Optimal temporal resolution for hydrological modeling studies

by

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ABSTRACT

The impact of climate change on water resources has been an important field of research over the recent decades. Better water management is one way to adapt to a changing climate. To achieve this, having better rainfall-runoff models would be beneficial. Rainfall-runoff models are essential for improving our understanding and ability to forecast floods and droughts. Most hydrological modeling studies have been conducted at the daily-scale since most meteorological data was only available at this time step. However, higher temporal resolution data has become increasingly available at the sub-daily time scales. Previous work has shown that using data with a higher temporal resolution often results in an improvement in modelling accuracy. However, using a finer time scale increases the computational requirements of running the hydrological model. Finding the best time step is therefore an exercise in maximizing simulation accuracy while keeping the computational burden as low as possible. Smaller catchments may benefit more from a smaller time step due to the faster reaction time, whereas larger catchments may be relatively insensitive to the computation time-step. This highlights the importance of taking catchment size and shape into account when trying to determine the best temporal resolution. Even though there have been numerous studies on runoff models with sub-daily and even sub-hourly time steps, a systematic knowledge of how catchment size affects the time resolution option and how to determine the most efficient time step for the model has not yet been achieved. This work therefore investigated how the temporal resolution of a lumped hydrological model impacts simulation results, and if the impact is related to catchment size. Three-hundred and thirty-nine (339) catchments with quality-controlled hourly precipitation were selected covering most of the contiguous United-States. Hourly meteorological data was aggregated at 2, 3, 4, 6, 12 and 24-hour time steps and one hydrological model was calibrated on all catchment and for each of the 8 time-steps. To study the impact of catchment size, the catchments were regrouped into 6 different size classes, from smaller than 500 km^2 to larger than 4500 km^2, each group containing approximately the same number of catchments. Results showed that using as small a time-step as possible was beneficial to all catchment size classes, as it systematically improved the simulated flow bias as well as the magnitude and timing of peaks flows. The smallest size classes benefited the most from a reduced time step whereas for larger catchments, going to time step smaller than 8-hour only provided marginal improvements.

Keywords: Hydrological modeling; Modeling accuracy; Temporal resolution; Catchment size.

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Résumé

L'impact du changement climatique sur les ressources en eau a constitué un important domaine de recherche au cours des dernières décennies. Une meilleure gestion de l'eau est un moyen de s'adapter au changement climatique. Pour y parvenir, il serait utile de disposer de meilleurs modèles de ruissellement pluvial. Les modèles de ruissellement pluvial sont essentiels pour améliorer notre compréhension et notre capacité à prévoir les inondations et les sécheresses. La plupart des études de modélisation hydrologique ont été menées à l'échelle quotidienne, car la plupart des données météorologiques n'étaient disponibles qu'à ce pas de temps. Cependant, des données à plus haute résolution temporelle sont de plus en plus disponibles à l'échelle infra-journalière. Des travaux antérieurs ont montré que l'utilisation de données à plus haute résolution temporelle entraîne souvent une amélioration de la précision de la modélisation. Cependant, l'utilisation d'une échelle temporelle plus fine augmente les besoins en calcul du modèle hydrologique. Trouver le meilleur pas de temps est donc un exercice visant à maximiser la précision de la simulation tout en maintenant la charge de calcul aussi faible que possible. Les petits bassins versants peuvent bénéficier davantage d'un pas de temps plus petit en raison du temps de réaction plus rapide, tandis que les bassins versants plus grands peuvent être relativement insensibles au pas de temps de calcul. Ceci souligne l'importance de prendre en compte la taille du bassin versant lors de la détermination de la meilleure résolution temporelle. Bien qu'il y ait eu de nombreuses études sur les modèles de ruissellement avec des pas de temps infra-quotidiens et même infra-horaires, une connaissance systématique de la façon dont la taille du bassin versant affecte l'option de résolution temporelle et comment déterminer le meilleur pas de temps pour le modèle n'a pas encore été réalisée. Ce travail a donc étudié l'impact de la résolution temporelle des modèles hydrologiques sur les résultats de simulation, et si cet impact est lié à la taille du bassin versant. Trois cent trente-neuf (339) bassins versants avec des précipitations horaires de qualité contrôlée ont été sélectionnés, couvrant la plupart des états contigus des États-Unis. Les données météorologiques horaires ont été agrégées à des pas de temps de 2, 3, 4, 6, 12 et 24 heures et un modèle hydrologique a été calibré sur tous les bassins versants et pour chacun des 8 pas de temps. Pour étudier l'impact de la taille du bassin versant, les bassins versants ont été regroupés en 6 classes de taille différentes, de moins de 500 km^2 à plus de 4500 km^2, chaque groupe contenant approximativement le même nombre de bassins versants. Les résultats ont montré que l'utilisation d'un pas de temps aussi petit que possible était bénéfique pour toutes les classes de taille de bassin versant, car elle améliorait systématiquement le biais du débit simulé ainsi que l'ampleur et le moment des pics de débit. Les classes de taille les plus petites ont bénéficié le plus d'un pas de temps réduit alors que pour les bassins plus grands, le passage à un pas de temps inférieur à 8 heures n'a toutefois apporté que des améliorations marginales.

Mots clés : Modélisation hydrologique ; précision de la modélisation ; résolution temporelle ; taille du bassin versant.

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LIST OF ABREVIATIONS

AWBM	Australian Water Balance Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA	ECMWF Re-Analysis
GR4H	Génie Rural à 4 Paramètres Horaires
GR4J	Génie Rural à 4 Paramètres Journalier
IDF	Intensity-Duration-Frequency
IDW	Inverse Distance Weighting
IRSTEA	National Research Institute of Science and Technology for Environment and Agriculture
KGE	Kling-Gupta Efficiency
MOPEX	The Model Parameter Estimation Experiment
MPSO	Modified Particle Swarm Optimization
NSE	Nash-Sutcliffe Efficiency
NSGA	Non-Dominated Sorting Genetic Algorithm
PESA	Pareto Envelope-Based Selection Algorithm
PET	Potential Evapotranspiration
SCE-UA	Shuffled Complex Evolution Method -University of Arizona
SMAR	Soil Moisture Accounting and Routing
USGS	The United States Geological Survey

INTRODUCTION

The way temperature and precipitation vary due to climate change, which may lead to floods and droughts in some cases, has always been a global concern (Suppan et al., 2008; Wurbs et al., 2005). For studying these changes as well as forecasting rainfall runoff, which is essential for applications like agriculture and drinkable water, hydrological models have been presented (Devia et al., 2015). In other words, hydrological models are techniques that are used to simulate the real-world hydrological system. These models may be used to simulate natural phenomena, such as groundwater resources, soil water flow, climate change, surface water flow, and so on. Hydrological models may be used to better understand the function of components in the hydrological cycle in catchments (Abbott & Refsgaard, 1996).

Model structure, quality of input data, and model temporal and spatial resolution all affect the accuracy and efficiency of hydrological models (Sood & Smakhtin, 2015). Because each catchment is different in terms of geology, soils, topography, land use and climate, it is essential to have a thorough understanding of the hydrological system before selecting the right model (Abbott & Refsgaard, 1996; Robock, 2015). According to the required features, the size of the catchment, and the catchment's response time, the user should choose the model's appropriate temporal resolution (Ficchì et al., 2019). For instance, for small watersheds it is important to use short time step dataset in hydrological models in order to accurately describe the flood features (Obled et al., 2009). Nowadays, access to high-resolution temporal data with sub-daily and even sub-hourly intervals (reanalysis, gridded interpolated datasets etc.) has significantly improved the quality and accuracy of hydrological models (Ficchì et al., 2019; Jeong et al., 2010). Moreover, in catchments for which only daily data are available, sub-daily data can be derived using disaggregation, statistical distributions, and other methods (Bennett et al., 2016; Kandel et al., 2005; Waichler & Wigmosta, 2003; Winter et al., 2019).

The issue of temporal resolution is also dependant on the size of the catchment. The smaller catchments with sub-daily response times may benefit from the better temporal resolution. Peak flows are expected to be better modelled on small catchments, with a lower probability of large streamflows being simulated with a one-day offset (Asadzadeh et al., 2016; J. Reynolds et al., 2017; Yang et al., 2016). On the other hand, using finer temporal resolution may be insignificant on large catchments as they require unessential additional computational cost (Y. Wang et al., 2009; Yang et al., 2016).

In fact, running the same model on a daily time step is less computationally costly than doing sub-daily hydrological modeling. The issue of choosing the optimal time step as a function of catchment size is a significant one to solve now that sub-daily meteorological data are more widely available. According to a review of prior studies, many investigations were done on daily time steps (Sudheer et al., 2007), and sub-daily time steps have been used in some models. Using time steps of 24 hours or fewer, sub-daily step hydrological studies are carried out with the goal of enhancing numerical accuracy (Clark & Kavetski, 2010) or sensitivity analysis of hydrological model parameters (Haddeland et al., 2006; I. G. Littlewood & Croke, 2008; Nalbantis, 1995). Despite this, many research do not justify or even analyse the choice of a certain modelling time-step (sub-daily or not).

As a result, extracting precise guidelines on the usage of a sub-daily time step from previously published studies is challenging. Is there a systematic measurable improvement in modelling accuracy as you progress to a finer step? Is there a watershed size limit beyond which sub-daily hydrological modelling adds to the computational effort while providing no observable benefit? Although there is some existing literature on these topics, there is currently a research gap.

The major goal of this thesis is to determine the appropriate runoff model time step while taking the size of the catchments into consideration. To do this, we must look at how the results of hydrological modeling are affected by temporal resolution. The specific objectives to attain that goal are then defined are to create a database of North American catchments with hydrometeorological inputs on hourly to daily time intervals (24hr, 12hr, 8hr, 6hr, 4hr, 3hr, 2hr, 1hr); simulate streamflows at different time intervals throughout all catchments; evaluate the influence of temporal resolution on simulation findings, as well as the effect of catchment size.

CHAPTER 1

LITERATURE REVIEW

1.1 Rainfall-runoff hydrological modeling

Hydrological modeling began as early as the 19th century in order to design and expand drainage networks, dam structures, canals, etc. Simple hydrological models were originally developed in the early 1960s, and the Stanford model (SWM) is one of the first hydrological models to take into account most of the hydrological cycle's activities (Crawford & Linsley, 1966). In the following decades especially between 1970 and 1980, many hydrological models were introduced that played an important role in the evolution of hydrological modeling (Singh & Woolhiser, 2002).

In general, hydrological modeling is simulating the hydrological cycle using a set of equations and input data such as rainfall, temperature and catchment characteristics (area, vegetation cover, soil characteristics, etc.) to estimate the rainfall-runoff (Devia et al., 2015).

Flood and drought forecasting, which require estimating streamflow over a specific temporal and spatial range, are among the applications of rainfall-runoff models that are routinely used by researchers (Blöschl & Sivapalan, 1995). Controlling the quantity of excess rainfall that runs through the land surface and returns to the seas is dependent on the study of runoff (Sitterson et al., 2018). The quantity of runoff depends on time and place, as well as the soil type, land cover, vegetation and slope (Perlman, 2016). The equation of water balance shows how runoff is calculated from excess rainfall over a period of time, as below:

$$Q_s = P - ET - \Delta SM - \Delta GW \tag{1.1}$$

Where Q_s is surface runoff, P is precipitation, ET is evapotranspiration, ΔSM is change in soil moisture, and ΔGW is the change in groundwater storage.

Surface runoff is calculated using the necessary input data using numerical hydrological models of runoff, which are used based on meeting the water balance equation and taking into account different hydrological components. These models provide a good view of how water behaves in a hydrological cycle in terms of both quantity and quality (Sitterson et al., 2018). Rainfall-runoff modeling approach is primarily chosen based on available data and prior knowledge of the system. This knowledge is transferred into equations that describe the physics or the behavior of the system. The complexity of a model is governed by this *a priori* knowledge, and thus, modeling techniques can be classified into three categories of empirical, conceptual and physical discussed by (Sitterson et al., 2018). The benefits and drawbacks of each modelling category, as well as the variables affecting their uses, will be covered in the following sections.

- **Empirical**: The advantages of this method include high speed and no need for a large number of variables. It may be argued that this approach is the greatest option for modeling ungauged catchments and in certain modeling where streamflow is the sole needed output due to its lack of connection with the actual catchment and input data distortion.
- **Conceptual**: In this method, the structure of model is not complex and calibration of the model is easy, but spatial variability for the basin is not considered and it can be said that this method is the best choice in cases where streamflow is the only required output, or when little data is available or when computation resources are limited.
- **Physical**: In this method, both spatial and temporal variability are considered in modeling with the ability to model within catchment characteristics. The disadvantage of this method is the high number of variables and also the complexity of calibrating the model. This method is the best choice to model small basins with high access to hydrological data.

Runoff models can be classified in different categories based on the representation of spatial processes. Models may be classified into three groups based on the structure of spatial processes: lumped, semi-distributed, and distributed models, which are succinctly explained below along with their main characteristics, advantages, and disadvantages (Beven, 1990; Sitterson et al., 2018).

- **Lumped models:** In these models, spatial variability is not considered and the basin is studied as one unit. In these models, the computational speed is high, but many assumptions are considered for modeling, and these models are not suitable for large and heterogenous basins (figure 1.1).

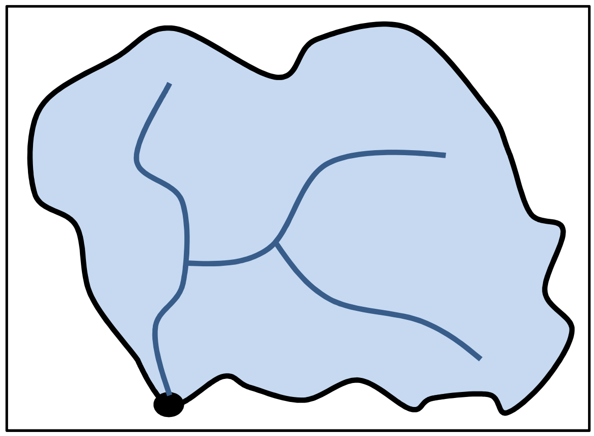

Figure 1.1 The spatial structure of lumped model adapted from Sitterson et al. (2018)

- **Semi-distributed models:** These models can be considered a combination of lumped and distributed models. In these models, modeling is done in more detail, but in the sub-catchments, spatial resolution is reduced (figure 1.2).

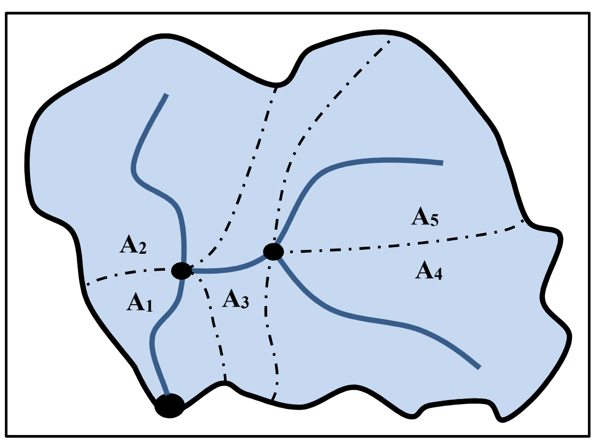

Figure 1.2 The spatial structure of semi-distributed model with sub-catchments adapted from Sitterson et al. (2018)

- **Distributed models:** These models, sub-divide each sub-catchment in smaller cells and in each cell input data are required. These models' strength is their physical interaction with hydrological processes, while their drawback is their slow computation speed and need for a large amount of input data for the basin (figure 1.3).

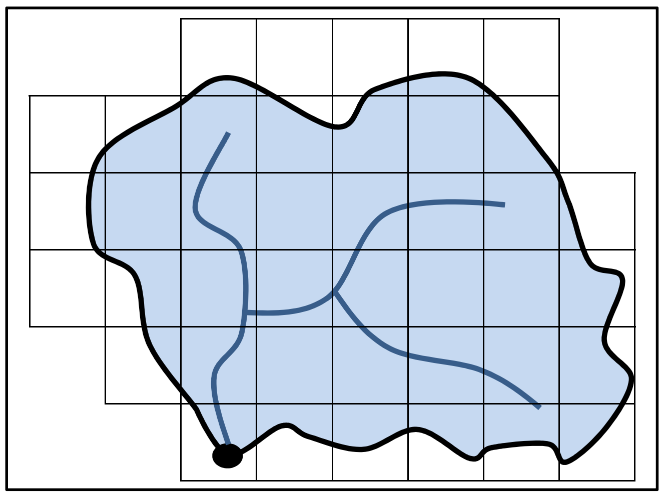

Figure 1.3 The spatial structure of distributed model with grid cells adapted from Sitterson et al. (2018)

Because physical and distributed models are more complicated and require more input data, conceptual models received more attention. In fact, conceptual models have adequate accuracy in estimating the streamflow, are simpler and require less input data (Kumari et al., 2021).

Although many lumped models were used in the past decades such as ABCD model (Alley, 1985), Sacramento (Burnash et al., 1973), Guo-5p (Lian, 1995), Témez (Rawat & Mishra, 2016), Thornwaite-Mather (Lyon et al., 2004), IHACRES (Croke et al., 2005), SIMHYD (Chiew & McMahon, 2002), AWBM (Boughton, 2009), and SMAR (O'connell et al., 1970) and reliable results were obtained from them, but among them, the 4-parameter GR4J model and its hourly version (GR4H) have received more attention (Boumenni et al., 2017; Lujano et al., 2020). Researchers often use this model because it is more useful at various time steps, easier to understand the algorithm, has fewer variables, can simulate large flows, and produces more accurate modeling results than other global lumped conceptual models (Darbandsari & Coulibaly, 2020; de Boer-Euser et al., 2017; Ficchì et al., 2019; Mouelhi et al., 2013; Tegegne et al., 2017). The model is described in more details below.

1.1.1 GR4H-CemaNeige description

Because of the availability of hourly input data, the daily GR4J model may be improved into an hourly GR4H model (Desclaux et al., 2018). The structure of both models is similar, except for the time steps of input data. In fact, the hourly GR4H runoff model uses evapotranspiration, temperature, and precipitation as input variables. Precipitation is measured in millimeters of liquid. Before being used as input for the GR4H model when precipitation takes the form of snowfall, the quantity of melted snow is first estimated and represented in millimeters of liquid using the snow model CemaNeige. In the following, we will discuss the snow model and rainfall-runoff model in more details.

- **Snow model (CemaNeige)**

Valéry (2010) in her PhD project introduced the CemaNeige two-parameter snow model with the aim of improving the performance of hydrological models with the presence of snow. This model helped in the hydrological simulation of snow-covered basins to apply the process of snow accumulation and its melting in the calculations. In recent studies, acceptable results of using the snow model with rainfall-runoff models like GR4J (and GR4H for hourly modeling) shows that CemaNeige is reliable to use and it is applicable for daily and sub-daily time steps. (Arsenault et al., 2015; Nicolle, 2010; Raimonet et al., 2017, 2018; Riboust et al., 2019; Tarek et al., 2020; H.-M. Wang et al., 2019; Youssef et al., 2018).

Precipitation and temperature are the only two input variables needed for the snow model. In this model, several equal-sized elevation zones (often five) may be taken into account for each catchment. By taking into account the snow covers at various elevations and improving modeling accuracy, these elevation zones are used. After importing input data (precipitation and temperature) for each zone, according to the snow model algorithm, the fractioning between solid and liquid precipitation, snow pack accumulation and snow pack melting will be calculated. The output of the snow model is millimeters of liquid precipitation that is the result of adding the amount of rainfall and snow pack accumulated melted in the selected time series. The output of snow model will ultimately be the input of the hydrological model (GR4H) (Riboust et al., 2019). (https://webgr.inrae.fr/en/models/snow-model/)

The snow model has two free parameters, including degree day factor and weighting coefficient for snow pack thermal state. Parameters can be considered fixed or optimized values (Valéry, 2010). To optimize the parameters of the snow model, the calibration process is performed along with 4 parameters of GR4H (X5 and X6 belong to snow model), which will be explained in more detail in the methodology chapter.

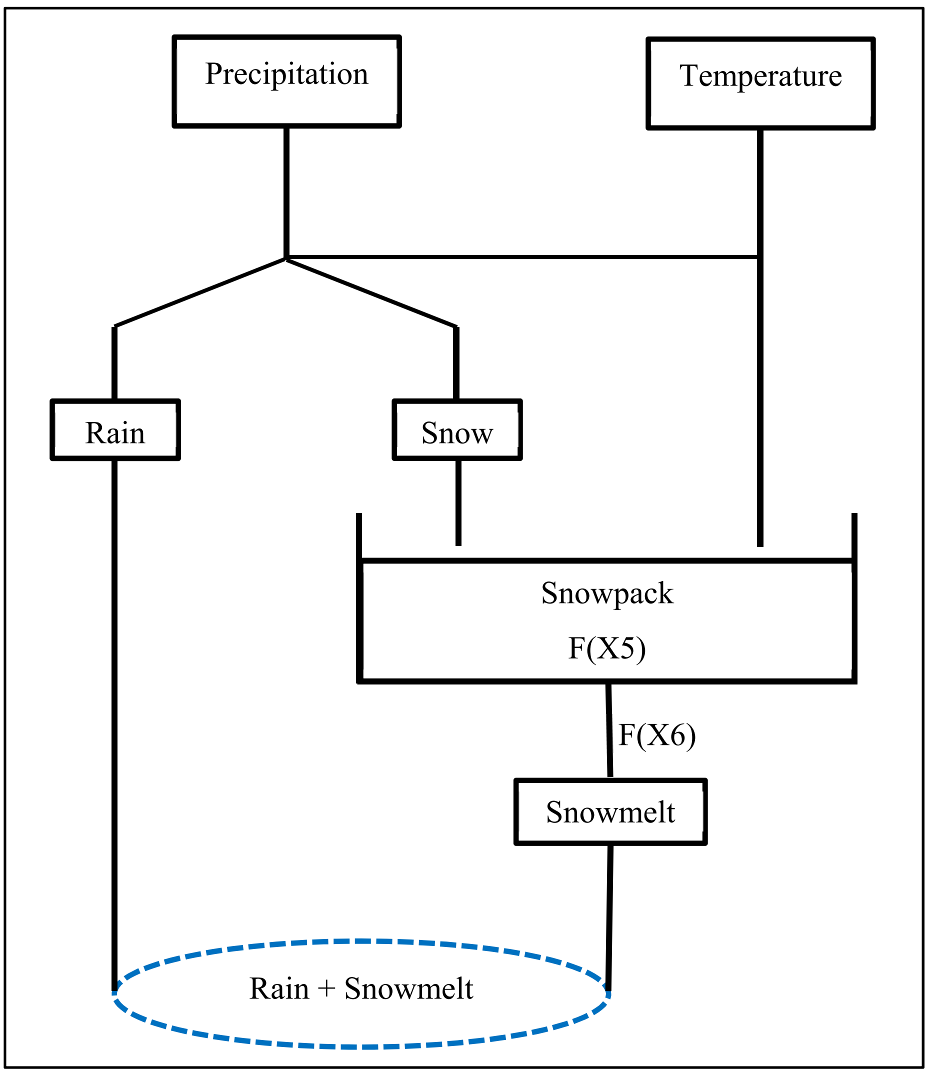

Figure 1.4 Schematic view of the CemaNeige snow model adapted from Valéry et al. (2014)

- **Rainfall-runoff model**

GR models developed by Catchment Hydrology Research Group in France including GR1A (with 1 parameter), GR2M (with 2 parameters) and GR4J (with 4 parameters) are used to simulate rainfall-runoff at annual, monthly and daily time steps, respectively.

Today, regarding more access to daily and hourly hydrological data and due to the higher accuracy of models with these time steps than monthly and annual models, the GR4J (Génie Rural à 4 paramètres Journalier) runoff model and its hourly version (GR4H) have received more attention (Caligiuri et al., 2019).

A single-parameter model first proposed in 1983 was gradually developed into GR4J, a 4-parameter lumped and conceptual model (Michel, 1983). The National Research Institute of Science and Technology for Environment and Agriculture (IRSTEA) enhanced this model, and as a result, its time-independent structure has been created (Mouelhi et al., 2013). Figure 1.5 shows the structure of the GR4J and GR4H models. The daily time step GR4J model was changed to make it appropriate for use at hourly time step, and this evolved into its GR4H version. The time step of the input data is the main difference between the two models. Thus, the input data to the model are namely the precipitation, temperature, potential, and potential evapotranspiration (PET). Precipitation, temperature, and runoff values (for the model calibration) are usually accessible in meteorological station databases, however computing evapotranspiration data might be challenging due to different calculation approaches (Dezsi et al., 2018; Srivastava et al., 2017). For instance, certain current PET calculating techniques involve difficult-to-get information that may necessitate the use of distant sensing data (Talsma et al., 2018). Alternative methodologies were used by researchers, in which PET was calculated using empirical relationships with factors like temperature and other meteorological data like wind speed and radiation (Ferreira et al., 2019; Flores et al., 2021).

In short, the original GR4H/GR4J model (Figure 1.5) calculates the discharge in the chosen catchment by using input data considering two stores, including production and routing and using two unit hydrographs to simulate the time lag between the rainfall event and the resulting flows (UH1 and UH2) and four calibration parameters. Parameters include X1 (capacity of the production soil store (mm)), X2 (water exchange coefficient (mm)), X3 (capacity of the routing store (mm)) and X4 (unit hydrograph base time (days)).

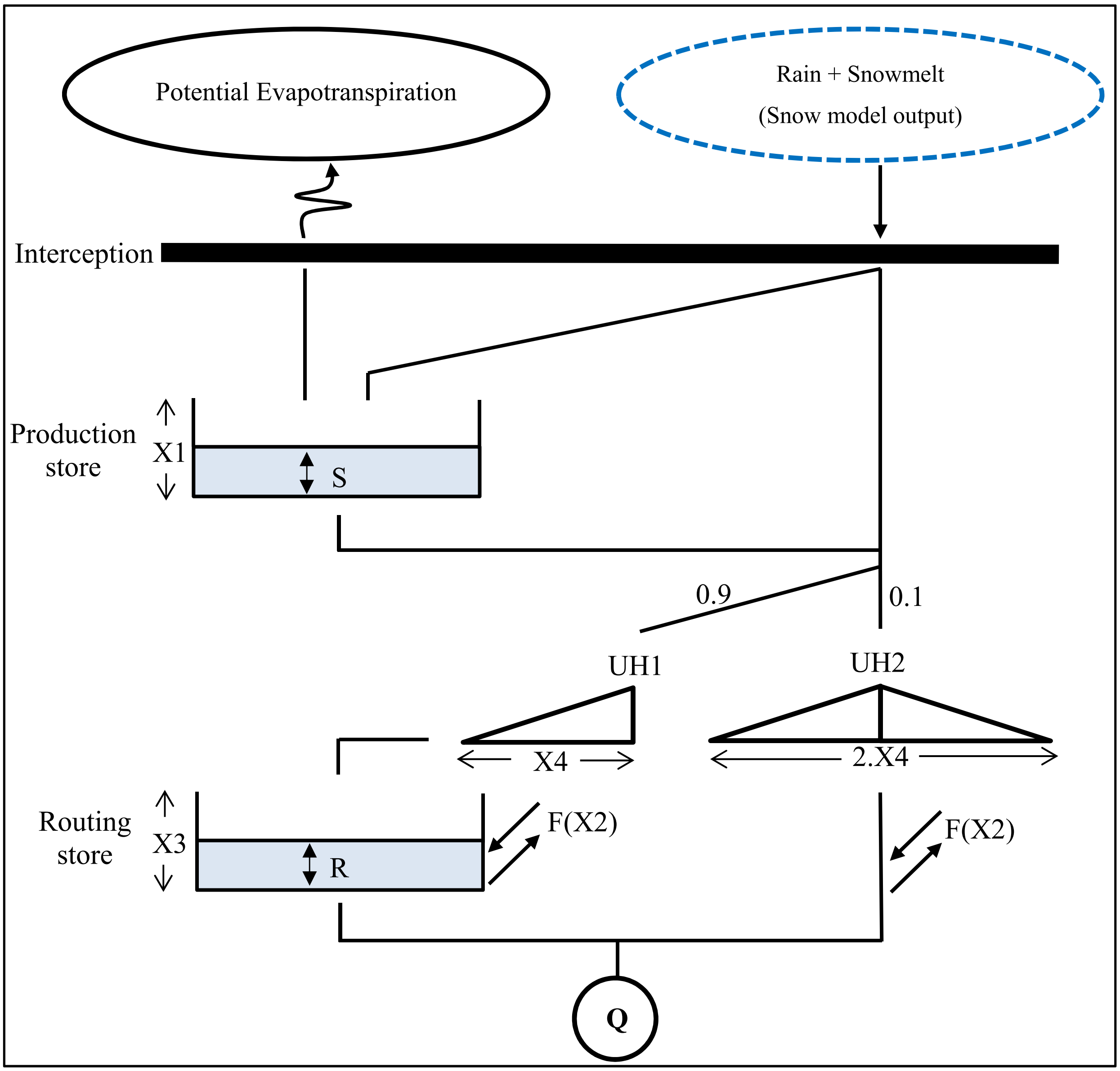

Figure 1.5 Schematic diagram of the GR4J/GR4H model adapted from Perrin et al. (2003)

1.1.2 Optimization method and objective function

For automatic calibration of hydrological models various optimization methods were used, such as Shuffled Complex Evolution (SCE-UA), Non-dominated Sorting Genetic Algorithm II (NSGA-II), the Multi-objective Particle Swarm Optimization (MPSO), Pareto Envelope-Based Selection Algorithm II (PESA-II), and the Strength Pareto Evolutionary Algorithm II (SPEA-II) (Mostafaie et al., 2018). Among different optimization techniques, Shuffled Complex Evolution (SCE-UA) global algorithm (Duan et al., 1992, 1994) which is used in this study, has received more attention and showed compatibility with various conceptual rainfall-runoff models including GR4J (Gan & Biftu, 1996; Jeon et al., 2014; Madsen, 2000; Y.-C. Wang et al., 2010).

The quality of the optimal variables obtained after calibration of the runoff model depends on a number of variables, including the quality of the input data, the effectiveness of the model in simulation, potential model structure errors, the performance of the optimization method, the objective function, and others (Feyen et al., 2007; Madsen, 2003). In flood forecasting, to evaluate the performance of the model and its reliability, monitoring and examination of three elements of the flood is important, which include runoff volume, flood hydrograph and flood peak (Moussa & Chahinian, 2009). Nash-Sutcliffe efficiency coefficient (NSE) as an objective function in the process of optimizing variables and model calibration, by comparing the flow rate calculated by the model and the amount of observations, evaluates goodness-of-fit of the simulated flood hydrographs (Gupta et al., 2009; Moriasi et al., 2007). By this evaluation criterion, the overall performance of the flood event is measured (Jie et al., 2016).

1.2 Input data temporal resolution issues in hydrological models

In hydrological modeling, the issue of temporal resolution of the model inputs has attracted the attention of many researchers (Brighenti et al., 2019; Yang et al., 2016). Jothityangkoon and Sivapalan (2001) evaluated water balances and flood peak events using different hydrological models by considering different time steps. Other researchers, such as Littlewood and Croke (2008) showed an empirical nonlinear relationship between the change of time steps and model parameters and made suggestions to find this relationship. Wang et al. (2009) using different time steps to a conceptual hydrology model, found a relationship between time steps and model parameters. Furthermore, Ostrowski et al. (2010) using different time steps on a hydrological model which was widely used in hydrological studies (GR4J) have investigated the relationship among time steps and the time dependency of hydrological model parameters and their linear and nonlinear changes by changing inputs temporal resolution. Although these results are sufficient for hydrological modeling, the research described in this thesis takes various time steps and the catchment size into account to improve model behavior. Nowadays, regarding the availability of hydrological data from various sources, including automatic rain gauges, radar, satellite, etc., and increasing the sampling rates (up to a few minutes), the possibility of hydrological modeling in sub-daily and even sub-hourly time steps is provided more than before (Ficchì et al., 2019; Jeong et al., 2010). There are many different studies which shows that sub-daily time steps are frequently used to flood forecasting using various hydrological models. e.g. (Marty et al., 2013; Wetterhall et al., 2011). The need for modeling on short time steps such as hourly and even sub-hourly is due to a more accurate view of all flood characteristics (Obled et al., 2009). The model user should be able to choose the appropriate temporal resolution based on the level of information wanted for the simulation when choosing the time step for the model inputs. However, fixed daily and hourly time steps were traditionally employed for hydrological simulations due to their simplicity of use and accessibility to data (Ficch et al., 2019).

Despite many modelings which were done at different time steps, there is still no systematic knowledge of the model behavior at different time steps, especially sub-daily time steps (Kirchner et al., 2004). It emerges of the importance of further studies for sub-daily and even sub-hourly time step modeling and to move beyond the daily and longer time steps, which has already received much attention (Fenicia et al., 2008; Gerrits et al., 2010). There are many studies that show that the behavior of the model changes with increasing time resolution of input data (Atkinson et al., 2002; Jothityangkoon et al., 2001; Kavetski et al., 2011), most of which studies have been done on annual to daily time steps and we see a small number of them with sub-daily time steps (Jeong et al., 2010; Kavetski et al., 2011) which also shows the importance of further research on the sub-daily time steps.

The modeling of small-scale catchments is another topic that emphasizes the need of taking the sub-daily time step into account. When late-day precipitation occurs in these catchments, the hydrograph peak will occur the following day, whereas the daily runoff model simulates the flood peak on the same day. This time difference is known as the one-day offset issue,and it occurs because of the short time of concentration (less than 24 hours) (Asadzadeh et al., 2016). It shows that taking catchment size into account when modeling rainfall-runoff helps in understanding model behavior. Although some studies were performed considering the impact of catchment area on runoff modeling (Adams et al., 2012; Huang et al., 2019; Shuai et al., 2022; Zhao et al., 2009), but investigating the impact of temporal resolution on different range of catchment sizes can be mentioned as a research gap which is the main objective of this study.

1.3 Preparation of collected data for use in hydrological models

The absence of long record of sub-daily historical data (at least 5 years) for catchments around the world has become an obstacle in sub-daily runoff modeling and flood forecasting (Merz et al., 2009; J. E. Reynolds et al., 2015). To tackle this problem, researchers have used techniques to convert the time step of available data. For example Bennett et al. (2016) selected a range of meso-scale catchments (150-3500 km^2). In his study, the time step of daily precipitation was converted to hourly using a disaggregation approach, and the model produced results that were satisfactory. From the other hand some other studies showed that converting the daily time step to hourly changes the parameters of the hydrological model (I. G. Littlewood & Croke, 2008; Y. Wang et al., 2009), which leads to a drop in model performance and lower quality of results. So far, various methods were used to disaggregate daily data to sub-daily time steps, some of them are simple to use and some others involve complex mathematical methods. Examples of disaggregation methods include computational techniques based on method of fragments (Pui et al., 2012; Westra et al., 2013), multiplicative cascade models (Förster et al., 2016; Müller & Haberlandt, 2018), and more complex mathematical methods (Kossieris et al., 2018; Koutsoyiannis et al., 2003).

Although many studies indicated that increasing the temporal resolution of the model and using hourly (or sub-hourly) data increases the accuracy of modeling (Ficchì et al., 2019), the computing process will be more time consuming. This is brought on by a rise in the volume of input data. Research on additional sub-daily time steps, including 3 hours, 6 hours, and so on, has been done as a consequence. With reasonable estimating accuracy and quick calculation, they were able to choose the proper time step for modeling. To generate data with sub-daily time steps such as 3 hours and 6 hours and etc., the input data for the model will be obtained with aggregating the hourly observed data to the desired time steps. If hourly data are not available, first the daily data is disaggregated to the hourly and then the desired time step is generated by the aggregation method (Sikorska et al., 2018). The findings of the mentioned researches show that despite considering different time steps as input of hydrological model and conducting studies on different catchments around the world, the issue of choosing the most optimal time step for hydrological modeling is still not completely clear and can be considered a research gap. To find a better view of the effect of temporal resolution changes of the input data on the model behavior, considering the size of the catchment and finding the relationship between the size of the catchment and the time steps can help solve this problem.

1.4 Conclusion

According to a review of prior studies, many investigations were done on daily time steps, and sub-daily time steps have been recently used in several models. Using time steps of 24 hours or shorter, sub-daily step hydrological studies are carried out with the goal of enhancing numerical accuracy or sensitivity analysis of hydrological model parameters. Despite this, many research are not able to justify or even analyze the choice of a certain modelling time-step (sub-daily or not).

As a result, deriving precise guidance on the usage of a sub-daily time step from previously published studies is challenging. Is there a systematic measurable improvement in modelling accuracy as you get to a smaller step? Is there a catchment size limit beyond which sub-daily hydrological modelling adds to the computational effort while providing no quantifiable gain? Although there is some existing literature on these topics, there is currently a research need.

This research offers a large-scale multi-time-step hydrological modelling analysis on numerous catchments of varied sizes across North America in an attempt to answer these problems.

To tackle these problematics, the following research objectives were established. First, the main objective of this study consists to explore the impact of temporal resolution on hydrological modeling results. Then, to achieve that objective, the specific objectives are defined as below:

- Set up a North-American catchment database with hydrometeorological inputs at the hourly to daily time scales.
- Simulate streamflows on all catchments at different time steps
    - Evaluate the impact of the temporal resolution on simulation results
    - Evaluate the impact of catchment size on results.

CHAPTER 2

METHODOLOGY

In this chapter, a detailed methodology is proposed to reach the research objectives. First, we describe the selection of catchments to generate a database. Then we follow with detailed steps of the study.

2.1 Selection of catchments

The catchments were selected for regions across the United States in such a way that the research results can be generalized to various climatic conditions. For the studied catchments, hydrometeorological data, such as precipitation, temperature and discharge in hourly time steps as well as characteristics of the catchments are needed. These data were collected from MOPEX, ERA5 and USGS databases, which are described below. The lack of access to hourly data in the MOPEX database caused that some watersheds were excluded. However, ERA5 database contained hourly data for all catchments. Finally, 339 catchments with sufficient data were selected for this study. They are located all over the United States, but most of them are located in the eastern part of the country.

2.2 Data collection

In the first stage of runoff modelling, input data for the hydrological model must be acquired over a set time period. Considering the limited availability of hourly rainfall (in MOPEX database) and discharge data for the studied catchments, the time period base on available data is defined as a period of 14 years from 1990 to 2003. Model input data include precipitation, temperature, evapotranspiration, catchment size and catchment boundaries (latitude and longitude). The following is a description of each of these databases and how to extract the data.

2.2.1 MOPEX

A worldwide effort called Model Parameter Estimation Experiment (MOPEX) tries to estimate the data needed for a hydrological model using existing methodologies. Data on hydrological and surface features for several watersheds in the United States and other nations over a long period of time are available in the MOPEX database (more than 50 years) (Duan et al., 2006). Hourly data on precipitation, daily maximum and minimum temperature, and catchment size and catchment boundaries were collected for 339 catchments over 14 years in the United States.

In this database, data related to thousands of catchments located in the United States are available on a daily time step, but in this study, regarding the need to run the model on sub-daily time steps and the lack of hourly data or limited time period of existing data, some catchments were excluded.

2.2.2 ERA5

ERA5 is an advanced reanalysis product that was developed by the European Center for Medium-Range Weather Forecasts (ECMWF) in an evolutionary process from older generation of reanalysis (ERA-Intrim) (Tarek et al., 2020). The data period covered by ERA5 spans from 1950 to the present, although in the previous edition this data was only accessible since 1979. This is one feature added to ERA5 over the previous generation. Additionally, ERA5 data has a higher number of elevation levels and smaller grids (30 km) for spatial resolution (137 levels from the surface up to a height of 80km). One of the most important features of ERA5 which did not exist in the previous generation is the hourly temporal resolution, which has made this database more impactful. In general, ERA5 is a very extensive hourly database of the earth hydrological characteristics including atmospheric, land, and oceanic climate variables which was available to users since the 1950 to present (ECMWF website https://confluence.ecmwf.int/pages/viewpage.action?pageId=74764925 https://confluence.ecmwf.int/display/CKB/ERA5%3A+data+documentation).

In this database, the atmospheric data of different locations of the earth are available in the spatial grids with the resolution of 30 km, which can be extracted by selecting the longitude and latitude of the desired location. The precipitation and temperature data were extracted for 339 catchments. To extract these hydrological characteristics for the catchments, three different scenarios occurred depending on the size of the catchments.

In the first scenario, which occurred in large and medium-sized catchments, two or more points of database grids were located within the catchments boundaries (figure 2.1).

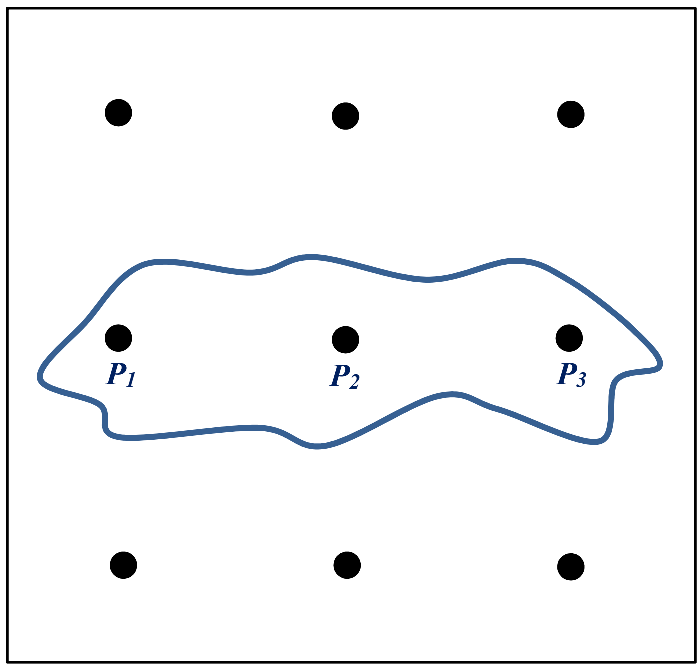

Figure 2.1 Collecting precipitation and temperature data when there are two or more grid points located inside the catchment boundaries

In this case, the average amount of precipitation and temperature for these points was considered for the catchments as follows:

$$P = \frac{1}{N}\sum_{i=1}^{N} P_{P_i} \tag{2.1}$$

$$T = \frac{1}{N}\sum_{i=1}^{N} T_{P_i} \tag{2.2}$$

In the second scenario, only one point of ERA5 grid points was located inside the boundaries of the catchments (figure 2.2).

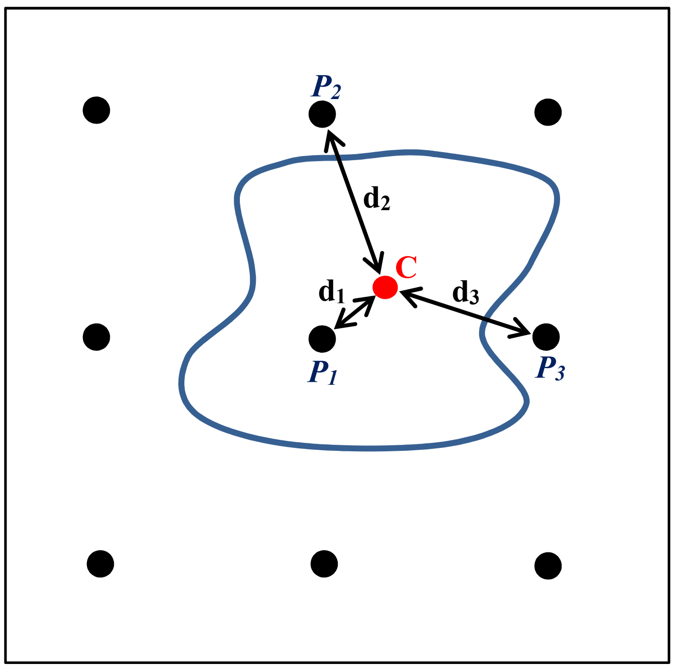

Figure 2.2 Collecting precipitation and temperature data when there is only one grid point located inside the catchment boundaries

In this case, to increase the accuracy of the extracted data for the catchment, two other points of the grid points that were located outside the boundary of the catchment and were closer to the centroid of the catchment were also selected and precipitation and temperature were calculated with the inverse distance weighting (IDW) equation as follows:

$$P = \frac{\sum_{i=1}^{3} \left(\frac{P_{p_i}}{d_i} \right)}{\sum_{i=1}^{3} \left(\frac{1}{d_i} \right)} \quad (2.3)$$

$$T = \frac{\sum_{i=1}^{3} \left(\frac{T_{p_i}}{d_i} \right)}{\sum_{i=1}^{3} \left(\frac{1}{d_i} \right)} \quad (2.4)$$

In the third scenario, which usually happened in smaller catchment, there is not any grid point inside the catchment boundaries (figure 2.3).

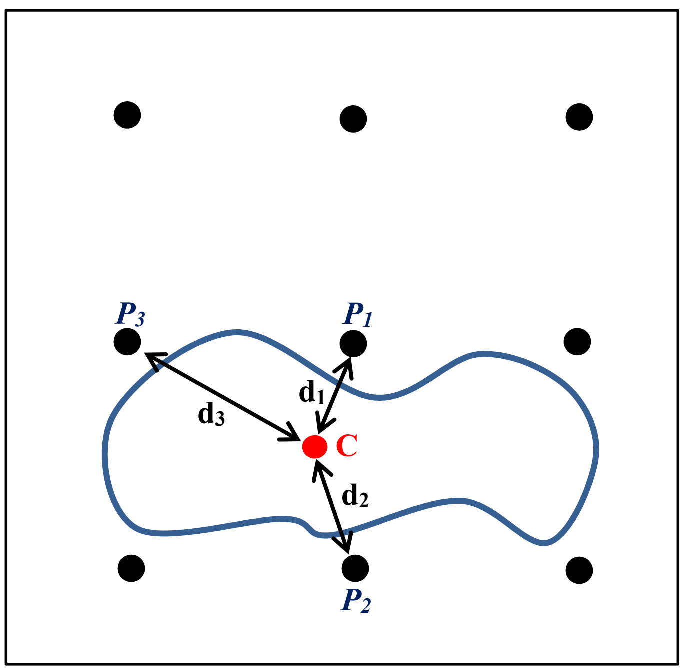

Figure 2.3 Collecting precipitation and temperature data when there is not any grid point inside the catchment boundaries

In this case, 3 points that were closest to the centroid of the basin were selected and precipitation and temperature were calculated with the inverse distance weighting equation (equation 2.3 and 2.4).

2.2.3 USGS

The United State Geological Survival (USGS) was established on March 3, 1879 with the purposes such as the classification of the public lands, and examination of the geological structure, mineral resources, and products of the national domain as the largest water, earth and biological sciences agency. Its operations have significantly advanced science and technology throughout the years, particularly in the area of hydrology. This database may be used to extract a broad range of data, including streamflow, flood, drought, earthquake, volcano, landslide, and landsat information as well as supplementary water and hazard research data. These data are recorded at intervals of 15 to 60 minutes at each station and is transmitted on the website every 4 hours.

Hourly discharge data were extracted from USGS database for all catchments. (https://help.waterdata.usgs.gov/faq/about-the-usgs-water-data-for-the-nation-site)

Table 2.1 Data extracted from MOPEX, ERA5 and USGS databases

Database	**Data extracted**
MOPEX	Hourly precipitation (mm)
	daily maximum and minimum temperature (°C)
	Watershed size (km^2)
	Watershed boundary – latitudes and longitudes (°)
ERA5	Hourly precipitation (mm)
	Hourly temperature (°C)
USGS	Hourly discharge (m^3/s)

2.3 Rainfall-runoff modeling

The modeling can be performed after generating the database. Thus, the chart below (figure 2.4) presents the workflow and the techniques applied for modeling. Three sections are presented in the chart and described separately in details in the remainder of this chapter.

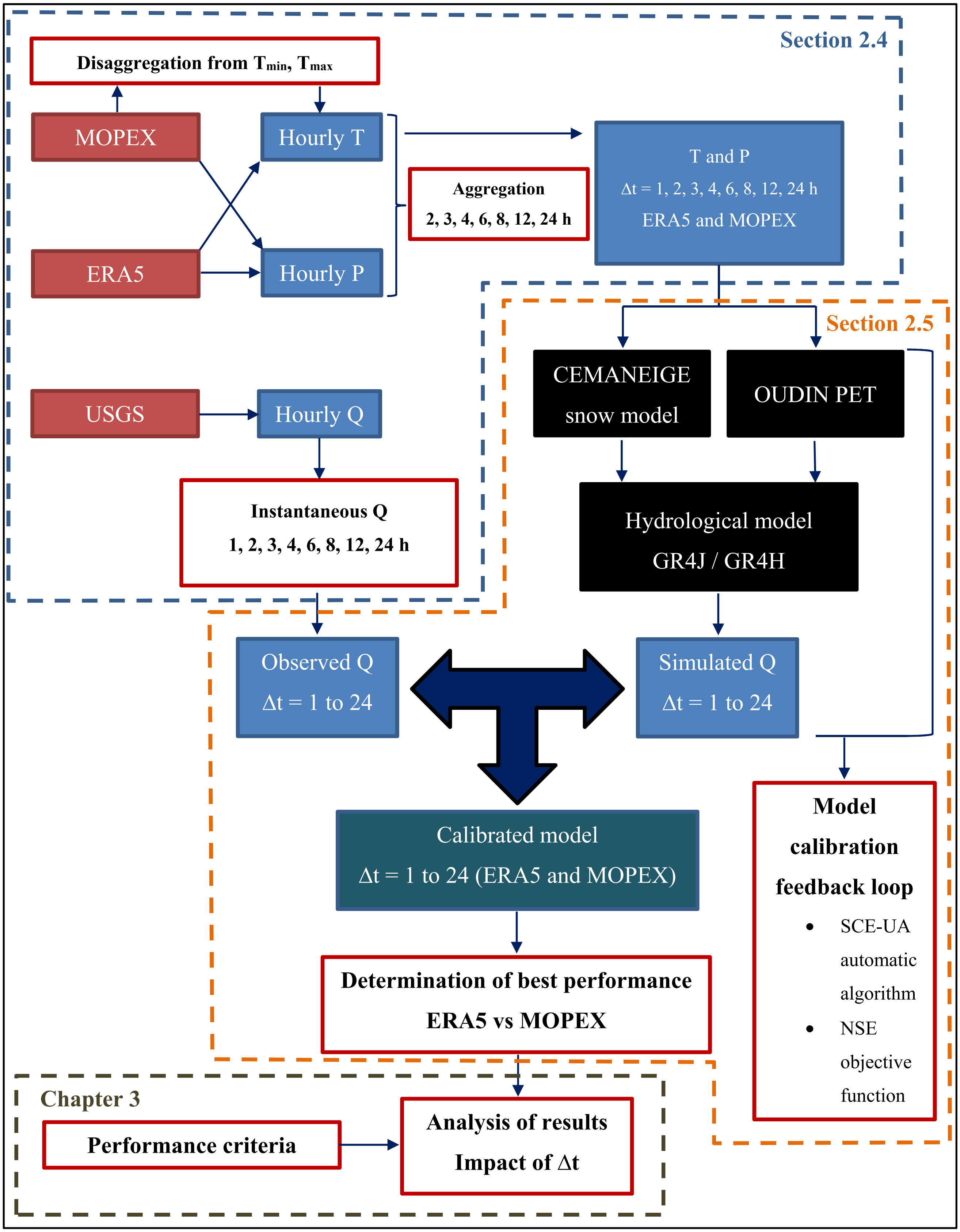

Figure 2.4 Methodological chart for each catchment

2.4 Model setup for use with different time steps

This study aims to investigate the effect of temporal resolution changes on the performance of hydrology model.

For this purpose, the rainfall-runoff model is used to calculate the discharge in 8 different time-steps. The GR4J is used for the daily time steps (24 hours), while the GR4H is used for the sub-daily and hourly time-steps, namely 1-hour, 2-hours, 3-hours, 4-hours, 6-hours, 8-hours and 12-hours time-steps.

According to the data collected from MOPEX, USGS and ERA5 databases mentioned earlier, the available data according to their original time step; they can be converted to the desired time steps by aggregation and disaggregation methods. The method of data time step conversion in different time steps is separately explained for each of the inputs of the hydrological model.

Conversion of MOPEX data time steps

Data extracted from this database are included in hourly precipitation and maximum and minimum of daily temperature for a period of 14 years.

To convert the precipitation from hourly time step to other desired time steps, simple aggregation method was used. In this method, hourly precipitation accumulated during chosen time intervals. For example, to have values in 8- hour time steps, we accumulate hourly values as below:

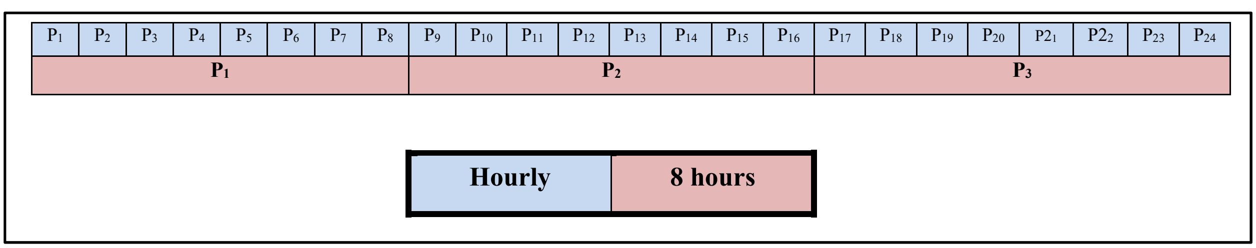

Figure 2.5 Collection of precipitation values for 8-hour time steps

To convert the temperature from the daily maximum and minimum to other desired steps, disaggregation method was used. In this method by using a shape-preserving piecewise polynomial interpolation function (pchip function), daily Tmin at 4AM and Tmax at 4PM disaggregated to sub-daily time steps.

Finally, PET (potential evapotranspiration) as the last input of hydrology model was calculated in all desired time steps using Oudin simple formula as follows:

$$\text{if } \mathrm{Ta}+5>0 \qquad PET=\frac{R_e}{\lambda\rho}\frac{T_a+5}{100} \qquad \text{Otherwise} \qquad PET=0 \tag{2.5}$$

In this formula PET is the rate of potential evapotranspiration (mm day^{-1} for daily modeling), R_e is extraterrestrial radiation (MJ m^{-2} day^{-1} for daily modeling), λ is the latent heat flux in (MJ kg^{-1}), ρ is the density of water (kg m^{-3}) and T_a is mean daily air temperature (°C) (Oudin et al., 2005). For sub-daily PET calculation, sub-daily temperature values were used in the Oudin formula.

Conversion of ERA 5 data time steps The hourly temperature and precipitation data were taken from the ERA5 database. Due to the availability of temperature data for 24 hours, the same aggregation procedure was used to transform temperature data for the appropriate time steps (sub-daily and daily) in order to gather precipitation for the necessary time steps.

- Conversion of USGS data time steps (Q_{obs} for model calibration)

Runoff data collected on an hourly time step from the USGS database was prepared by instantaneous picking for the desired time steps. In this method, according to the desired time step, values were picked from hourly runoff values at specific intervals and the rest of the data were ignored. For example, data on an 8-hour time scale were collected as follows:

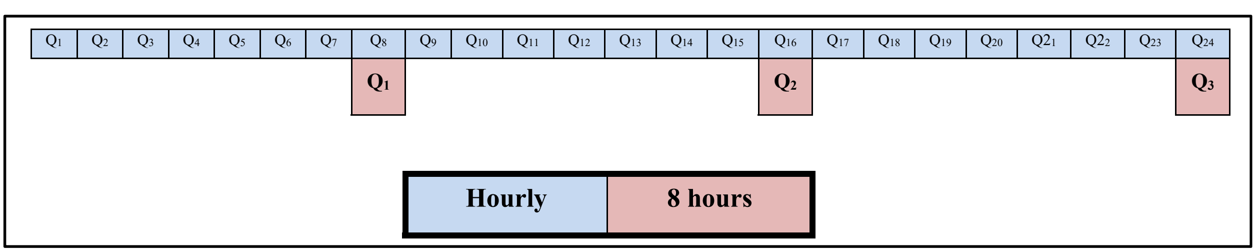

Figure 2.6 Collection of discharge values for 8-hour time steps

2.5 Hydrological modeling and calibration

The hourly version of GR4J (GR4H) which is a lumped conceptual hydrological model was used. Besides, CemaNeige snow model was chosen to calculate the melted snow and was combined to the GR4H model. This is due to the presence of areas with snowfall when selecting the catchments from all over the US. Thus, the resulted model consists of a 6-parameter hybrid model called GR4H-CemaNeige.

Hydrology model calibrating is the process of finding the optimal values for the model variables somehow the model simulates the rainfall-runoff as close to the observations as possible.

In this procedure, the variables are initially assigned some random values within a meaningful range of numbers, and runoff is then estimated over a 14-year period for all catchments. Then, using the optimization method that works with an objective function and repeating the calculations, the model will be calibrated by changing the values of parameters so that the calculated runoff (Qsim) is closest to the observed runoff (Qobs).

To find the optimal values for the parameters of the GR4H hydrological model, which includes the 6 parameters mentioned earlier, SCE-UA optimization method worked with Nash-Sutcliffe coefficient as the objective function and by repeating the optimization operation automatically, the optimal values of the parameters were collected.

Results are presented in the paper in the next chapter of this work.

CHAPTER 3

OPTIMAL TEMPORAL RESOLUTION FOR HYDROLOGICAL MODELING SIMULATIONS

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3.1 Abstract

This work investigated how the temporal resolution of hydrological models impacts simulation results, and if/how the impact is related to catchment size. Three hundred and thirty-nine (339) catchments with quality-controlled hourly precipitation were selected, covering most of the contiguous United States. Hourly meteorological data was aggregated at 2, 3, 4, 6, 8, 12 and 24-hour time steps, and one hydrological model was calibrated on all the catchments and for each of the 8 time steps. To study the impact of catchment size, the catchments were grouped into 6 different size classes, from smaller than 500 km^2 to larger than 4500 km^2, with each group containing approximately the same number of catchments. Results showed that using as small a time step as possible was beneficial to all catchment size classes, as it systematically improved the simulated flow bias as well as the magnitude and timing of peaks flows. The smallest size classes benefited the most from a reduced time step, whereas for larger catchments, going to time steps smaller than 8 hours only provided marginal improvements.

Keywords: Hydrology; Modeling; Hydrological modeling; Modeling efficiency; Temporal resolution; Catchment size.

3.2 Introduction

Hydrological models are commonly used to simulate streamflow resulting from the combined contribution of rainfall, snowmelt and groundwater. Hydrological models aim to represent, with various levels of simplification, the main components of the hydrological cycle such as evapotranspiration, groundwater movement, soil water flow, snow accumulation and snowmelt.

Like most environmental models, hydrological models are run at a discrete temporal time step, at which numerical calculations representing physical processes are being made. Depending on the purpose of the modeling, this discrete time step may vary from a few minutes all the way to a year. In most cases, hydrological models are run at the daily time step. The daily time step is convenient since the most common long-term data archives of meteorological data are only available at this time step. Not that long ago, saving data at a sub-daily time step created important storage issues in data loggers and the data was therefore internally averaged and saved at the daily time step. Even today, sub-daily weather data are harder to come by, and especially so for precipitation (J. Reynolds et al., 2017). In addition, the daily-time resolution has been shown in the past to be adequate to tackle many common engineering design problems. Even in cases when sub-daily modeling would have been useful, for example for the determination of instantaneous peak flow, engineers have typically used workarounds such as peak-flow factors to provide some level of temporal disaggregation (e.g. Chen et al., 2017; Fill & Steiner, 2003; Jimeno-Sáez et al., 2017). These reasons explain why there has been comparatively much less modeling work done at the sub-daily time step. Various disaggregation and statistical approaches have been proposed to generate sub-daily datasets from daily data and improve sub-daily hydrological modeling (Bennett et al., 2016; Kandel et al., 2005; J. Reynolds et al., 2017; Waichler & Wigmosta, 2003; Winter et al., 2019).

There are however more and more meteorological databases available at the sub-daily time step. These originate from traditional weather stations data, satellite products, reanalysis and from a combination of such products (e.g. Beck et al., 2017; Sudheer et al., 2007). This access to sub-daily data and recent work on the amplification of short-duration precipitation extremes in a changed climate (Fowler et al., 2021) and its impact on Intensity-duration-frequency (IDF) curves (Martel et al., 2020; Martel et al., 2021) will likely result in a renewed interest in sub-daily hydrological modeling. However, since hydrological models have mostly been evaluated at the daily time step, the potential advantages of the higher temporal resolution should be examined, and how to best choose the right time step for the model (Hughes, 1993). The issue of temporal resolution is closely related to catchment size. Small catchments with a sub-daily response time to precipitation may benefit the most from the finer temporal resolution. It is expected that peak flows may be better simulated on small catchments, with less risk of having large streamflow simulated with a one-day offset (Asadzadeh et al., 2016; Bevelhimer et al., 2015; Jeong et al., 2010; J. Reynolds et al., 2017; Yang et al., 2016). At the other end of the spectrum, the additional computational effort of the finer temporal resolution may be wasted on large catchments with the routing process filtering out precipitations pulses (Y. Wang et al., 2009; Yang et al., 2016).

Sub-daily hydrological modeling is computationally more expensive than running the same model at the daily temporal step, with computational cost being essentially inversely proportional to temporal resolution. Finding an optimal time step and its relation to catchment are important issues to resolve now that sub-daily weather data is becoming more common.

A review of previous studies indicates that most studies have been conducted using a daily time step (Collischonn et al., 2008; J. Reynolds et al., 2017; Sudheer et al., 2007). In the last decade, researchers have started to focus more on sub-daily (and even sub-hourly) modelling due to the increasing availability of sub-daily hydrological data in many parts of the world (Brighenti et al., 2019; Ficchì et al., 2019; Jeong et al., 2010). Sub-daily step hydrological studies are performed with as the objective of improving numerical accuracy (Clark & Kavetski, 2010; Huang et al., 2019; Pang et al., 2020; Shuai et al., 2022; Yang et al., 2016) or to explore the sensitivity of hydrological model parameters to temporal resolution (Haddeland et al., 2006; I. Littlewood et al., 2010; Nalbantis, 1995). Still, in most studies, the choice of a specific modeling time-step (sub-daily or not) is not justified or even discussed.

It is therefore difficult to extract clear guidelines on the use of a sub-daily time step from previously published work. Are there systematic quantifiable gains in modeling accuracy when going to the finer step? Is there a catchment size limit where sub-daily hydrological modeling only adds to the computational burden with no measurable improvement? The existing body of literature provides glimpses into these issues, but a research gap still remains. To try answering these questions, this work presents a large scale multi-time-step hydrological modeling study on several catchments of varying sizes and climate zones across North-America. The main objective of this work is therefore to explore the impact of temporal resolution on hydrological modeling results. To achieve that objective, four specific objectives are hereby defined:

- Set up a North-American catchment database with hydrometeorological inputs at the hourly to daily time scales;
- Simulate streamflows on all catchments at different time steps;
- Evaluate the impact of the temporal resolution on simulation results;
- Evaluate the impact of catchment size on simulation results.

3.3 Materials and methods

3.3.1 Study areas and datasets

First specific objective in this study was to make a selection of catchments based on diversity of sizes and for which reliable data was available at the hourly time step. The MOPEX database was used to this extent. The Model Parameter Estimation Experiment (MOPEX) was an international project looking at model parameter identifiably (Duan et al., 2006) and one of its objectives was to provide a large number of high quality hydrological data for a wide range of river catchments. Using a minimum time series length of 14 years for hourly streamflow data, 339 catchments were extracted from the MOPEX database. The selected catchments vary in size from 65 to 10,000 square kilometers. The smallest catchments have a clear sub-daily response time whereas the largest ones have a clear daily to multi-day time of concentration. The transition from sub-daily to daily response is generally expected to be in the 500 to 1000 square kilometers range (Faghih et al., 2022; J. E. Reynolds et al., 2015). Hourly precipitation data was taken directly from the MOPEX database and corresponding hourly streamflow data extracted from the US Geological Survey (USGS) database. The MOPEX database does not provide hourly temperature, but it contains minimum and maximum daily temperature. Two approaches were tested to obtain hourly temperature. In the first approach, a piece-wise spline interpolation method was used to fit the minimum and maximum daily temperatures, which were assumed to respectively occur at 4AM and 4PM. In a second approach, hourly temperature from the ERA5 reanalysis (Hersbach et al., 2020) was used as a proxy to observed hourly temperature. Both approaches provided good hydrological modeling results. However, the first one yielded slightly, but systematically better modelling result (results not shown) and was therefore chosen for this work. From hourly values, all data was then aggregated at 2,3,4,6,8,12 and 24-hour intervals. Instantaneous streamflow values are used at the end of each interval while accumulated precipitation was summed up over the preceding time steps. Minimum and maximum temperature over the same preceding time steps were recorded. Evapotranspiration was calculated using the Oudin formulation (Oudin et al., 2005).

To study the impact of size at the desired time step, all catchments were regrouped into six size classes as presented in Table 3.1. The size classification is somewhat arbitrary and was designed to include a relatively similar number of catchments in each class. Catchment size is a proxy for time of concentration, which is truly the key variable that best represents response time, but is more complex to compute.

Table 3.1 Catchments size classification

Size group	Watershed size	Number of watersheds in the size range
1	Area < 500 km^2	23
2	Area Between 500 km^2 and 1000 km^2	46
3	Area Between 1000 km^2 and 2000 km^2	84
4	Area Between 2000 km^2 and 3000 km^2	46
5	Area Between 3000 km^2 and 4500 km^2	56
6	Area > 4500 km^2	84

Figure 3.1 presents the spatial distribution of the 339 study catchments. They cover most the continental US, but the density of catchments is larger in the eastern half of the US, and particularly so for smaller catchment size classes.

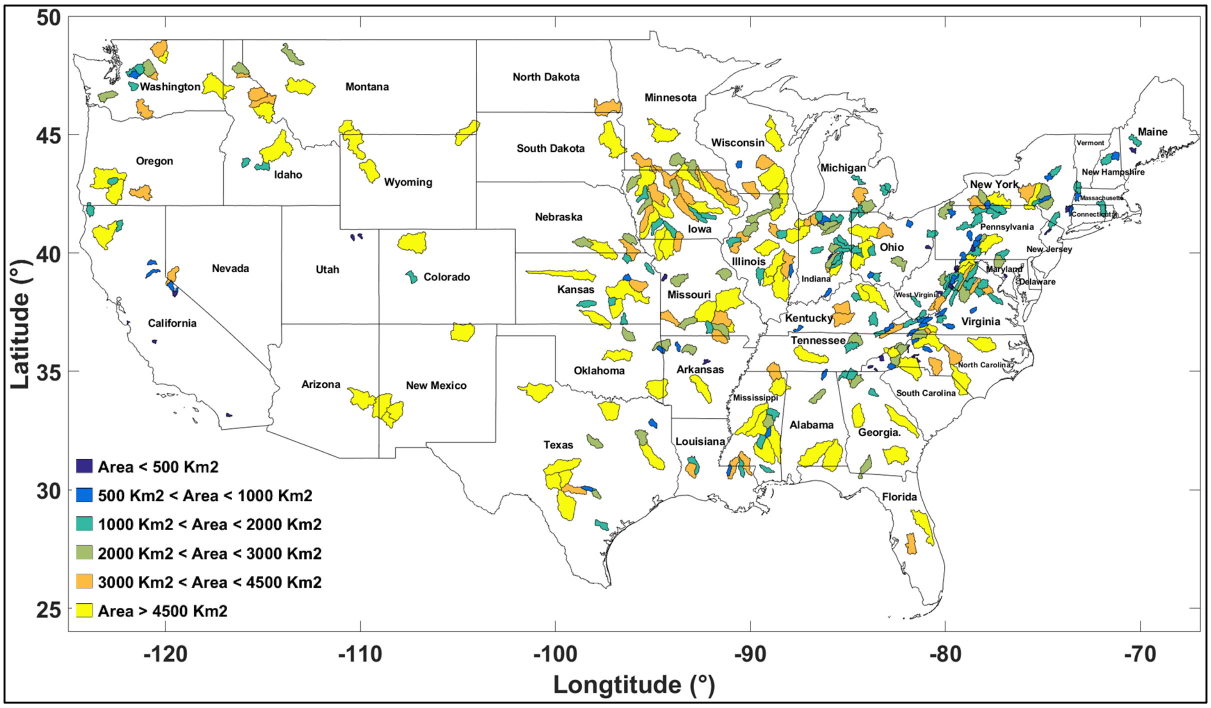

Figure 3.1 Selected MOPEX catchments. The six size classes are shown as different colors. In the cases of nested catchments, the larger ones are plotted first so that all catchments are at least partly visible

The catchments cover a wide variety of climate zones (Jehn et al., 2020). Figure 3.2 presents boxplots of the distribution of mean annual precipitation and temperature as well as catchment size for the 339 selected catchments. The central blue rectangle shows the 25th, 50th (red line) and 75th quantiles of the distribution. The lower and upper whiskers show the 5th and 95th quantiles. Red points are catchment below and above those quantiles. Precipitation ranges from 384 mm/year in the Harding County of South Dakota (USGS station 06334500) up to 2909 mm/year for Snohomish County, Washington (USGS station 12134500). Eighty-three (83) percent of all catchments (278 catchments) have a mean annual precipitation between 700 mm/year and 1500 mm/year, whereas 8 and 9 percent have a respective mean annual precipitation of less than 700 mm/year and more than 1500 mm/year. The mean annual temperature ranges from 0.7 °C in the Yellowstone River near Altonah - Utah (USGS station 09292500) up to 22.9 °C in the Peace river Arcadia - Florida (USGS station 02296750). Forty-four (44) percent of catchments (150 catchments) have a mean annual temperature varying between 10 °C and 15 °C, whereas 38 and 16 percent (130 and 57 catchments) have a mean annual temperature of less than 10 °C and more than 15 °C respectively.

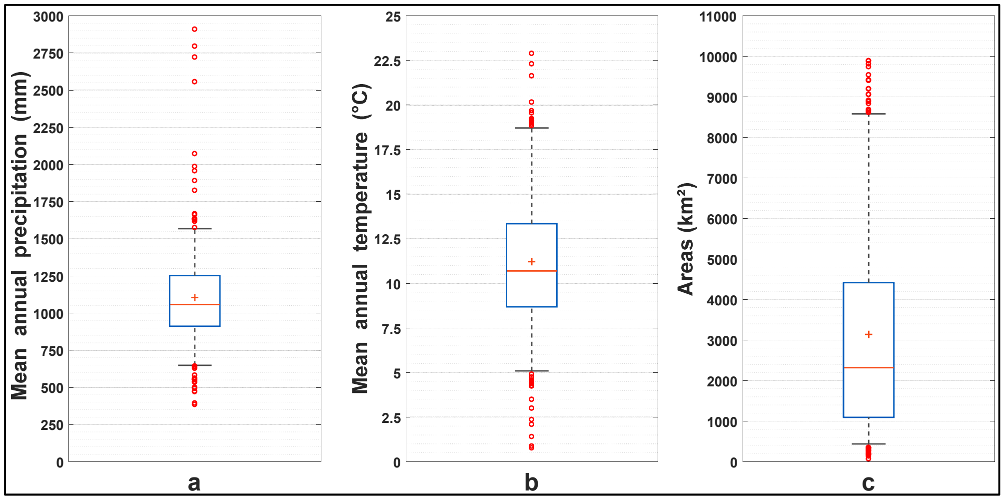

Figure 3.2 a) Mean annual precipitation (mm) b) Mean annual temperature (°C) c) Areas (km^2)

3.3.2 Hydrological model (GR4H)

Choosing the appropriate rainfall-runoff model has been an important issue for hydrological modeller, since no single model can be expected to be the best performing across all possible hydrometeorological conditions. In this study, due to the large number of catchments and temporal resolutions ($339 \times 8 = 2712$), a lumped model with a proven track record was selected. Lumped models have been shown in many studies to perform just as well as distributed models when it comes to simulating streamflows at a cactchment's outlet (e.g. dos Santos et al., 2018; Reed et al., 2004; Smith et al., 2004). The GR4H model, the hourly version of the daily GR4J hydrological model (Perrin et al., 2003) was chosen for this work. It is a 4-parameter rainfall-runoff model that can be used with a daily or sub-daily time steps. It is a simple, parsimonious, yet high-performing model compared to many other lumped conceptual models. (de Boer-Euser et al., 2017; Ficchì et al., 2019; Mouelhi et al., 2013; Tegegne et al., 2017).

The GR4H model calculates the outlet discharge for any catchment using precipitation and potential evapotranspiration (PET) as well as catchment surface area as its sole inputs. The model uses two storage reservoirs (production and routing) and two unit hydrographs to generate streamflow resulting from a precipitation event. The model has four parameters which need to be calibrated: X1 (maximum capacity of the production reservoir - mm), X2 (the water exchange coefficient - mm), X3 (maximum capacity of the routing store - mm) and X4 (unit hydrograph's base time – hours).

Because many of the catchments selected in this study are located in regions with snow accumulation, the GR4H model is linked with the Cemaneige snow module, which was specifically developed to be used with GR4H (Valéry et al., 2014). The end model is therefore a 6-paremeter model. The 2 additional parameters consist in X5 (Degree-day snowmelt factor) and X6 (Snowpack inertia factor). The GR4H/J model has been used in many studies and has shown to perform very well in a wide range of conditions (Arsenault et al., 2015; Perrin et al., 2003; Raimonet et al., 2017; Riboust et al., 2019; Tarek et al., 2020; H.-M. Wang et al., 2019). Figure 3.3 shows the simplified GR4H-CemaNeige model algorithm.

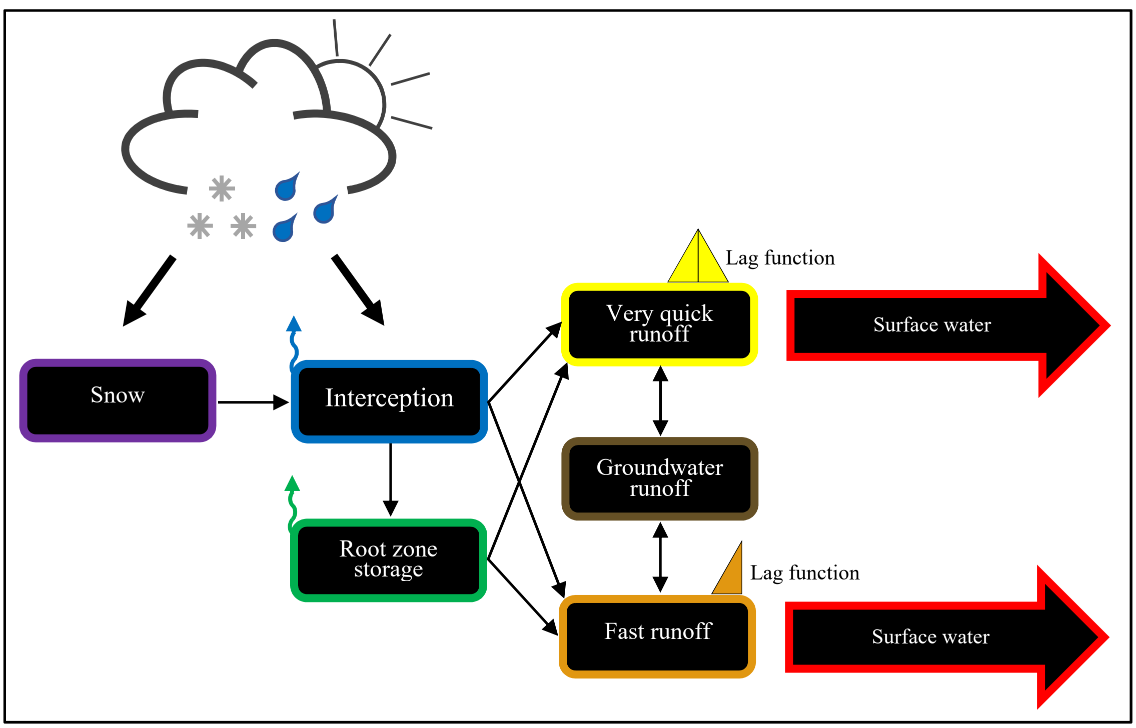

Figure 3.3 Schematic and simplified view of GR4H-CemaNeige. Lines indicate the fluxes between model storages modified from Boer-Euser et al. (2017)

3.3.3 Model Calibration

A common 14-year period covering 1990 to 2003 was used for model calibration. Calibration was performed for all 339 catchments for each of the 8 temporal steps (1-2-3-4-6-8-12 and 24 hours), since previous studies have shown a dependence of hydrological model parameters on temporal resolution (e.g. Cullmann et al., 2006; Ficchì et al., 2019). This amounts to a total of 2712 (339x8) model calibrations. Au automatic calibration algorithm was therefore used. The Shuffled Complex Evolution (SCE-UA) algorithm (Duan et al., 1992, 1994) was chosen for this task. The SCE-UA algorithm has been widely used for the calibration of hydrological models and has been consistently shown to be among the best-performing algorithms (Jeon et al., 2014) and especially for models of reduced parametric complexity (Arsenault et al., 2014). Initial parameter values were randomly selected using the parametric space presented in Table 3.2. The parametric space was based on previous studies using the same hydrological model in a similar setting (e.g. Perrin et al., 2003; Shin & Kim, 2017; Tian et al., 2015).

Table 3.2 Description and ranges of parameters of the GR4H-CemaNeige model

Parameters	Description	Minimum	maximum	Unit
X1	capacity of the production soil store	10	2000	Mm
X2	water exchange coefficient	-8	6	Mm
X3	capacity of the routing store	10	500	Mm
X4	unit hydrograph base time	0	5	D
X5	Degree-day factor	0	4	-
X6	Snowpack inertia factor	0	4	-

The Nash-Sutcliffe efficiency criteria (NSE) was used as the objective function for the calibration. The NSE has been the most widely used metrics for hydrological model calibration (Gupta et al., 2009; Moriasi et al., 2007). It is calculated according to the following equation:

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_{Sim}^{t} - Q_{Obs}^{t})^2}{\sum_{t=1}^{T}(Q_{Obs}^{t} - \bar{Q}_{Obs})^2} \tag{3.1}$$

Where $\bar{Q}_{Obs}$ is the mean of observed discharges, and Q_{Sim} is simulated discharge and Q_{Obs}^{t} is observed discharge at time t.

NSE possible values range from negative infinity up to 1. A value of 1 indicates perfectly modeled flows, whereas a value of 0 corresponds to a performance equal to that of using the mean annual streamflow as a benchmark predictor. In recent years, the NSE is gradually supplanted by the KGE criteria (Gupta et al., 2009) whose interpretation is not as straightforward (Knoben et al., 2019). Based on the work of (Arsenault et al., 2018) and (Shen et al., 2022) who have conclusively shown that calibrating over the entire time period was preferable to the traditional split-sample approach, the entire 14-year period was used for model calibration with no validation period set aside. The first year of data was used for model spin-off and not used in the computation of the NSE metric.

3.4 Results

Figure 3.4 presents the main calibration results for all 339 catchments and 8 time steps. Catchments are regrouped in six classes as per Table 3.1. The boxplots represent the distribution of all catchments within each size class. Results indicate that modeling results are very good with median NSE values above 0.75 across all time steps and size classes. Results show that regardless of catchment size, the NSE values present a slight downward trend with increasing temporal resolution (decreasing time step). This is made clearer in Figure 3.5 which focuses on the median value of each size class. As will be discussed later, this should not be interpreted as a decreasing model performance because NSE values are not strictly comparable across different temporal steps. The spread of NSE values, as represented by the interquartile range (height of the blue box) or by the whiskers (90% of all values) tends to increase slightly for the larger size classes, but otherwise, results are very similar. Figure 3.5 also shows that NSE values get progressively larger from size class 1 to 4, and then decrease for classes 5 and 6.

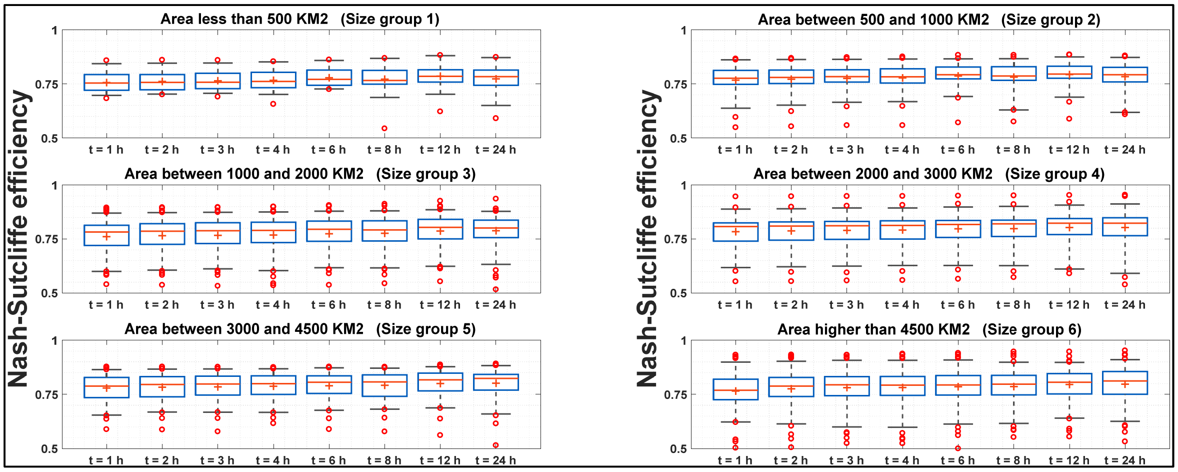

Figure 3.4 NSE calibration scores for all catchments as a function of temporal resolution. The six sub-figures correspond to the 6 size classes described in Table 3.1

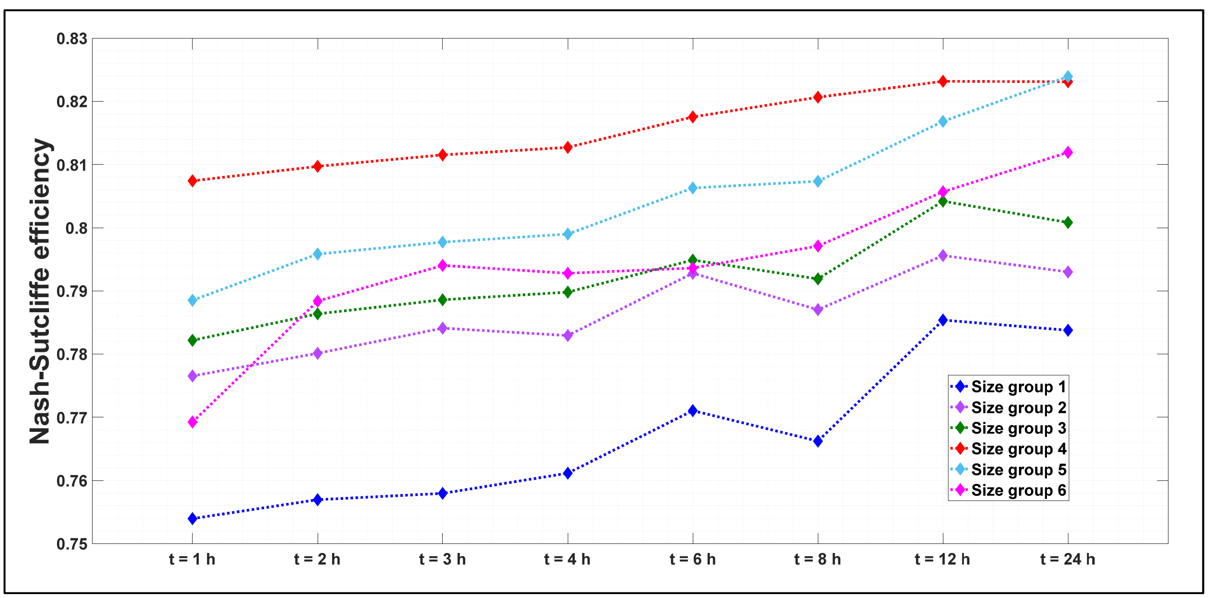

Figure 3.5 NSE calibration scores for all catchments as a function of temporal resolution. The six sub-figures correspond to the 6 size classes described in Table 3.1

The accurate simulation of peaks flows is one of the key goals of hydrological modeling. A well-simulated peak flow should have a magnitude and time of occurrence close to the observed one. Depending on catchment size, flow peaks may occur during or shortly after rainfall events for small catchments, and up to several hours and days for larger ones. For the analysis of runoff peaks, the 30 largest independent peaks were selected from the observational record for each catchment. These peaks were selected between June 1 and October 31 (to exclude peaks related to snowmelt or mixed precipitation events) during the 14 years of available data (1990 to 2003).

Peak selection was based on two criteria: consecutive peaks had to be at least 24 hours apart and the minimum flow between two consecutive peaks had to be less than 40% of the value of the smaller peak. The hourly occurrence and peak streamflow value of each recorded peak was extracted. The same values were taken from the simulated streamflow for all 8 temporal modeling scales. For each observed peak, the time delay (absolute difference in hours between the observed and simulated peaks) and magnitude ratio (simulated peak streamflow value divided by the observed one) were noted.

Figure 3.6 shows an example of peak selection for a class 4 catchment (2114 km^2). For the observed peaks, the time of occurrence was taken as the hour of the maximum recorded streamflow. For modeled streamflow, the peak time of occurrence was taken at the mid-interval as shown on Figure 3.6, with the exception of the 1-hour modeling time step which was treated just like observations. It can be seen that peak magnitude is typically better represented as the modeling time step gets smaller, but that the gains become rapidly marginal below a 4-hour time step for this particular medium-size catchment. The same can be said of peak timing. While the elements described above are the expected advantages of using a smaller time step, it remains to be seen how these results translate to a larger number of peaks and how they relate to catchment size.

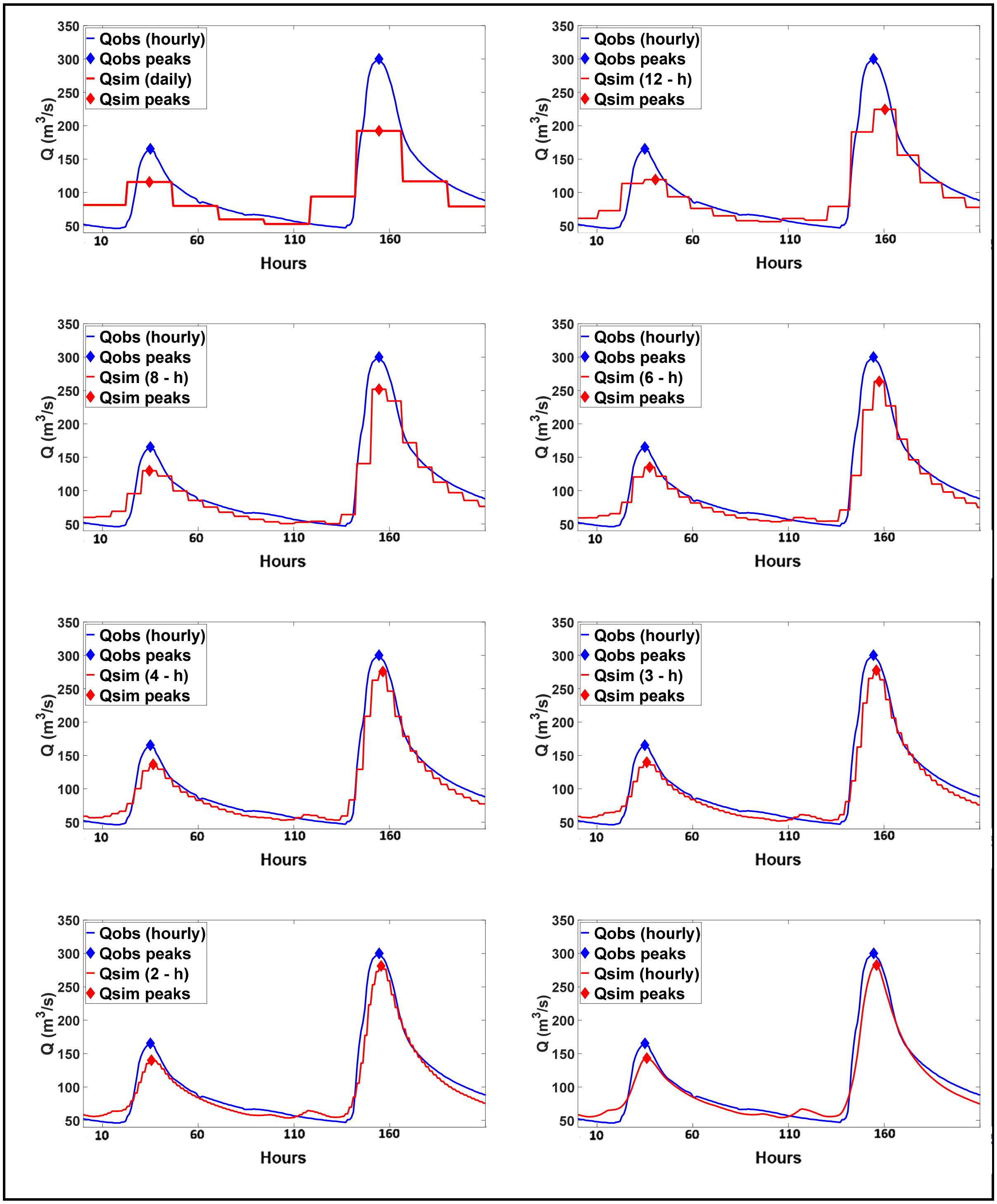

Figure 3.6 Simulated peak flows for a class 4 (2114 km2) catchment. The eight graphs correspond to the different time steps from 24 hours (upper left) to hourly (lower right)

Figure 3.7 presents the peak magnitude (simulated/observed) ratios for all catchments and computational time steps. Each boxplot presents the distribution of the ratio for the 30 largest observed peaks for all catchments. For example, for the first size class (< 500 km2), the boxplots are made of 690 values corresponding to the largest 30 peak for each of the 23 catchments (30 × 23). The accompanying Figure 3.8 presents the median of the boxplots presented in Figure 3.7.

In all size groups, the representation of peak size gets progressively better as the time step decreases from daily to hourly. The improvement is rapid when going to the sub-daily scale but levels off at we get to the finer time scales. Most of the improvement is attained when going from the 24-hour to the 6-hour time step, with the exception of the two smallest size classes which see additional improvements with a finer time step. The two smaller catchment classes beneficiate the most from the finer time scale, but even the largest size class (> 4500 km2) where many of the catchments have a multi-day time response, see a noticeable increase in peak magnitude representation up to a 6-hour time step. This metric suggests that a 6-hour time step appears optimal for catchments larger than 1000 km2 whereas a 3-hour time step is preferable for the smaller catchments.

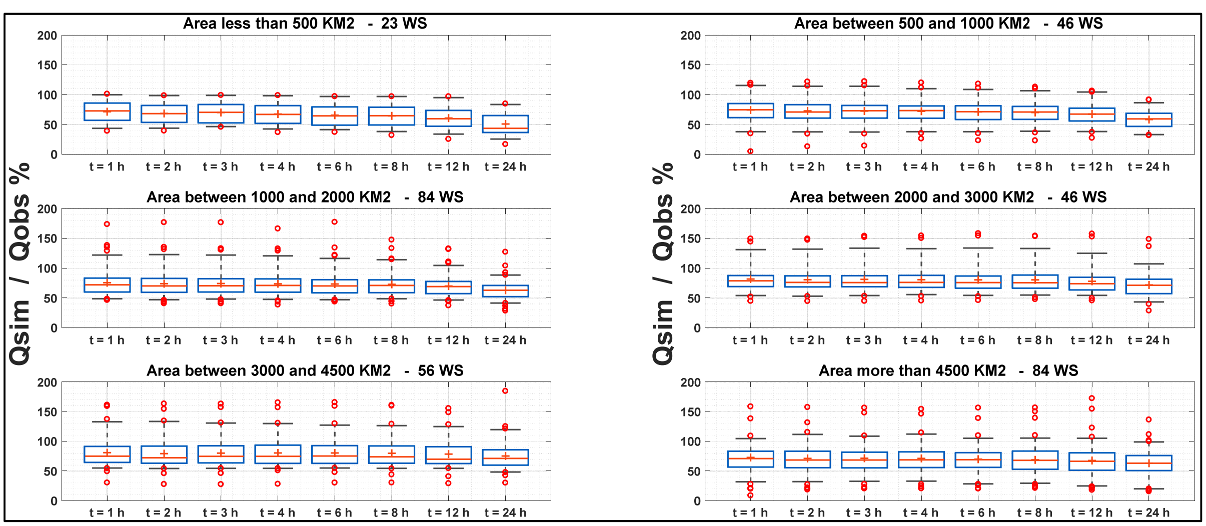

Figure 3.7 Ratio of peak magnitude (simulated/observed) for all catchments and computational time steps. Each boxplot represents the distribution of the ratio for the largest 30 observed peaks for each of the catchments within each size class (WS = Watersheds)

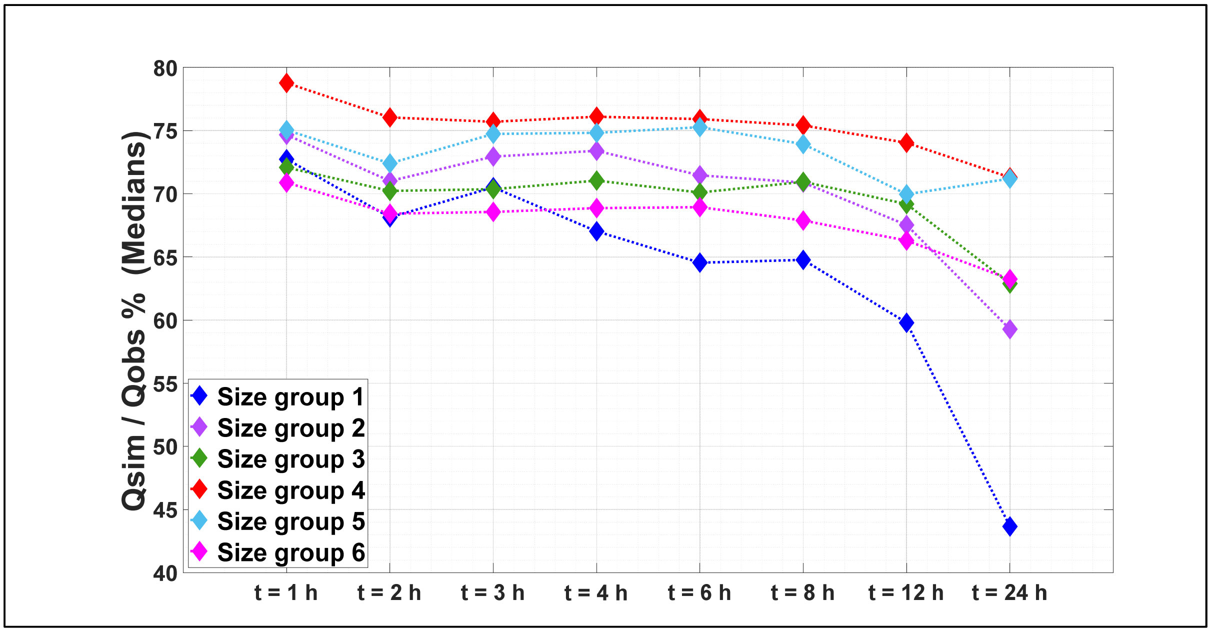

Figure 3.8 Median of peak magnitude ratio (horizontal red line of each boxplot of Figure 3.7)

Figure 3.9 and 3.10 present results in the same format as Figure 3.7 and 3.8, but for the absolute hourly time difference between modeled and observed time of peak flow occurrence. As was the case for peak magnitude, there is a rapid improvement in the simulation of the timing of peak flows and especially so for the smaller catchments. There is a diminishing return as the time step becomes smaller. Most of the improvement is obtained with an 8-hour time step for all catchment size classes, although minor improvements are observed with the hourly time step. There is a clear bias in the hydrological model ability at representing peak timing. For the larger time steps, some of this bias is related to assigning modeled peak occurrence at the middle of the time step (e.g. 12 o'clock for the daily time step), but even at the hourly time step, there is a median time lag of 5 hours between observed and modeled peak time of occurrence.

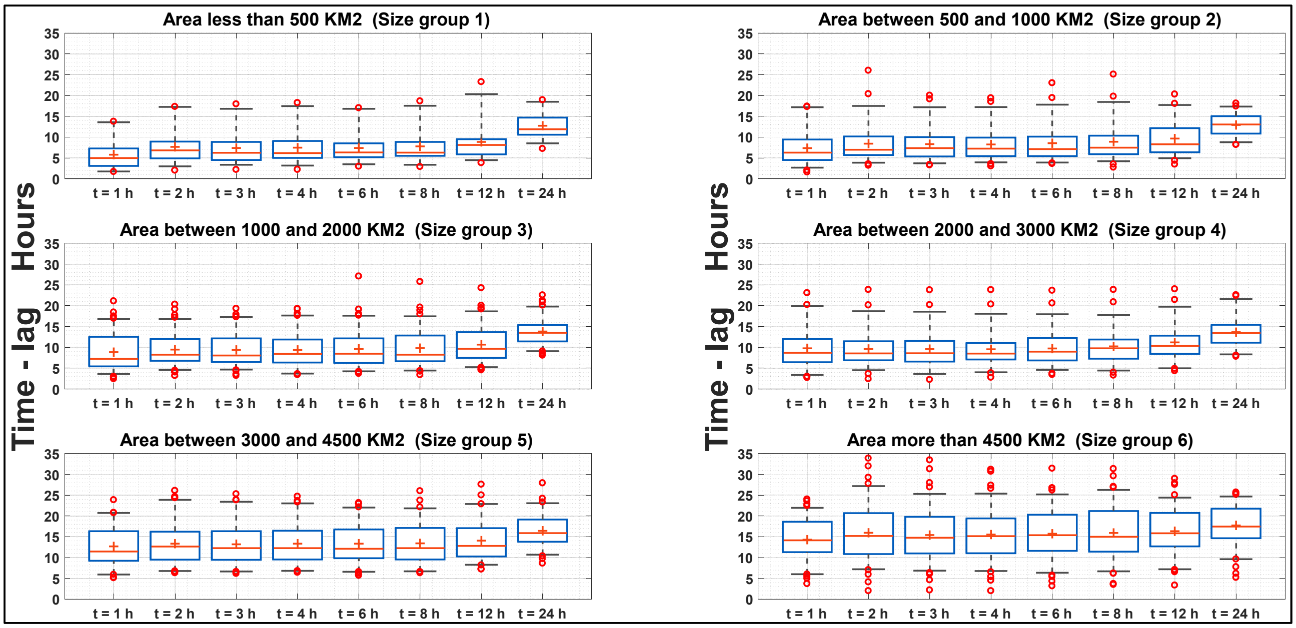

Figure 3.9 Absolute hourly time difference between modeled and observed time of peak flow occurrence for all catchments and computational time steps. Each boxplot represents the distribution of the difference in peak flow time of occurrence for the largest 30 observed peaks for each of the catchments within each size class

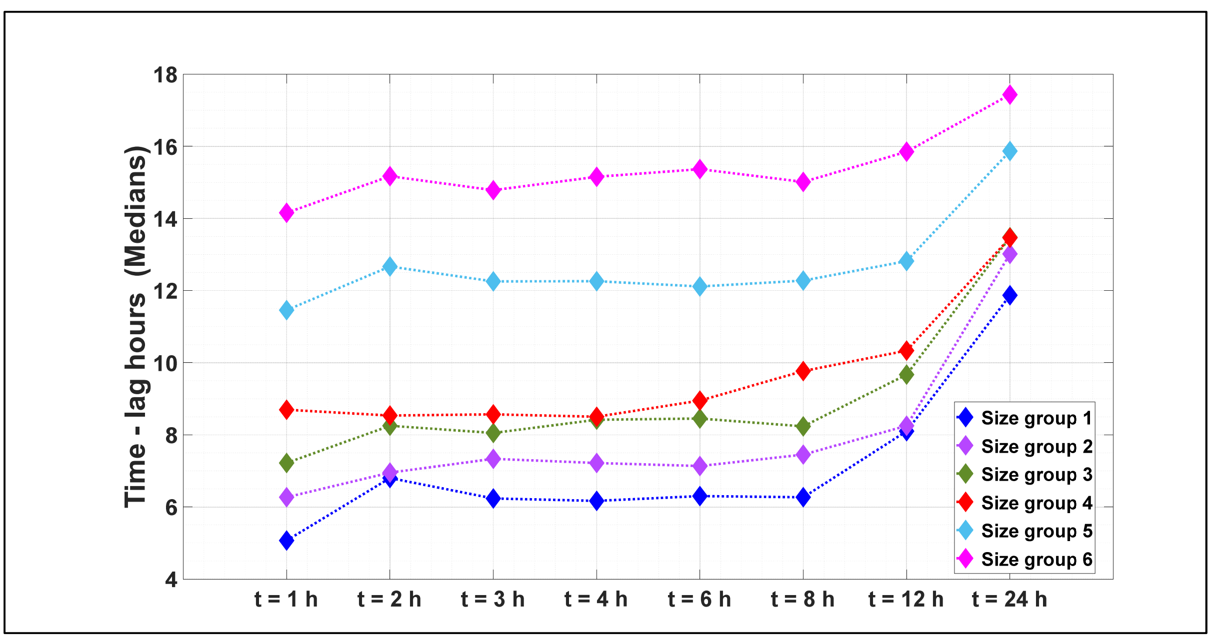

Figure 3.10 Median of absolute hourly time difference (horizontal red line of each boxplot of Figure 3.9)

3.5 Discussion

This work has presented an analysis of the impact of hydrological modeling temporal resolution on simulation results on 339 North-American catchments.

Figure 3.11 summarizes the results with respect to improvements in the simulation of peak flows. The axis corresponds to the median value of the peak magnitude ratio extracted from Figure 3.7 (Y-axis) and median of the absolute hourly time difference from Figure 3.9 (X-axis). Each colour is related to a class size whereas the symbols correspond to the different time steps used in this study. Several observations can be made from this Figure.

1- For all size classes, peak simulation improvements as a function of time-step can be approximated by straight lines with negative slopes.

2- The length of this line is proportional to the improvements. The longest line corresponds to the smallest size class, and the shortest line is for the largest size class. The order matches perfectly that of the size classes.

3- The slope of the line determines which of the two metric improves more rapidly. The slope is also related to catchment size, with the slopes diminishing as the catchments become larger. The exception is for the largest size class which has the second steepest slope.

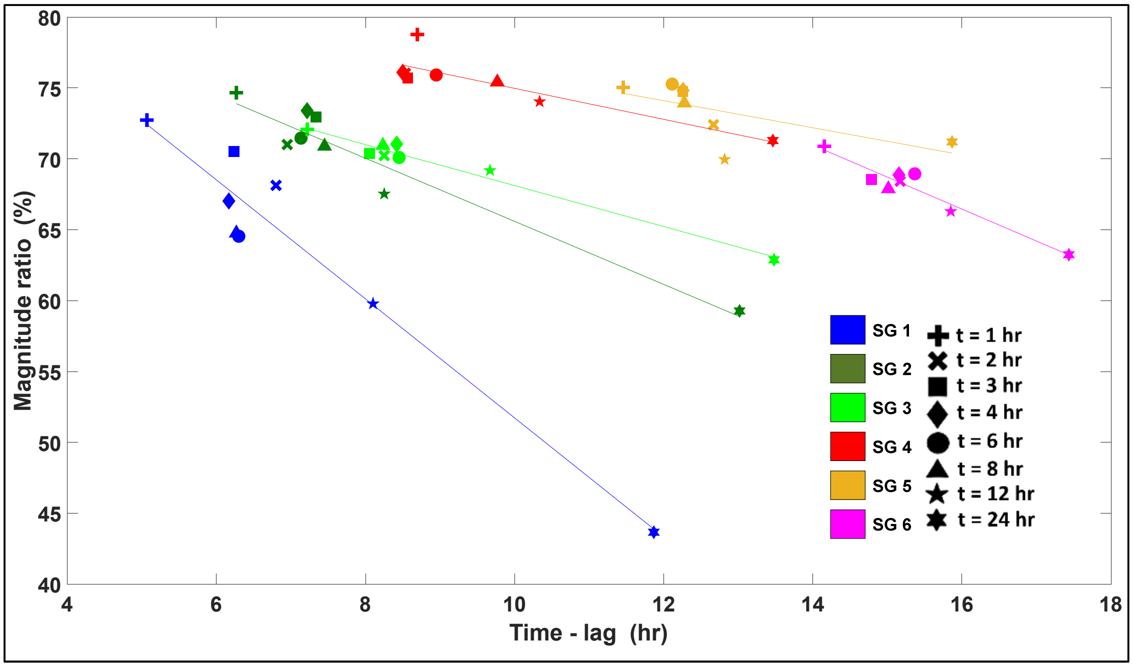

Figure 3.11 Relationship between improvements in the simulation of peak flow magnitude (Y-axis) and timing of the peak (X-axis) as a function of catchment size class (colors) and computational time step (symbols)

These results clearly show that the smaller catchments gain the most from the finer modeling resolution. This is not surprising considering that the two smaller size classes (< 500 km^2 and (< 1000 km^2) are comprised of catchments that would mostly be characterized has having a sub-daily response time to a precipitation impulse. However, the continuous improvement for all size classes when going to a finer temporal scale was not expected. While there is a diminishing return on the computational investment of the finer resolution, all size classes gain in performance even when going from 2 to 1 hour. This is particularly surprising for the larger size classes with a response time at least an order of magnitude larger than the smallest computation time steps.

The above findings are based on the median of the catchment distribution within each size class. The spread of the distribution shows that there a lot of variability is present within each size class as shown in the boxplots of Figures 3.7 and 3.9. The same boxplots show that the spread is similar for all size classes. For example, Figure 3.12 shows the distribution of peak delays classified into four time-difference categories (0-6, 6-12, 12-18 and 18-24 hours) for all 6 catchment size classes. Predictably, the timing of the modelled peaks is better simulated on average for the smaller catchments (higher proportion of small errors), but there are many badly simulated peaks in all 6 size classes. For large catchments, the largest differences are typically related to peaks being simulated on the wrong day, which is common when using a 12 or 24-hour computational time step. For the small catchments, large timing errors are most often related to longer rainfall events with blunt peaks. Some errors may also be due to time stamp reporting errors in streamflow discharge and/or precipitation data. An additional potential problem is related to the use of global databases which typically report data on standardized time, in which case a time offset has to be computed. This time offset is often based on the maximum correlation with local data. For ERA5 temperature, in most cases, the time offset was close to the expected UTC time-offset, but for some catchments, relatively large differences were observed. This shows that systematically predicting peak flow magnitude and timing accurately continues to be a challenge.

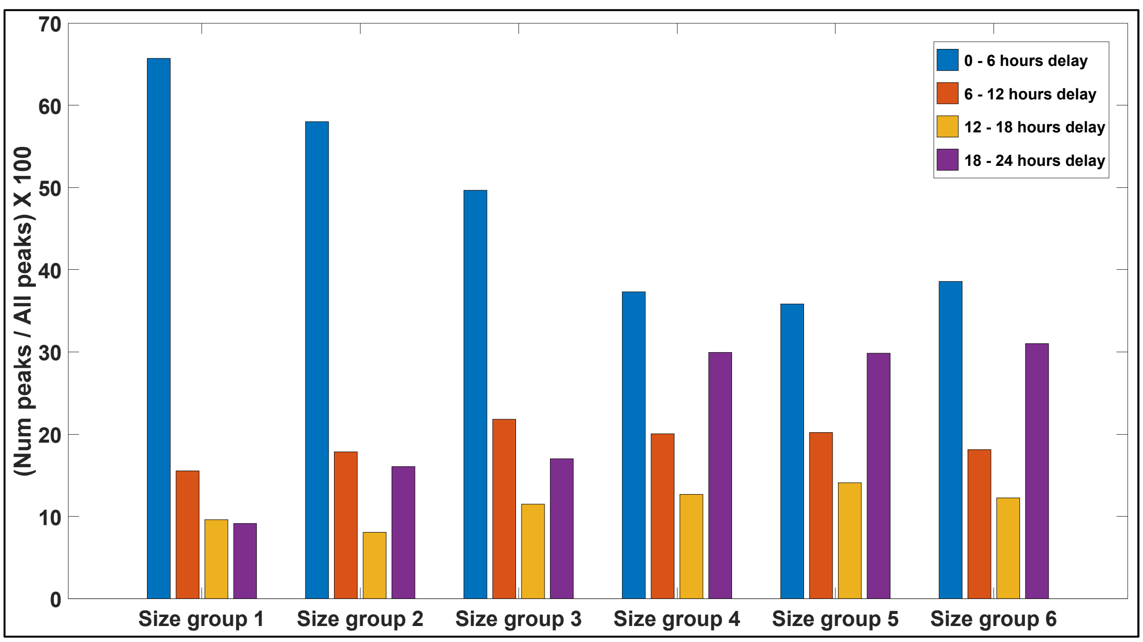

Figure 3.12 Percentage of catchments having a median of absolute hourly time difference between observed and simulated peaks (for the largest 30 peaks) between 0-6, 6-12, 12-18 and 18-24 hours for all six size classes

This paper has focused on the simulation of peak flows as the main comparison metric. This choice was partly made based on the work of (Jeong et al., 2010) who showed that the improvement in the hydrological model performance with a sub-hourly time interval was mostly due to improvements in predicting high flows. In addition, as discussed by (Gupta et al., 2009) an underestimation of peak flows is to be expected when using NSE for model calibration, and especially so in the case of highly variable data. Peak flows are therefore of particular interest for such a study. One additional problem with comparing simulation results across different computational time steps is that many of the traditional metrics are not strictly comparable across different time scales. Let's take the traditional NSE metric at the daily time and hourly time steps for example (with subscripts, *o*, *s*, *d* and *h* being the short form for *observed*, *simulated*, *daily* and *hourly*.

$$NSE_{daily} = 1 - \frac{\sum_{t=1}^{T}\left(Q_{o\_d}^{t} - Q_{s\_d}^{t}\right)^2}{\sum_{t=1}^{T}\left(Q_{o\_d}^{t} - \bar{Q}\right)^2} \tag{3.2}$$

$$NSE_{hourly} = 1 - \frac{\sum_{t=1}^{T}\sum_{i=1}^{24}\left(Q_{o\_h}^{t,i} - Q_{s\_h}^{t,i}\right)^2}{\sum_{t=1}^{T}\sum_{i=1}^{24}\left(Q_{o\_d}^{t,i} - \bar{Q}\right)^2} \tag{3.3}$$

Knowing that $Q_{o\_d}^{t} = \sum_{i=1}^{24}\left(Q_{o\_h}^{i}\right)$ and that $Q_{s\_d}^{t} = \sum_{i=1}^{24}\left(Q_{s\_h}^{i}\right)$ it is easy to show empirically that:

$$\frac{\sum_{t=1}^{T}\sum_{i=1}^{24}\left(Q_{o\_h}^{t,i} - Q_{s\_h}^{t,i}\right)^2}{\sum_{t=1}^{T}\sum_{i=1}^{24}\left(Q_{o\_d}^{t,i} - \bar{Q}\right)^2} \neq \frac{\sum_{t=1}^{T}\left(\sum_{i=1}^{24}\left(Q_{o\_h}^{i}\right) - \sum_{i=1}^{24}\left(Q_{s\_h}^{i}\right)\right)^2}{\sum_{t=1}^{T}\left(\sum_{i=1}^{24}\left(Q_{o\_h}^{i}\right) - \bar{Q}\right)^2} \tag{3.4}$$

The same applies for the common metrics of RMSE and correlation coefficient. The NSE results presented in Figure 3.4 and 3.5, where a slight but constant decrease in median NSE with the finer time scale was observed, cannot therefore be used to differentiate model efficiency, although some insights on the impact of time step as a function of catchment size were gained. One metric that can be used to differentiate model performance is the simulation bias $(\bar{Q}_s - \bar{Q}_o)$.

Figure 3.13 presents the ratio of simulated discharge $\left[\frac{(Q_{sim})}{Q_{obs}} x\ 100\right]$ for all 339 catchments. All catchments are lumped into a single group because the results were very similar for all six group classes. A value of 100 indicates that modeled streamflow is unbiased whereas values above and below 100 respectively correspond to positively and negatively biased simulated streamflow. Results indicate that simulated mean annual streamflow are generally negatively biased but that biases are significantly reduced when using a shorter computational time step. For the 24-hour time step, the median bias is 94% and it progressively increases to 99% at the hourly time step. Using a smaller time-step has therefore a positive influence on mass-balance, irrespective of catchment size. A detailed analysis of the results (not shown) indicate that this is due to the progressively better representation of the daily evapotranspiration cycle.

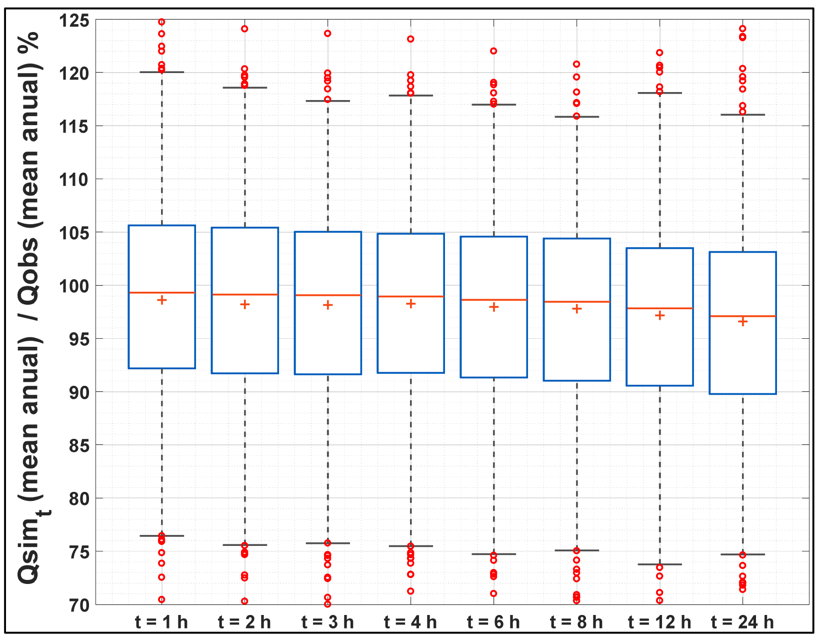

Figure 3.13 Distribution of the streamflow ratio $\left[\frac{(Q_{sim})}{Q_{obs}} x\ 100\right]$ of all 339 catchments for each of the 8 modeling time steps

3.6 Conclusion

This work compared the impact of hydrological modeling time step on the streamflow simulation of 339 North-American catchments all calibrate with time steps varying between 1-

hour to 24-hours. The 339 catchments were separated into 6 size classes (from smaller than 500km^2 to larger than 4500 km^2) to study the impact of catchment size on simulated results. The main conclusions that can be drawn from this study are:

- Using a smaller time step improved the simulation of the timing and magnitude of peak flows for all 6 size classes;
- A rapidly diminishing return of using a smaller time step was observed for the larger size classes. Going from a 24-hour to an 8-hour time step yielded satisfactory results for the largest size classes;
- The smallest size class (< 500km^2) benefited the most from the smaller time step all the way to the 1 hour, suggesting that an even smaller time step may have been beneficial;
- The simulation bias (difference in mean flow) was systematically reduced when using a smaller time step for all size classes.

These results strongly suggest that using as small a times-step as possible is beneficial, provided that adequate input and computational capability are available.

Acknowledgments

This work was partly supported by the Ouranos consortium on regional climatology and adaptation to climate change (Ouranos.ca) and the Quebec Ministry of Economy and Innovation through the PSR-SIIRI grant no 992. Support from the Natural Science and Engineering Research Council (NSERC) though the Discovery Grant program is also acknowledged.

Data availability

Code and Database	Access
MOPEX climate database	https://hydrology.nws.noaa.gov/pub/gcip/mopex/US_Data/ (Duan et al., 2006)
USGS streamflow Data	U.S. Geological Survey website (https://waterdata.usgs.gov/nwis)
The GR4J model (Perrin et al., 2003) and CemaNeige snow model (Valéry et al., 2014)	Matlab File Exchange: https://github.com/TBenkHyd2/GR4J_Deterministic (Benkaci, 2022)
The SCE-UA global optimization algorithm	https://www.mathworks.com/matlabcentral/fileexchange/7671-shuffled-complex-evolution-sce-ua-method (Duan, 2020).

Appendix 1

List of MOPEX catchments used in this study.

Catchment ID									
01048000	01606500	02329000	03164000	03349000	04178000	05517500	06888500	07307800	11025500
01055500	01608500	02347500	03165500	03361500	04185000	05518000	06892000	07340000	11160000
01064500	01610000	02365500	03167000	03361650	04191500	05520500	06894000	07346050	11224500
01076500	01611500	02375500	03168000	03362500	04198000	05526000	06897500	07363500	11342000
01127000	01628500	02383500	03173000	03363000	04201500	05552500	06898000	07375500	11413000
01197500	01631000	02387000	03175500	03364000	04221000	05554500	06899500	07378000	11427000
01200000	01634000	02387500	03179000	03365500	04223000	05555300	06908000	07378500	11501000
01321000	01643000	02414500	03180500	03381500	05053000	05569500	06913500	08013500	11530000
01334500	01649500	02437000	03182500	03410500	05280000	05570000	06933500	08015500	11532500
01348000	01664000	02448000	03183500	03438000	05320500	05582000	07019000	08032000	12027500
01371500	01667500	02456500	03184000	03443000	05408000	05584500	07029500	08033500	12098500
01372500	01668000	02472000	03186500	03451500	05412500	05585000	07049000	08055500	12134500
01421000	01674500	02475000	03198500	03455000	05418500	05592500	07052500	08095000	12144500
01423000	02016000	02475500	03237500	03465500	05422000	05593000	07056000	08146000	12149000
01426500	02018000	02478500	03238500	03473000	05430500	05594000	07057500	08150000	12340000
01445500	02030500	02479300	03251500	03504000	05435500	06191500	07058000	08150700	12358500
01500500	02055000	02482000	03253500	03512000	05440000	06192500	07067000	08167500	12413000
01503000	02058400	02486000	03265000	03524000	05447500	06225500	07068000	08171000	12413500
01512500	02083500	02492000	03266000	03528000	05451500	06334500	07069500	08171300	12449500
01518000	02102000	03010500	03269500	03531500	05454500	06480000	07072000	08172000	12449950
01520000	02116500	03011020	03274000	03532000	05455500	06600500	07144780	08189500	12459000
01520500	02118000	03020500	03281500	03540500	05457700	06606600	07147070	08205500	12462500
01531000	02126000	03024000	03289500	03550000	05458500	06607200	07147800	09132500	13186000
01541000	02135000	03032500	03301500	03567500	05462000	06609500	07152000	09251000	13200000
01543500	02138500	03051000	03303000	03574500	05471500	06808500	07172000	09292500	13302500
01548500	02143000	03054500	03308500	03603000	05472500	06810000	07177500	09299500	13336500
01556000	02143040	03065000	03324300	04073500	05476500	06811500	07183000	09430500	13337000
01558000	02143500	03069500	03326500	04079000	05479000	06815000	07186000	09431500	13340600
01559000	02156500	03075500	03328500	04100500	05481000	06817000	07196500	09444500	13351000
01560000	02202500	03079000	03331500	04113000	05482500	06820500	07197000	09497500	14113000
01562000	02217500	03109500	03339500	04115000	05484500	06869500	07211500	10296000	14308000
01567000	02228000	03111500	03345500	04164000	05514500	06883000	07243500	10296500	14321000
01574000	02236000	03159500	03346000	04165500	05515500	06884400	07261000	10309000	14359000
01595000	02296750	03161000	03348000	04176500	05517000	06885500	07290000	10312000	

CONCLUSION AND FUTURE WORK

This work compared the impact of hydrological modeling time step on the streamflow simulation of 339 North-American catchments. The GR4H hydrological model coupled to the CemaNeige snow model was used to simulate all streamflows. The model was calibrated with input data collected from 3 different hourly sources (MOPEX database for hourly precipitation, ERA5 reanalysis for hourly temperature and USGS for hourly measured streamflows). The hydrological model was calibrated over a common period of 14 years using 8 different time steps varying between 1-hour to 24-hours (1, 2, 3, 4, 6, 8, 12 and 24). A total of 2712 model calibrations was therefore performed (339 x 8) using the Nash-Sutcliffe efficiency (NSE) criteria. For the time steps longer than 1 hour, the input data was aggregated from the hourly data. The 339 catchments were separated into 6 size classes (from smaller than 500 km^2 to larger than 4500 km^2) to study the impact of catchment size on simulated results. The NSE values, mean flow bias, and peak simulation accuracy (based on the 30 largest independent peak flows for each catchment) were used as comparison metrics.

Then main findings of this work are:

- Regardless of catchment size, the obtained NSE value show a small but systemic downward trend with increasing temporal resolution. However, since NSE values cannot be strictly compared across different temporal scales, it is difficult to draw conclusions based on this observation;
- In general, the NSE values were highest for the larger catchments with the exception of the largest size class. This is likely related to the generally smoother hydrographs of large catchments with the flood waves being attenuated during the longest travel time to the catchment outlet. Smaller catchments have more rapidly variable hydrographs, making them more challenging for hydrological models. The apparently anomalous behavior of the largest size class is likely the result of the large proportion of catchments within this size class being located in the arid and semi-arid zones where traditional rainfall-runoff hydrological models like GR4J don’t perform as well;

- With respect to the ability to simulate peak flows, the results conclusively show that using a smaller time step improved the simulation of the timing and magnitude of peak flows for all 6 size classes;
- While improvements were observed for all size classes, a rapidly diminishing return of using a smaller time step was observed for the larger size classes. Going from a 24-hour to an 8-hour time step yielded satisfactory results for the largest size classes;
- On the other hand, the smallest size class (< 500 km^2) benefited the most from the smaller time step all the way to the 1 hour, suggesting that an even smaller time step may have been beneficial;
- A surprising finding was that using a smaller time step resulted in a systematically reduced simulation bias (difference in mean flow), which appear to be related to a better representation of the evapotranspiration cycle.

Ultimately, this study suggests that using a finer temporal time step is desirable, irrespective of catchment size, with the main downside being the increased computational time. While this is not an important issue with lumped and conceptual models, this can be a problem with distributed physical models. An additional downside is the added difficulty in setting up sub-daily input data since there are no existing precipitation and temperature observation databases at sub-daily time steps.

There are some limitations in this study which could be addressed in future studies. All results should be validated with at least another hydrological model including a different evapotranspiration formulation. The use of a different snow model is less likely to be important since this comparison was mostly based on summer-fall peak flows. Since this was a large-sample study, it was not possible to look into the finer details of the various hydrographs to gain a finer understanding of the observed improvements. The impact of time step on hydrological model parameters, an area that has been the subject of various studies, should also be investigated.

Finally, it would be interesting to look at even smaller catchments at a sub-hourly time step, but finding appropriate data for North-American catchments would be a challenge. Such a study would therefore have to be conducted on a very small number of catchments.

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