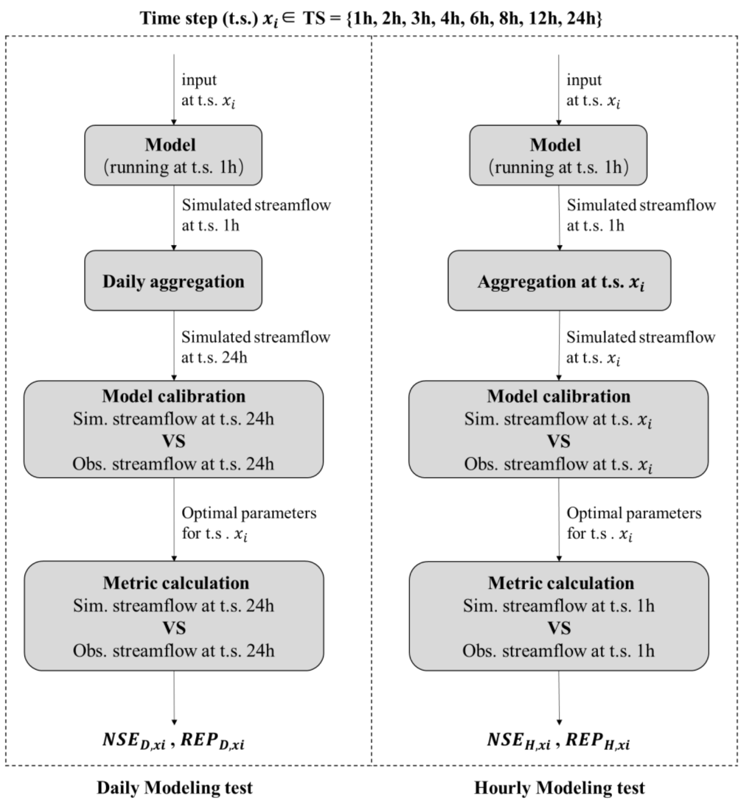

Figure 3: Flowchart of the daily modeling and hourly modeling tests

2.4 Experimental design for parameters transferability

To test the potential impact of the resolution of training data and the computational time step on calibration of model parameters, as well as the transferability of these parameters across different time scales, we designed two tests: the data resolution test and the computational timestep test. The flowchart of the tests was shown as Figure 4, and the details are as follows.

(1) Data resolution test: in this test, the model's computational time step was fixed as 1 hour, while the temporal resolution of the input and measured streamflow varied from 1 hour to 24 hours (as in the hourly test). Previously, optimal parameter sets, Par_{xi}, have been obtained under varying resolutions (x_i) of input and measured streamflow data in hourly modeling tests. In this data resolution test, the optimal parameter set obtained at one resolution (referred to as the pre-transfer resolution) was used to drive the model with input data at another resolution (referred to as the post-transfer resolution), resulting in hourly simulated streamflow. The simulation accuracy, measured by NSE, was then calculated. By comparing

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

the changes in the simulation metrics obtained by a same set of parameters and different input resolutions, the transferability of the parameters across varying resolutions was tested.

(2) Computational time step test: in this test, the model's computational time step varied from 1 hour to 24 hours, while the temporal resolution of the input rainfall and measured streamflow data was fixed as 24 hours. Firstly, input data at the resolution of 24 hours was fed into the model, and the model was run at varied time steps, resulting simulated streamflow at varied time steps. Next, the simulated streamflow was aggregated in daily, and the model parameters were calibrated based on observed daily streamflow. In this way, the model parameters under different computational steps are obtained. Then, the optimal parameter set obtained at one computational time step (referred to as the pre-transfer computational time step) was used to drive the model at another computational time step (referred to as the post-transfer computational time step), and the NSE was calculated based on the simulated daily streamflow obtained at this time step. By comparing the changes in simulation metrics, the transferability of parameters obtained at one computational time step to another was tested.

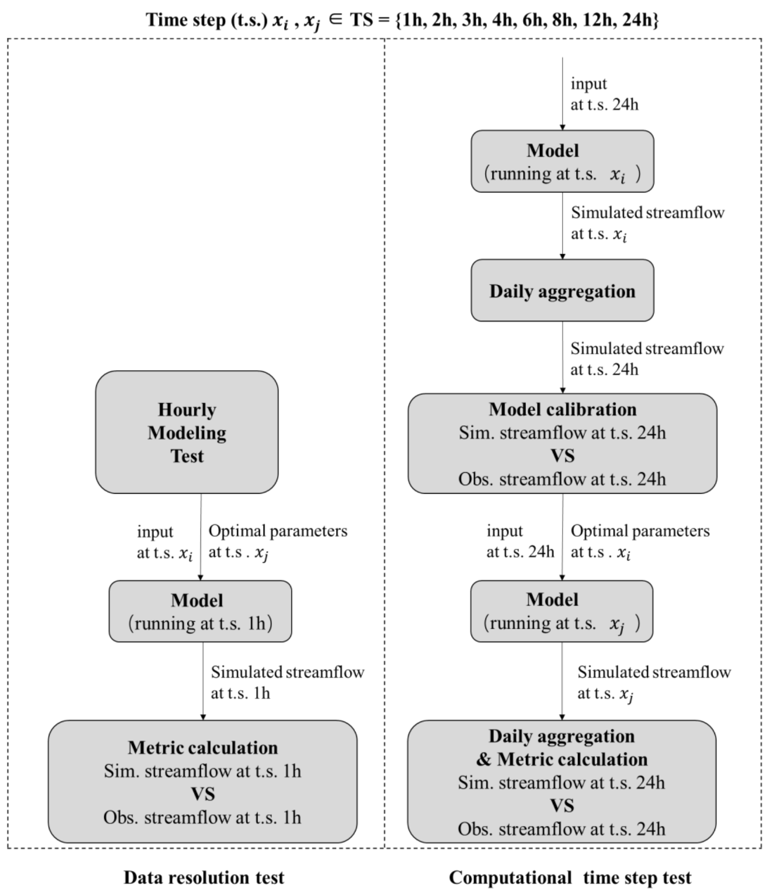

Figure 4: Flowchart of the data resolution and computational time step tests

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

3 Results

3.1 The value of high-resolution data

The results of the daily and the hourly modeling tests are shown in Figure 5. Subplots (a) and (b) represent the NSE and absolute values of REP in the daily modeling test, respectively. Subplots (c) and (d) depict these two metrics in the hourly modeling test. In the daily test, the average NSE obtained by various data resolutions varied in the range of 0.91 - 0.94. The model performed worst when using 24-hour resolution data, but even then, the lowest NSE value was 0.82 in the Yanqihe catchment at BYC station, and in the other 6 catchments, the NSE exceeded 0.89. As for REP, the average $|REP_D|$ at various data resolutions ranged between 2% and 4% indicating high accuracy in simulation on peak flow at daily scale. In the hourly modeling test, the metrics got slightly worse compared with the daily test. The average NSE across various data resolutions ranged from 0.78 to 0.87. The model performed worst when using 24h resolution data, with the lowest NSE of 0.64, but the NSE exceeds 0.8 in five of the study catchments. The model produced NSE higher than 0.83 in 6 catchments when using 1h rainfall and streamflow data. The average $|REP_H|$ varied in the range of 16% - 27%. Compared to the daily modeling test, the model's accuracy in simulating peak flow declined noticeably in hourly modeling, as the evaluation is more strict. Overall, these results demonstrated the high performance and reliability of the model in these catchments, with high NSE and low |REP|.

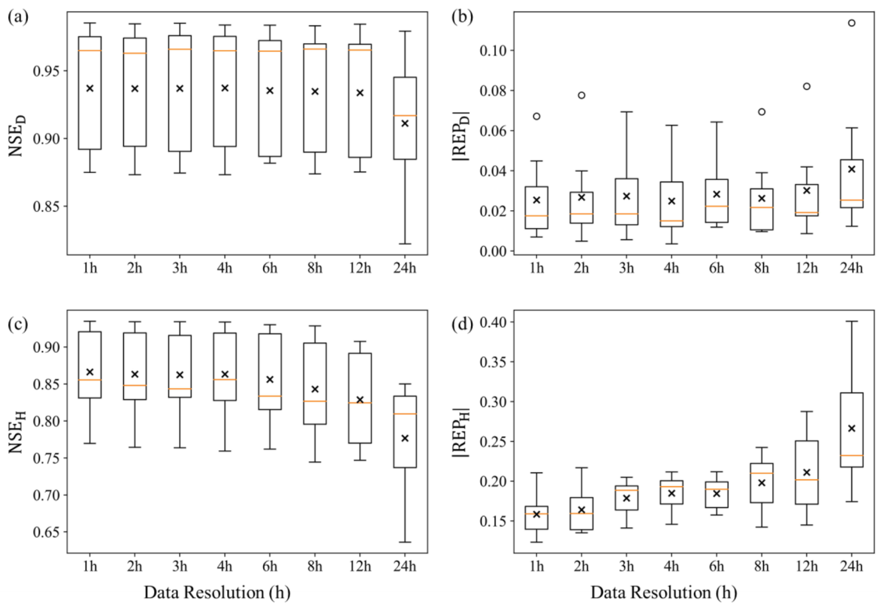

Figure 5: Box plot of NSE, |REP| in the daily and the hourly modeling tests across 7 catchments

In both daily and hourly modeling tests, there was an obvious improvement in model performance when the data resolution increased. For instance, in the daily modeling test, when the data resolution shifted from 24h to sub-daily 12h, the average NSE increased from 0.91 to 0.93 and the average |REP| decreased from 4.08% to 3.02%. In the hourly modeling test, the improvement was more obvious. The average NSE increased from 0.78 to 0.83 and the average |REP| decreased from 27% to 21%, when the data

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

resolution shifted from 24h to sub-daily 12h. But such improvement got increasingly limited as the resolution further increased.

To quantify the difference in the model performances when adopting data with different resolutions, paired two-sample t-tests were conducted, and the results are shown in Table 2. In the daily modeling test, significant improvement (at 0.05 significance level) on streamflow simulation was brought by sub-daily (1h – 12h) resolution rainfall data compared to the daily data, as indicated by the low p values in the last row of Table 2a and Table 2b. However, compared to 12h resolution, only the 1-hour resolution brought a significant improvement in NSE at the significance level of 0.05. As for |REP|, there were significant differences in |REP| at 2h and 8h resolution compared to 12h resolution. Overall, the results suggested that for daily streamflow forecasting, continuously increasing rainfall data resolution beyond the 12h threshold did not bring significant improvement on model performance. That is, the simulated daily streamflow obtained from a model driven by 12h rainfall input had comparable reliability to that forced by 1h data, and the effect of rainfall data with a temporal resolution exceeding 12h on enhancing daily forecasted flow was negligible.

Similar results were observed in the hourly modeling test (Table 2c and Table 2d). Compared to the daily data, utilizing higher-resolution data effectively enhanced the model's forecasting performance for hourly streamflow. Specifically, regarding the NSE, there were significant differences in the model's performance when using 8h resolution data compared to that obtained by 2h to 6h resolution data. But, when the data resolution reached 6 hours or higher, there were no statistically significant differences in NSEs, indicating that further increasing the resolution did not consistently enhance overall simulation accuracy. Consequently, taking NSE as the performance metric, simulated hourly streamflow obtained by a model driven and calibrated by 6h data was comparably accurate to that obtained by higher resolution data. Data with a resolution higher than 6h did not provide significant additional value. Compared to NSE, the improvement in |REP| was more pronounced with the increase in data resolution in the hourly modeling test. Compared with daily (24h) resolution data, all sub-daily resolution (1h-12h) data showed significant improvement in |REP| (at 0.05 significance level). Comparing the effects of sub-daily scale data, although there was no significant difference in the |REP| when resolutions were close (e.g., 6-hour and 8h resolutions), significant differences in |REP| still existed when the resolution was sufficiently high (e.g., 1h) compared to other resolutions. For instance, the first column of Table 2d indicated that only the |REP| obtained with 2h resolution data showed no statistically significant difference when compared to 1h resolution data. This suggests that continuously increasing data resolution has greater value in improving the accuracy of predictions on peak flow.

Table 2 P-values of the paired two-sample t-tests for each metric

Table 2a P-values of the paired two-sample t-tests for NSE in daily modeling test

Resolution	1h	2h	3h	4h	6h	8h	12h
2h	0.987						
3h	0.932	0.962					
4h	0.459	0.562	0.693				
6h	**0.033***	0.175	**0.043***	0.054			
8h	0.223	0.330	0.109	0.157	0.770		
12h	**0.041***	0.095	0.148	0.061	0.537	0.599	
24h	**0.036***	**0.042***	**0.031***	**0.036***	**0.039***	**0.031***	**0.046***

Table 2b P-values of the paired two-sample t-tests for |REP| in daily modeling test

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

Resolution	1h	2h	3h	4h	6h	8h	12h
2h	0.5581						
3h	0.1446	0.8063					
4h	0.6260	0.8122	0.3503				
6h	0.3196	0.9739	0.7922	0.6138			
8h	0.8420	0.6117	0.4098	0.8532	0.3476		
12h	0.0743	**0.0164***	0.2985	0.1927	0.2364	**0.0412***	
24h	**0.0314***	**0.0189***	**0.0490***	0.0582	0.0763	**0.0352***	**0.0497***

Table 2c P-values of the paired two-sample t-tests for NSE in hourly modeling test

Resolution	1h	2h	3h	4h	6h	8h	12h
2h	0.368						
3h	0.283	0.571					
4h	0.370	0.666	0.559				
6h	0.088	**0.044***	0.109	0.096			
8h	**0.037***	**0.017***	**0.032***	**0.028***	**0.016***		
12h	**0.013***	**0.007***	**0.010***	**0.011***	**0.007***	**0.028***	
24h	**0.009****	**0.007****	**0.008****	**0.009****	**0.008****	**0.011***	**0.011***

Table 2d P-values of the paired two-sample t-tests for |REP | in hourly modeling test

Resolution	1h	2h	3h	4h	6h	8h	12h
2h	0.327						
3h	**0.006****	0.084					
4h	**0.001****	**0.009***	0.194				
6h	**0.000****	**0.001****	0.113	0.378			
8h	**0.005****	**0.006***	0.145	0.123	0.411		
12h	**0.018***	**0.023***	0.066	0.066	0.149	0.112	
24h	**0.011***	**0.015***	**0.018***	**0.020***	**0.036***	**0.031***	**0.016***

Note: ** and * indicates significance at 0.01 and 0.05

3.2 Parameters transferability across data resolutions

The optimized model parameters at various data resolutions were obtained under a fixed computational time step of 1-hour in the hourly modeling test. To assess the transferability of these parameters under different data resolutions, the data resolution test was conducted following the experimental design outlined in Section 2.4. The results are shown in Figure 6. In each subplot, each curve represents the NSE values obtained when the optimal parameters calibrated from a specific input resolution are transferred (without any transformation) to drive the model with other input resolutions.

First, when examining the differences among the curves, it was found that in most catchments, the curve representing the 24h resolution consistently fell below the others. This aligns with the results from the previous section, indicating that the model's performance was the lowest when using 24h resolution rainfall and streamflow data. When these parameters are transferred to other resolutions, they also exhibited the lowest performance.

In all catchments except for XTZ, when parameters calibrated with a specific data resolution were transferred to other resolutions, simulation accuracy improved as the resolution of the data used increased.

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

Notably, when the resolution increased from 24h to 12h, the NSE showed the most significant improvement. However, when the input data resolution ranged between 1h and 8h, the NSE remained relatively stable. This observation is consistent with the results and conclusions from Section 3.1. Even though there were some variations in model performance when parameters were transferred to other time scales, the performance remained acceptable, with the lowest NSE still exceeding 0.5. This lowest NSE occurred at the QXZ station when the pre-transfer resolution is 6h and post- transfer resolution is 24h. When the post- transfer resolution was finer than 24h, the NSE at QXZ was consistently above 0.7. Overall, after parameter transfer, the model continues to demonstrate satisfactory simulation performance.

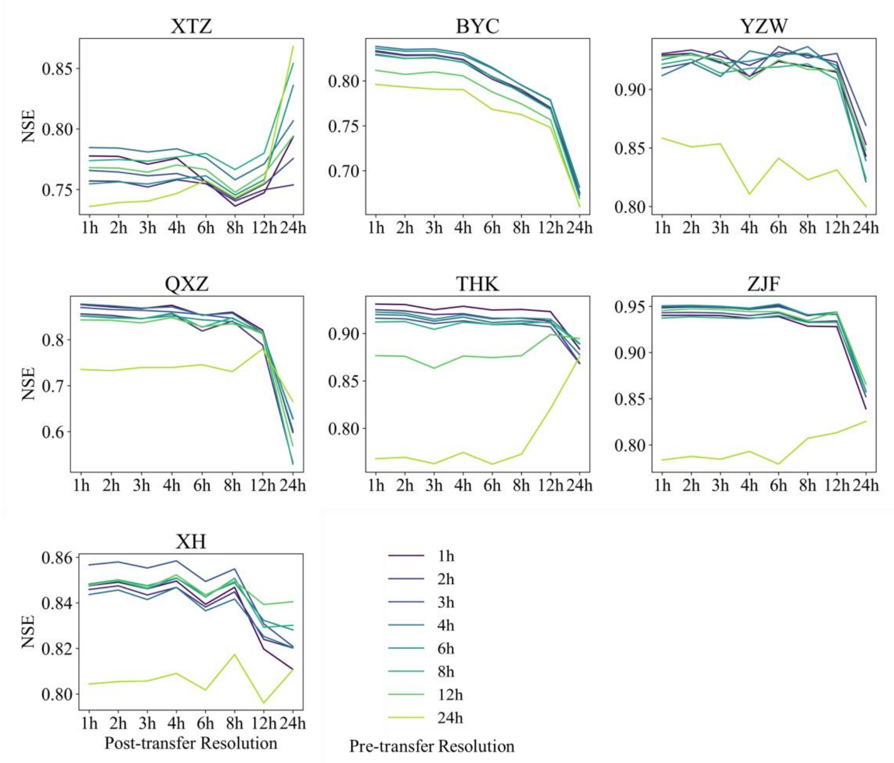

Figure 6: The NSE values after transferring the parameters obtained at one resolution to other resolutions

3.3 Parameters transferability across computational time steps

To assess the transferability of parameters under different computational time steps, the computational time step test was conducted following the experimental design outlined in Section 2.4. The results are shown in Figure 7. The value in the row i and column j represents the NSE value obtained when transferring the parameters calibrated with a computation time step of x_i directly to a model with a computation time step of x_j (x_i, x_j ∈{1h, 2h, 3h, 4h, 6h, 8h, 12h, 24h}, referred to as pre-transfer and post-transfer computational time step, respectively). The values on the diagonal represent the NSE values obtained when running the model with a specific computational time step and calibrating the parameters with daily streamflow. In this case, the parameters were not transferred (i.e., the pre-transfer and post-transfer time steps are the same). First, the values on the diagonal are all greater than 0.7, with most

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

exceeding 0.85, and the average is 0.88. This indicates that the model performs well across different computation time steps, further confirming its reliability. Secondly, within each basin, the values on the diagonal are very close to each other, implying that when both the input rainfall data resolution and the output streamflow resolution are at the daily scale, nearly identical simulation accuracy can be achieved regardless of the computation time step used (within the 1h-24h range).

When parameters calibrated at one computation time step were transferred to other computation time steps (values in the same row in the Figure 7), the NSE values varied significantly. Compared to the results with the data resolution test in Section 3.2, the variation in NSE under the varying computation time step was much greater. In many cases, the NSE value after transferring parameters was even less than 0, indicating that the model parameters lose their transferability (with unreliable accuracy) when the model's computation time step is varied. Notably, in each subfigure, the values in the lower left part are even lower than those in the upper right part, suggesting that the model's performance is particularly unreliable when parameters calibrated at larger computation time steps are transferred to smaller ones.

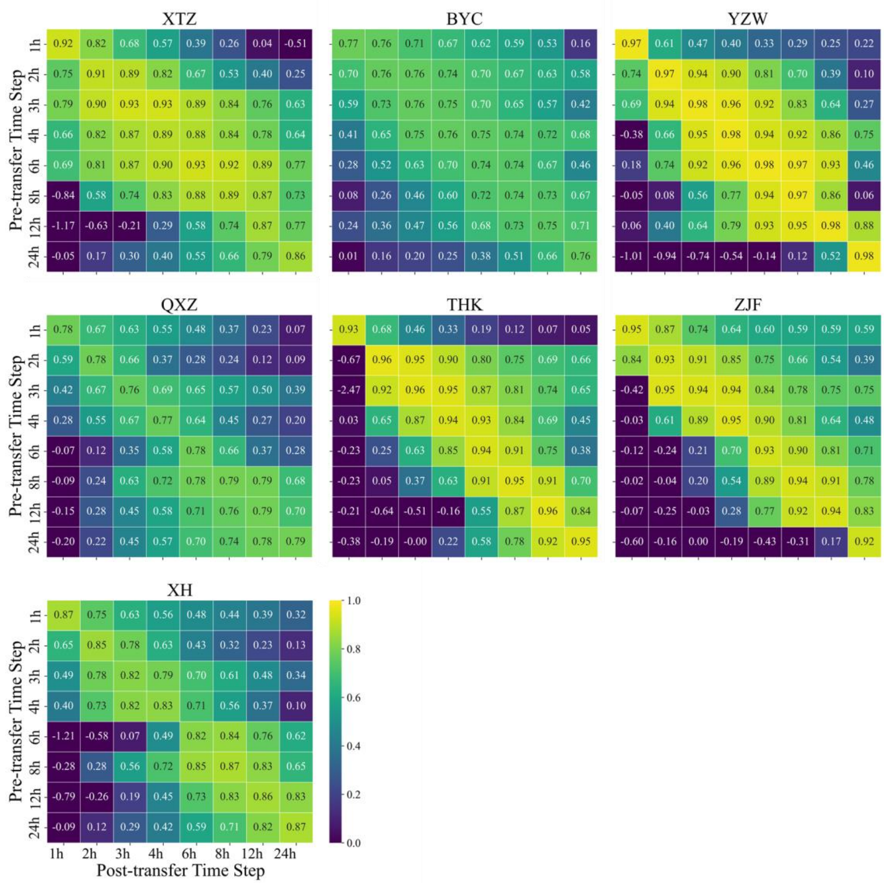

Figure 7: NSE values after transferring the parameters obtained at one computation time step to other time steps.

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Preprint. Discussion started: 21 October 2024

4 Discussion

4.1 Potential factors for the limited impact of high-resolution data

The results indicated that increasing input data resolution, especially from 24 to 12 hours, significantly boosted simulation accuracy for daily streamflow, consistent with expectations regarding the benefits of high-resolution data. However, beyond the 12-hour mark, performance became marginal or even declined. Similar patterns emerged in hourly simulations, where benefits of finer-than-6-hour data were negligible or negative, contradicting the intuitive expectations that higher-resolution data always enhances hydrological models. Similar findings were reported by previous studies that investigated the effects of temporal resolution on hydrological models across different regions and model types. Ficchì et al. (2016) explored 240 catchments in France using the GR4 rainfall-runoff model across eight temporal scales, ranging from 6 minutes to 1 day. Their analysis revealed that, on average, finer resolution data provided no additional value when model outputs were aggregated to a 6-hour reference scale. Similarly, Reynolds et al. (2017), while calibrating the HBV model in two small Central American basins, observed that using daily streamflow data produced results comparable to those obtained with sub-daily resolution.

While the catchments and models vary across different studies, the overall findings are largely consistent, suggesting that simply increasing data resolution doesn't always lead to better model performance. Several factors may limit the additional benefits of higher resolution data. Firstly, a straightforward reason could be the choice of the evaluation metric. In the hourly modeling test, when the resolution exceeded 6 hours, there was no significant improvement in the NSE, but the |REP| showed a marked change. In some cases, different metrics may conflict with each other, making it impossible to optimize them simultaneously. Secondly, due to spatial and temporal autocorrelation in variables like rainfall and runoff, increasing resolution beyond a certain threshold may not provide effective new information. There may be no significant difference between actual high-resolution data and high-resolution data obtained by resampling from coarser data. The extent of this difference is related to the characteristics of the climate of the catchment and its runoff generation processes. Thirdly, model input data, particularly rainfall, may have a lower signal-to-noise ratio at higher temporal resolutions due to difficulties in data validation and increased uncertainty in areal average rainfall estimates (Ficchì et al., 2016; Moulin et al., 2009). Besides, since hydrological models inherently simplify natural processes, they may dampen the natural smoothing effect seen in rainfall-runoff interactions. As a result, using high-resolution temporal data to drive the model could introduce excessive variability in the simulated flow, potentially degrading the model's performance. Finally, the model's structure might not be adequately designed to handle the added complexity that comes with shorter time steps. Melsen et al. (2016) pointed out that calibration and validation time intervals should align with the spatial resolution to accurately capture the relevant processes. Some empirical formulas within the model may not be applicable at shorter time scales.

4.2 Further explanation of the transferability of parameters

The results in Section 3.2 indicated that when the computation time step is fixed at 1-hour, the model demonstrated good performance even when parameters are transferred to input conditions with different resolutions. As shown in Figure 6, in most cases, as the input resolution improved, the NSE also increased. However, some exceptions were found. At hydrological stations such as the THK and ZJF, when using parameters calibrated with 24-hour data, there was an increase in NSE as the rainfall resolution decreased.

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

At the XTZ station, NSE also increased when the rainfall resolution dropped below 8 hours, regardless of the parameters used. This anomaly was particularly pronounced at the THK station. Conversely, at the BYC station, the NSE consistently decreased as the rainfall resolution decreased across all parameters. We selected the THK and BYC stations as representative cases and compared the streamflow processes driven by 1h and 24h rainfall resolutions using parameters calibrated with 24h data (as shown in Figure 8). Based on these flow processes, we explored the reasons behind these observed phenomena.

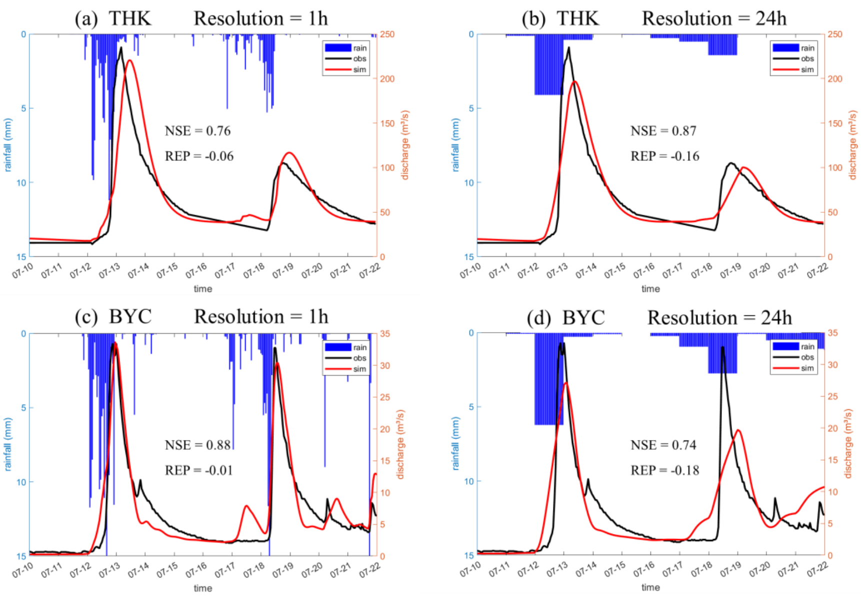

Figure 8: streamflow processes at THK and BYC driven by 1h and 24h rainfall resolutions using parameters calibrated by 24h data

In Figures 8(a) and (b), the model parameters were calibrated using 24h data, but the rainfall data used to drive the model were at resolutions of 1h and 24h, respectively. The same setup was applied in Figures 8(c) and (d). We observed that when using 1h resolution rainfall data, the simulated value of the first flood peak at the THK station was closer to the measured value, even though the NSE at 1h resolution was statistically lower than the NSE at 24h resolution.

To more comprehensively evaluate the simulation accuracy and the impact of different parameters, we conducted further analysis. As mentioned in Section 2.2, we ran 100 iterations using the pySOT program for parameter calibration, which resulted in 100 sets of optimized parameters. Using these 100 parameter sets and the rainfall data at both 1h and 24h resolutions, we evaluated the simulation accuracy of the THK station's streamflow using NSE, KGE, and REP indicators, as shown in Figure 9.

Among the results obtained using the 100 sets of optimal parameters, the NSE values driven by 1h resolution rainfall data were generally lower than those driven by 24h resolution rainfall, with average values of 0.63 and 0.77, respectively. The KGE values were relatively close under both resolutions, with average values of 0.81 and 0.84, respectively. As for the |REP| indicator, the trend was reversed, with the 1h resolution rainfall data yielding better results than the 24h resolution data, with average |REP| values of 9% and 16%, respectively. Based on the runoff processes shown in Figure 8 and the different indicators in Figure 9, we infer that the observed phenomenon, where simulation accuracy decreases as resolution increases, may be related to the evaluation metrics used and the flood characteristics of the basin. Compared to the BYC station, the THK station exhibited a slower streamflow process during flood events, particularly during the recession phase. We defined a concept similar to half-life period, denoted as T_{hl}, to characterize the rate of flood recession. T_{hl} is the time taken for the streamflow to decay from its peak to half of the peak value. At the THK station, T_{hl} is 16 hours, while at the BYC station, T_{hl} is 8 hours, indicating that the flood recession at THK is slower than at BYC. In catchments with a more gradual recession, observed streamflow at a 24h resolution does not provide as much effective information for model's calibration as higher-resolution data. Furthermore, when 24h resolution rainfall is used as input and 1h as the computational time step, the model tends to produce a smoother simulated streamflow process, since it distributes the rainfall evenly over each hour. Consequently, parameters related to flow routing are not accurately calibrated. As a result, when the model is driven by higher resolution rainfall data such as 1h, larger errors occur in the predicted peak time. However, when using 24h resolution rainfall data, the smoothing effect of the 1h computational time step leads to a simulated recession process that more closely matches the observed values, thus improving the NSE.

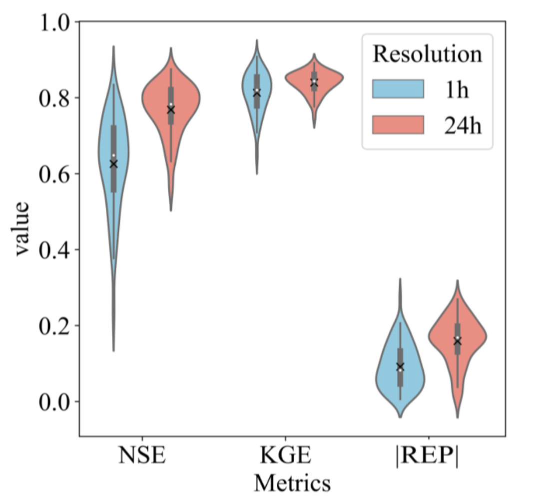

Figure 9: Metrics at THK station using 100 sets of parameters and different resolutions of rainfall

The results indicated that when the computational time step is fixed as 1h, parameters calibrated under different data resolutions can be transferred and used in models with other resolutions. To further explain the transferability of parameters and identify any patterns as resolution changes, we compared parameters across different resolutions. However, due to the parameter equifinality (Her and Chaubey, 2015; Foulon and Rousseau, 2018), a single optimal parameter set may not be representative enough to accurately reflect the patterns. Therefore, we analyzed 100 sets of parameters calibrated at each resolution, with partial results shown in Figures 10-12. The findings revealed that most parameters did not exhibit a significant and consistent trend of variation with changes in resolution. In other words, parameters calibrated under different resolutions showed little variability, which explains their transferability across resolutions. However, some parameters did show a certain consistent trend with resolution changes. Figure 10 illustrates the trend of the parameter Lag1 with changes in resolution. This parameter in the model reflects the lag time of surface runoff (the time from the generation of surface runoff until it

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

reaches the outlet of the sub-basin). As the resolution becomes coarser (from 1h to 24h), the effective information provided by the observed streamflow to the model decreases, and the requirement for precision in peak time also reduces. This relaxation in constraints led to an increase in both the mean value and the range of variation of Lag1. Notably, at stations XTZ, THK, and ZJF, when the data resolution is 24h, the mean value of Lag1 exceeds 10h or even 15h, showing a significant difference from the value at 1h resolution. In contrast, at stations BYC, YZW, and QXZ, when the data resolution is 24h, the mean value of Lag1 is less than 5h, which is not significantly different from the value at 1h resolution. This also validates the previous explanation for why the NSE at stations like THK decreases as resolution improves.

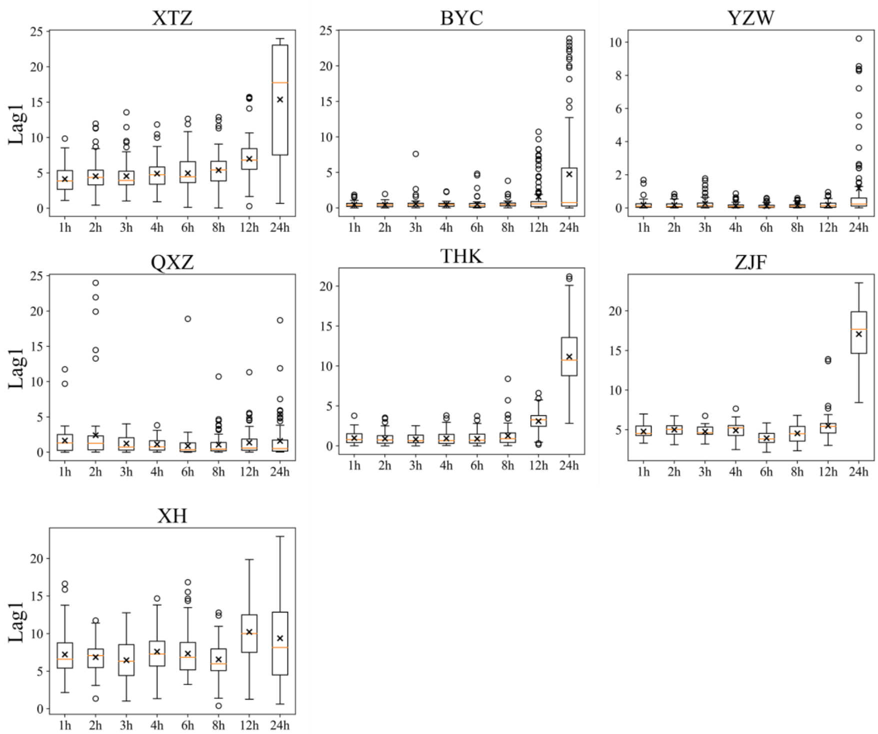

Figure 10: optimized values of Lag1 across various resolutions

The parameter C_1+C_2 also exhibited a regular trend of variation with changes in resolution (Figure 11). Generally, the larger this parameter, the faster the model's runoff responds to rainfall, resulting in a flood process that rises and falls sharply. When the time resolution is coarse, the variability of runoff may not be fully captured in the observed data. As a result, a model calibrated by a coarser resolution data tend to produce a smoother streamflow process. This is evident at stations such as YZW and QXZ, where the optimized C_1+C_2 value decreased as the resolution became coarser. However, we also observed that at most stations, including XTZ, THK, ZJF and XH, this parameter increased as the resolution became coarser. This may be due to the model's computational time step of 1h; when driven by coarse-resolution data, the input data are averaged over each hour, causing the runoff to be smoothed. Consequently, a larger C_1+C_2 value was selected by the parameter optimization algorithm to counterbalance this excessive smoothing.

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

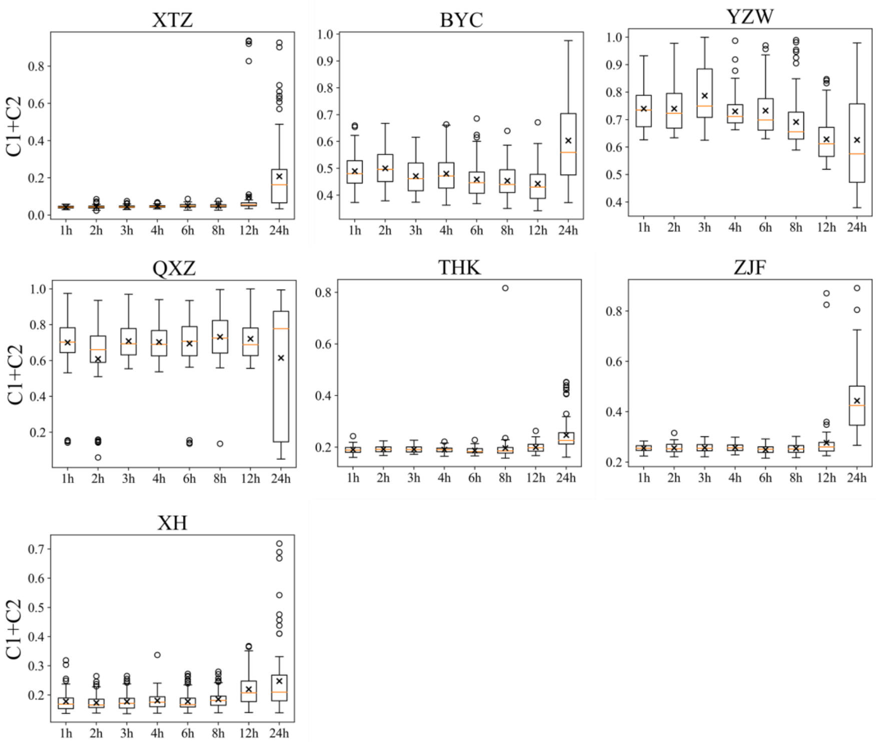

Figure 11: optimized values of C_1+C_2 across various resolutions

Besides, in certain catchments, specific parameters exhibited regular changes across varying resolutions. At BYC station, the parameter Ksg decreased as the resolution became coarser. Ksg represents the ratio of water transfer from the shallow subsurface layer to the deep groundwater layer. A decrease in Ksg would lead to the shallow subsurface layer becoming saturated more easily, resulting in more surface runoff. Similarly, at YZW station, the parameter Kg decreased with coarser resolution. Kg represents the ratio of water conversion from the groundwater layer to groundwater runoff. A reduction in Kg would cause the groundwater layer to saturate more readily, also indirectly leading to increased surface runoff. The 1h computational time step evenly distribute rainfall under coarse resolution, which reduces the simulated peak runoff compared to the actual peak. Therefore, the lower Ksg and Kg values improve simulation accuracy under coarse resolution conditions by increasing surface runoff.

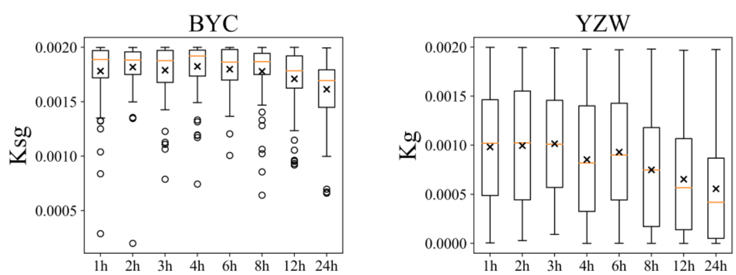

Figure 12: optimized values of Ksg at BYC station and Kg in YZW station across various resolutions

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

4.3 Implications for the selection of data resolution and computation time step

The findings of this study offer several key insights for building hydrological models with limited data.
1) Data Resolution Considerations:
For daily runoff simulations, it is found that a data resolution of 12h is sufficient to provide accurate simulation results with relatively high precision. This suggests that higher resolution data may not yield significant additional benefits for daily scale modeling. However, for hourly runoff simulations, the adequacy of data resolution depends on the specific objectives of the simulation. If the primary focus is on capturing the overall flood process, such as total runoff volume and approximate duration, a 6h resolution is adequate. On the other hand, if the simulation aims to achieve higher accuracy in peak flow estimation, employing data with finer temporal resolution can enhance the precision of these predictions. This offers practical insights for building numerical models and establishing monitoring stations, suggesting that high-resolution monitoring may not always be necessary. It is essential to balance the additional information gained from higher resolution against the associated costs, aligning with our objectives, enabling efficient resource allocation and ensuring that expenditures yield valuable returns.
2) Selection of Computational Time Step:
Regardless of whether the model is intended for daily or hourly runoff simulations, and irrespective of the input data resolution, it is advisable to adopt a smaller computational time step when constructing the model. This is because the results showed that the simulation accuracy on the coarse scale (24h) with different computation time steps is almost the same, while the model running at a smaller computation step can produce results on a finer scale, which provides the possibility for further analysis. And the model's performance is particularly unreliable when parameters calibrated at larger computation time steps are transferred to smaller ones. This approach also ensures that the model parameters remain applicable across different data resolutions, thereby enhancing the model's flexibility and enabling it to generate accurate simulation results across a range of temporal scales. With the appropriate spatial scale and sufficient computational capacity, opting for a lower computational time step can make the model better equipped to maintain robust performance under varying input conditions and produce results at more time scales, which is crucial for ensuring the transferability of the model parameters and achieving consistent results.

5 Conclusions

5.1 Summary

This study assessed the value of different resolution data for daily and hourly streamflow simulations utilizing meteorological and runoff data with resolutions ranging from 1 hour to 24 hours from 7 small-to-medium-scale catchments in northern China. Additionally, the transferability of model parameters across varying data resolutions and computation time steps were investigated. Key findings are summarized as follows:
1) For both daily and hourly streamflow simulations, utilizing sub-daily resolution rainfall and streamflow data leads to substantial improvements in model performance compared with the using of the daily data. However, further enhancements in data resolution yield diminishing returns. Specifically, for daily streamflow simulations, improvements in model performance become negligible when the resolution exceeds 12 hours. As for hourly streamflow simulations, improvements in overall flood

https://doi.org/10.5194/egusphere-2024-2966
Preprint. Discussion started: 21 October 2024

process accuracy become negligible when the resolution exceeds 6 hours, while higher resolutions further enhance the precision of peak flow predictions.

2) When the model's computation time step is fixed at 1h, most parameters, are generally independent of the input data resolution. Even when using model parameters obtained from daily data, utilizing sub-daily resolution data helps improve the accuracy of hourly streamflow simulations. Conversely, when the computation time step varies, the model parameters are not applicable for direct transfer to other time steps. In particular, the performance of the model deteriorates more when the computation time step is shifted from large to small.

3) It is recommended to utilized smaller computational time step when constructing hydrological models even in the absence of high-resolution input data. This strategy ensures that the same prediction accuracy is achieved while preserving the transferability of model parameters, thus enhancing the robustness of the model.

5.2 Limitations and further research needs

While this study has provided valuable insights into the impacts of data temporal resolution and computational time step on hydrological models, several limitations should be acknowledged. First, this study focuses on a specific geographical area in Northern China and covers a limited temporal range. The findings, therefore, may not be fully generalizable to other regions with different climatic, hydrological, or geological conditions. Further studies across various regions and under different hydrological conditions are necessary to validate and extend the applicability of these results. Second, the study's conclusions are drawn based on a particular hydrological model and specific parameter settings. Other models or configurations might exhibit different sensitivities to data resolution and computational time step. Therefore, the generalization of these findings to other hydrological models should be approached with caution. Next, results showed that the benefit of high-resolution rainfall/streamflow data to daily and hourly streamflow simulation was negligible when the temporal resolution was higher than a threshold, and the possible mechanism of such phenomenon was primarily discussed according to the variation of runoff process and some parameters under different conditions and other existing literatures. However, a deeper analysis and validation on such threshold effect are still lacking, which needs further investigation. Last, the number of iterations for the optimization algorithm during the model calibration process was limited. Although our previous modeling and calibration practices (e.g., Nan and Tian, 2024a, 2024b) demonstrated that the current number of iterations is sufficient to produce a good simulation, it does not guarantee the discovery of a globally optimal result. Consequently, it is challenging to determine whether the slight decline in model performance in certain catchments is due to the high-resolution data or the influence of local optima.

Competing interests. At least one of the (co)-authors is a member of the editorial board of Hydrology and Earth System Sciences.

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Preprint. Discussion started: 21 October 2024

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Code and data availability. The data and the code of the model used in this study are available by contacting the authors.

Author contributions. YN and FT conceived the idea; MT and YN conducted analysis; FT provided comments on the analysis; and all the authors contributed to writing and revisions.

Appendix A: List of equations for structure the model light in this study

Evaporation equations:

$$E_w = PET * K_{ew} \qquad (A1)$$

where PET is the mean potential evapotranspiration of the basin, E_w is the actual evaporation in W layer, K_{ew} is the linear coefficient. E_s, E_g are calculated by similar equations with the linear coefficients of K_{es}, K_{eg}.

Runoff equations:

$$\mathrm{WMM} = \mathrm{WM} * (1+\mathrm{B}) \qquad (A2)$$

$$\mathrm{A} = \mathrm{WMM}\left[1\text{-}(1\text{-}\frac{\mathrm{W}}{\mathrm{WM}})^{\frac{1}{1+\mathrm{B}}}\right] \qquad (A3)$$

$$R = P - E_w + W - WM, \quad if\ P - E_w + A \geq WMM \qquad (A4)$$

$$R = P - E_w + W - WM\left[1 - \left(1 - \frac{P - E_w + A}{WMM}\right)^{1+B}\right], \quad if\ P - E_w + A < WMM \qquad (A5)$$

$$\mathrm{SMM} = \mathrm{SM} * (1+\mathrm{EX}) \qquad (A6)$$

$$\mathrm{AU} = \mathrm{SMM}\left[1\text{-}(1\text{-}\frac{\mathrm{S}}{\mathrm{SM}})^{\frac{1}{1+\mathrm{EX}}}\right] \qquad (A7)$$

$$RS = R + S - SM, \quad if\ R + AU \geq SMM \qquad (A8)$$

$$RS = R + S - SM \times \left[1 - \left(1 - \frac{R + AU}{SMM}\right)^{1+EX}\right], \quad if\ R + AU < SMM \qquad (A9)$$

$$R_{ss} = S * K_{ss} \qquad (A9)$$

$$R_g = G * K_g \qquad (A10)$$

$$R_i = P \qquad (A11)$$

where WM, SM, B and EX are storage of W, S layer and their exponential coefficients.

Routing equations:

$$Q_{i,t} = R_{i,t} * Area * imp/dT \qquad (A12)$$

$$Q_{s,t} = \left[R_{s,t-1-lag1} * Cs + R_{s,t-lag1} * (1 - Cs)\right] * Area * (1 - imp)/dT \qquad (A13)$$

$$Q_{ss,t} = \left[R_{ss,t-1-lag2} * Css + R_{ss,t-lag2} * (1 - Css)\right] * Area * (1 - imp)/dT \qquad (A14)$$

$$Q_{g,t} = \left[R_{g,t-1} * Cg + R_{g,t} * (1 - Cg)\right] * Area * (1 - imp)/dT \qquad (A15)$$

where $Area$ is the area of the basin, imp is the proportion of impervious area, and dT is the calculation time step.

https://doi.org/10.5194/egusphere-2024-2966
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