Spatio-Temporal Discretization Uncertainty of Distributed Hydrological Models

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Abstract

Quantifying the uncertainty linked to the degree to which the spatio-temporal variability of the catchment descriptors (CDs), and consequently calibration parameters (CPs), represented in the distributed hydrology models and its impacts on the simulation of flooding events is the main objective of this paper. Here, we introduce a methodology based on ensemble approach principles to characterize the uncertainties of spatio-temporal variations. We use two distributed hydrological models (WaSiM and Hydrotel) and six catchments with different sizes and characteristics, located in southern Quebec, to address this objective. We calibrate the models across four spatial (100, 250, 500, 1000 m^2) and two temporal (3 hours and 24 hours) resolutions. Afterwards, all combinations of CDs-CPs pairs are fed to the hydrological models to create an ensemble of simulations for characterizing the uncertainty related to the spatial resolution of the modeling, for each catchment. The catchments are further grouped into large ($> 1000\,km^2$), medium (between 500 and $1000\,km^2$) and small ($< 500\,km^2$) to examine multiple hypotheses. The ensemble approach shows a significant degree of uncertainty (over 100% error for estimation of extreme streamflow) linked to the spatial discretization of the modeling. Regarding the role of catchment descriptors, results show that first, there is no meaningful link between the uncertainty of the spatial discretization and catchment size, as spatio-temporal discretization uncertainty can be seen across different catchment sizes. Second, the temporal scale plays only a minor role in determining the uncertainty related to spatial discretization. Third, the more physically representative a model is, the more sensitive it is to changes in spatial resolution. Finally, the uncertainty related to model parameters is larger than that of catchment descriptors for most of the catchments. Yet, there are exceptions for which a change in spatio-temporal resolution can alter the distribution of state and flux variables, change the hydrologic response of the catchments, and cause large uncertainties.

1 Introduction

Understanding the spatio-temporal scale of the representation of hydrological processes, and confronting the issue of scale mismatch within inter-connected hydrological units are two major challenges in hydrological modeling (Beven, 2011; Blöschl et al., 2019; Blöschl & Sivapalan, 1995; Fatichi et al., 2016). To better understand the complexity (heterogeneity) in hydrological systems, which is present under continuous internal change (e.g., land use change) and boundary conditions (e.g., changing climate), distributed hydrological models have been used across different spatio-temporal scales (Addor et al., 2014; Blöschl, Reszler, & Komma, 2008; Famiglietti & Wood, 1995; Kumar, Samaniego, & Attinger, 2010, 2013; Martel, Brissette, & Poulin, 2020; Merz & Blöschl, 2004; Rakovec et al., 2016; Thober et al., 2019; Wanders & Wada, 2015). However, the models themselves suffer from inadequate simulation of hydrological processes due to a lack of scale-relevant theories in watershed hydrology (Blöschl & Sivapalan, 1995; Dooge, 1986; Peters-Lidard et al., 2017; Samaniego et al., 2017). In fact, changes in the spatio-temporal discretization of the physiographical characteristics of a catchment can alter the dynamic interactions between state variables and fluxes, resulting in different model responses (e.g., Cao et al., 2020; Krebs, Kokkonen, Valtanen, Setälä, & Koivusalo, 2014). Therefore, part of the modeling uncertainty is due to the extent to which the physiographic characteristics of the catchment are described, more or less finely, by the model. Such uncertainty is normally ignored in practice, and is the focus of the present research. Specifically, we aim to quantify the relative roles of the spatial resolution of the physiographic characteristics, as well as that of the model's parameters obtained by calibrating the model using different spatio-temporal representations of catchments. To this end, two different distributed hydrological models will be used, as well as six catchments, all grouped into an ensemble-based approach (Krzysztofowicz, 2001), involving 16 simulations per model and per catchment.

Unlike to lumped models, which treat the whole catchment as a unique homogeneous area, distributed models incorporate the spatial heterogeneity of the catchments. Depending on the level of discretization, distributed models can be classified into two broad categories: semi-distributed and fully distributed (Clark et al., 2017; Clark et al., 2015). In semi-distributed models, of which SWAT (Arnold, Srinivasan, Muttiah, & Williams, 1998) and VIC (Liang, Lettenmaier, Wood, & Burges, 1994) are two well-known examples, the level of spatial discretization is limited to defining the number of Hydrological Response Units (HRU). On the other hand, models such as WaSiM (Schulla & Jasper, 2007), MIKE-SHE (Refsgaard, 1995) and HYDRUS-3D (Šimunek, van Genuchten, & Šejna, 2008) are considered as fully distributed, as instead, they discretize the catchment using grids, and the computation of the fluxes and state variables is performed for each grid cell. Distributed models can also be viewed based on a physical or conceptual representation of the processes. Physically based models attempt to solve the conservation of mass, energy and momentum equations to represent hydrological processes at micro-scale control volumes (Fatichi et al., 2016; Hrachowitz & Clark, 2017). MIKE-SHE (Refsgaard, 1995) and HYDRUS-3D (Šimunek, van Genuchten, & Šejna, 2008) are typical examples. Conceptual models represent processes more simply, through macro-scale conceptualization(Clark et al., 2017; Devia, Ganasri, & Dwarakish, 2015). The distributed version of the HBV model (Bergström et al., 1995), mHM (Samaniego, Kumar, & Attinger, 2010) as well as CEQUEAU (St-Hilaire et al., 2015) can be placed in this category.

In flood forecasting, analyses of hydrological processes, or in climate change impact assessment studies, the underlying assumption for implementing a specific model over different spatio-temporal resolutions, is usually that the parameters are scale-invariant, ensuring the production of similar states and fluxes regardless of the spatio-temporal resolution (Samaniego et al., 2017). However, such assumption is questionable in the absence of scale-relevant theories for natural catchments, as the heterogeneity of the system dominates the consistency needed across different catchments to develop a general theory (Hrachowitz et al., 2013; Nearing et al., 2020). In fact, different hydrological processes that take place under different spatio-temporal scales at different catchments highlight the "uniqueness of the place" (Beven, 2000), as opposed to the generality of hydrological response. The problem is that the lack of such scale-relevant theories directly affects modeling practices. Model parameters, for example, typically represent hydrological processes that are either complex, or take place on a very small scale, or that are not yet well understood (Barrios & Francés, 2012; Brynjarsdottir & OHagan, 2014; Pokhrel & Gupta, 2010). In practice, for most cases, model parameters lack physical reality, as very often, there are no tangible links between catchment attributes and parameters(Beven, 1995). Furthermore, the dearth of knowledge regarding upscaling theories and their application in hydrological modeling exacerbates the problem (Kitanidis & VoMvoris, 1983; Neuman, 1990). Therefore, the parameters cannot be considered scale-invariant and the conditions of flux-matching across diverse spatio-temporal scales cannot be satisfied with current knowledge (Wood, Sivapalan, Beven, & Band, 1988).

The randomness of hydrological processes, attributable to a lack of knowledge related to the complexity of the system, can be addressed by replacing the deterministic results of modeling with an ensemble of simulations using probabilistic or deterministic approaches (Beven, 2006; Dooge, 1986; Nearing & Gupta, 2015; Nearing, Gupta, & Crow, 2013; Nearing et al., 2020). We suggest that the principles of ensemble simulations can also be useful in addressing the uncertainty linked to the spatio-temporal variability of the physical descriptors of a catchment. As such, an ensemble of simulations derived from variations of CDs-CPs resolutions can be constructed for each catchment to quantify the uncertainties corresponding to the spatio-temporal resolution of the modeling. While multiple studies focus on accounting for and quantifying different sources of uncertainties in hydrological modeling, some include input data uncertainty, structural uncertainty, parametric uncertainties, or a combination of the preceding (e.g., Butts, Payne, Kristensen, & Madsen, 2004; Craig et al., 2020; Dixon & Earls, 2012; Euser et al., 2013; Faramarzi et al., 2013; Joseph, Ghosh, Pathak, & Sahai, 2018; Poulin, Brissette, Leconte, Arsenault, & Malo, 2011; Refsgaard, Van der Sluijs, Brown, & Van der Keur, 2006; Tarek, Brissette, & Arsenault, 2020a; Thiboult, Anctil, & Boucher, 2016; Zhao et al., 2018), less attention has been directed towards the uncertainty related to spatio-temporal variability and how it impacts modeling. This may be attributable to a belief that such uncertainty has but trivial impacts on the modeling. However, among the limited research works that have been conducted in this context, Tegegne, Kim, Seo, and Kim (2019) demonstrated that changing the sub-basin spatial scale in the SWAT model has a small impact on the entire flow simulations, but that a substantial sensitivity could be observed when reproducing more extreme flow quantiles. Their study, however, was limited to varying the number of HRUs, as opposed to changing the spatio-temporal discretization of the model's parameters. Moreover, no mechanisms were considered to account for the uncertainties related to spatio-temporal variability of the physical descriptors of a catchment.

Varying the spatial resolution used to represent land use in the model might also lead to a range of simulations, and therefore help to quantify the corresponding uncertainty. Distributed models have widely been used to account for land use change across the globe (e.g., Li et al., 2019; Singh et al., 2015; Tavangar, Moradi, Massah Bavani, & Gholamalifard, 2019; Yang, Long, & Bai, 2019). In a series of papers (Bormann, Breuer, Gräff, Huisman, & Croke, 2009; Breuer et al., 2009; Huisman et al., 2009; Viney et al., 2009) under the project on 'Assessing the impact of land use change on hydrology by ensemble modeling (LUCHEM)', an ensemble of 10 hydrological models were used, with a range of structural complexity. More recently, Chen et al. (2019) investigated parameter uncertainty stemming from land use change across different time-scales. They used two distributed models and three land use scenarios to simulate streamflow on a catchment located in China. Their results suggest that land use change does not have substantial effects on runoff simulations, but a large range of uncertainty can be observed for extreme streamflow values. It is worth noting that these research works focus on land use change scenarios, while the impact of change of spatio-temporal resolution on the modeling and the uncertainties are yet to be investigated.

The impact of spatial discretization on flood events has been investigated with a focus on urban catchments (e.g., Cao et al., 2020; Krebs, Kokkonen, Valtanen, Setälä, & Koivusalo, 2014; Zhou et al., 2017). It was found that changes in resolution of the topographic information provided by digital elevation models (DEM), for instance, could reorient the flow direction and flow accumulation, and alter surface and channel routing (Cao, Ni, Qi, & Liu, 2020). Furthermore, altering soil textures modifies the imperviousness, the Manning coefficient, the soil water content, etc., in addition to reshaping the final response in terms of both runoff generation and routing processes (Cao et al., 2020). Given the high degree of imperviousness and the complexity of surfaces in urban catchments, changes in spatial resolution could affect the results of flood simulations, which may leave such catchments more vulnerable to flooding events (Zhou et al., 2017). Furthermore, changes in model response due to the degree to which the spatial heterogeneity of the catchment is represented might potentially affect the simulation in terms of peak timing and magnitude (Ichiba et al., 2018). However, there is still no consensus on the impacts of refining the spatial resolution, as many studies show contradictory results, i.e., overestimation or underestimation of extreme flows (Warsta et al., 2017).

The impacts of the choice of a particular level of spatio-temporal discretization on streamflow simulation in natural catchments need to be further investigated. The respective roles of catchment area and characteristics, the time step of the simulation, as well as the model structure and parameters, are potentially important determinants of a hydrological model's response, and this paper aims at investigating their roles. More specifically, we propose to test the following hypotheses:

i Larger catchments are susceptible to larger uncertainties in the simulation of streamflow, when varying the spatial resolution of their physiographic characteristics.

ii Finer time steps introduce a higher degree of variability in the simulation, leading to increased uncertainty in streamflow simulation.

iii The more finely distributed and physically realistic a model is, the more sensitive to changes in spatial resolution it is.

iv The uncertainty related to model parameters is larger than that of catchments descriptors (DEM resolution, land use, soil texture).

These hypotheses will be examined through multiple experiments performed using two distributed models and six catchments of various sizes.The experiments will result in an ensemble of simulations to be investigated per catchment and per model. The structure of the paper is as follows. Section 2 provides details about the study area and the characteristics of the selected catchments, a brief description of the models used for simulations and the details of the experimental design. Results are presented in section 3 and discussed in section 4, taking one specific catchment as a representative example. Finally, concluding remarks and perspectives for future work are presented in section 5.

2 Method and Data

2.1 Study Area

Six catchments ranging from 100 km^2 to more than 2500 km^2 located in Quebec, Canada, are selected for this study (see Figure 1). The selection procedure is based on the following criteria: First, a broad range of catchment sizes should be covered to analyze the sensitivity of hydrological responses to the catchment size. Second, catchments should not belong to the same hydrological region, but rather, should be distributed across the territory (here the province of Quebec). Third, at least 10 years of streamflow data for 24- and 3- hour time steps need to be available to fulfill the calibration and validation procedures. Table 1 describes the main characteristics of the catchments used in this study, which are identified in Figure 1. The catchments are sorted in descending order based on their area.

2.2 Hydrometeorological data

The present study employs meteorological data (i.e. precipitation and temperature) extracted from ERA5 (ECMWF ReAnalysis5) gridded dataset to force the hydrological models for the historical time-period. Gridded reanalyses datasets are considered as an alternative to observed historical meteorological data. Using such datasets allow to solve major flaws of observational datasets, including missing data (particularly for higher resolutions), measurement errors, uneven distributions, etc. (Tarek, Brissette, & Arsenault, 2020b). The European Centre for Medium-Range Weather Forecasts (ECMWF) proposed multiple reanalysis datasets (ERA-Inerim, ERA5, ERA-Land), which are widely used by hydro-climate modelers (Belmonte Rivas & Stoffelen, 2019; Wang, Graham, Wang, Gerland, & Granskog, 2019). ERA5 is the fifth generation of ECMWF reanalyses of global climate products. The spatial resolution of ERA5 is 31km and the temporal resolution is hourly. Currently, the dataset covers the period from 1979 to today, and is expected to be updated to 1950 in the near future.

Observed streamflow series are obtained from the Direction de l'Expertise Hydrique (DEH) of the Ministère de l'Environnement et de la Lutte contre les changements climatiques (MELCCC) for the 2000-2017 time period, with daily and 3-hour time steps.

2.3 Hydrological models

2.3.1 WaSiM

The Water balance Simulation Model (WaSiM; Schulla & Jasper, 2007) is a process-based model that operates on a raster (grid) system. Its submodels run each grid cell of a catchment for each time step, providing the opportunity to use parallel computation algorithms based on the OpenMP standard. The model represents hydrological processes through its submodel structure, in which several options for interpolation, evapotranspiration, snow accumulation and melt, interception, glacier model, silting-up, unsaturated zone including heat transfer, saturated zone, surface discharge routing, and discharge routing including lakes and reservoirs are available. The distinguishable feature of WaSiM is its provision of options to calculate infiltration and to represent water in the soil layers, with the calculation being more detailed than for most surface hydrology models. Two methods can be used namely, the modified conceptual Topmodel approach, and Richard's Equations approach (or unsaturated zone model). Since the second approach is more physically-based, we selected this version for simulations. The 1-D Richards equation, which represents fluxes in the unsaturated zone, is represented by Equation 1 (Schulla & Jasper, 2007):

$$\frac{\partial \Theta}{\partial t} = \frac{\partial q}{\partial z} = \frac{\partial}{\partial z}(-k(\Theta)\frac{\partial \Psi(\Theta)}{\partial z}) \tag{1}$$

where $\Theta(m^3/m^3)$ is the water content, $t(seconds)$ is time, $k(m/s)$ is the hydraulic conductivity, $\Psi(m)$ is the hydraulic head, $q(m/s)$ is the flux, and $z(m)$ is the depth of the soil column. WaSiM solves Equation 1 for multiple soil layers (the default is 30 layers for each type) of a grid cell using the finite difference method.

The unsaturated zone model controls multiple hydrologic variables such as infiltration, exfiltration, interflow, baseflow, real evapotranspiration, groundwater recharge, etc. Given the physical approach adopted to represent the flux of water in soil, WaSiM leans towards physically-based models. However, considering the simplified 1-D version of the continuity equation (instead of 3-D), and the existence of other empirical elements in the submodels (e.g., potential evapotranspiration) hinders the classification of the model among full physically-based distributed models. Table 2 specifies the choices that were made for each submodel of WaSim and for Hydrotel, which are described in the next sub section.

2.3.2 Hydrotel

Hydrotel is an HRU-based distributed model that is widely used operationally for flood forecasting by the DEH (e.g., Lucas-Picher et al., 2020; Martel, Brissette, & Poulin, 2020; Turcotte, Morse, & Pelchat, 2020). The model adopts a mixture of physical, conceptual and empirical relationships to represent hydrological processes. Like WaSiM, it provides multiple options for calculating the hydrological processes of a catchment. The main particularity of Hydrotel is its compatibility with GIS and remotely sensed data (Fortin et al., 2001). Therefore, the model is capable of representing the spatial variability and the topography of catchments through a digital elevation model (DEM), soil texture maps and land use data through its components.

The model uses BV3C (Bilan Vertical 3 Couche) for soil modeling, which is specifically developed for Hydrotel. In this approach, the soil column is divided into three layers: The first layer is a surface layer that controls infiltration and is affected by surface evaporation; the second layer is associated with interflow, and the third one controls the baseflow. For the whole soil column, a moisture accounting equation is designed to represent macroprocesses of fluxes (Fortin et al., 2001). As a result, from a model classification perspective, the model leans towards the group of conceptual, distributed models, even though Hydrotel comprises certain physically-based elements related to surface and channel routing. Table 2 shows the submodels of Hydrotel used in this study for simulations.

It should be noted that we developed two types of configurations for the simulations with Hydrotel, in order to allow the comparisons between a grid-based model (i.e., WaSiM) and an HRU based model (i.e., Hydrotel). In the first configuration (referred to as Hydrotel1 hereafter), we keep the number of HRUs constant, while the spatial resolution varies. In the second configuration, we adjust the number of HRUs to match the change in resolution. We manually set the number of HRUs equal to the number of subbasins, which are automatically created for WaSiM based on the spatial resolution of CDs. This configuration is referred to as Hydrotel2 hereafter.

2.4 Experimental plan

Figure 2 delineates the different steps of our methodology and the experiments designed to answer the question posed in the introduction. The first column of the figure shows the "Data Domain", comprised of forcings (precipitation-temperature), calibration data (observed streamflow), and gridded Catchment Descriptors (CDs- e.g., DEM, land use, soil texture). For CDs, the highest available resolution is $100\,\mathrm{m}^2$ and we used resampling and interpolation methods to upscale the grids to $250\,\mathrm{m}^2$, $500\,\mathrm{m}^2$, and $1000\,\mathrm{m}^2$ resolutions. The second column, which is referred as "time domain" shows the time step of forcing and calibration data. For this project, the subdaily time step is equal to 3 hours.

Regarding the third column titled "Calibration", as per usual, we split the time-series into calibration and validation periods. The duration of both periods are equal unless there exists a large part of missing data in between them that could reduce the accuracy of the calibration. It is worth mentioning that the time-series of data related to winter streamflow in 3-hour time step is not available, and as a result, we removed this part of the year from the analyses.

We used the Dynamically Dimensioned Search (DDS; Tolson & Shoemaker, 2007) algorithm to calibrate the hydrology models. Furthermore, the Kling-Gupta Efficiency (KGE; Gupta, Kling, Yilmaz, & Martinez, 2009) is adopted as the objective function for optimizations. The KGE is computed using Equation 2:

$$KGE = \sqrt{(r-1)^2 + (\frac{\sigma_{sim}}{\sigma_{obs}} - 1)^2 + (\frac{\mu_{sim}}{\mu_{obs}} - 1)^2} \qquad (2)$$

where r is the linear correlation between observations and simulations, σ_{sim} is the standard deviation in observations, σ_{obs} is the standard deviation in simulations, μ_{sim} is the simulation mean, and μ_{obs} is the observation mean.

When the distributed models are fed and calibrated against streamflow at the outlet of the catchment, several calibration parameter sets are obtained according to the spatio-temporal discretization of the input data (forth and fifth columns titled "Parameter Resolution" and "CD Resolution"). In the next step, all combinations of CPs-CDs are used to force both hydrology models for simulations. With $\mathrm{n} = 4$ different resolution for each calibration, an ensemble of $\mathrm{n}^2 = 16$ simulations is obtained for each model (i.e. WaSiM, Hydrotel1, and Hydrotel2).

To explore the uncertainty due to the spatial discretization, we first separate the catchments based on their surface areas to investigate the possible relations between discretization uncertainty and catchment size. Catchments are separated into three categories: larger than $1000\,\mathrm{m}^2$ (hereafter "large"), between $500\,\mathrm{m}^2$ and $1000\,\mathrm{m}^2$ (hereafter "medium"), and less than $500\,\mathrm{m}^2$ (hereafter "small"). As shown in Table 1, each category comprises two catchments. Second, we compare the efficiency of simulations in calibration and validation across different spatio-temporal resolutions and explore the sensitivity of the efficiency of simulations to the changes in the CPs' and CDs' resolution. Third, we apply extreme value theory (Coles, Bawa, Trenner, & Dorazio, 2001) to simulate flood events with different return periods by fitting the Log-Pearson distribution to the annual flow maximas. We calculate summer-fall floods with 5, 10, 20, and 50 years return periods for each simulation and calculate the relative error in flood simulations according to Equation 3:

$$e_{T,ij} = \frac{QT_{ij} - QT_{obs}}{QT_{obs}} \tag{3}$$

where e is the relative error of simulations, i is the CP resolution, j is the CD resolution, QT is the magnitude of a flood event with return period T, and obs represents the observation. Given the 16 possible combinations of simulations, a range of relative error will be obtained from Equation 3 for a specific return period, which can further be separated into uncertainties corresponding to CPs and CDs according to Equations 4 and 5:

$$MDE_{T,i}^{CD} = |\max(e_{T,ii}, e_{T,ij}, ..., e_{T,in}) - \min(e_{T,ii}, e_{T,ij}, ..., e_{T,in})| \tag{4}$$

$$MDE_{T,j}^{CP} = |\max(e_{T,ij}, e_{T,jj}, ..., e_{T,nj}) - \min(e_{T,ij}, e_{T,jj}, ..., e_{T,nj})| \tag{5}$$

where $MDE_{T,i}^{CD}$ is the Maximum Difference of Errors when the resolution of CPs is constant and $MDE_{T,j}^{CP}$ is the Maximum Difference of Errors when the resolution of CDs is constant, for a return period *T*. Following this approach, we can investigate the dominant source of uncertainty (i.e., CDs or CPs) in the system. Also, this can potentially help understand the possibility of using the combination of lower resolution CPs and higher resolution CDs to reduce the computational demand and timing, while we maintain a good level of detail in the simulations.

3 Results

This section is structured as follows: in section 3.1, mean annual hydrographs of simulations are presented. Section 3.2 gives the results related to the model efficiency (KGE of simulation) and corresponding uncertainties. Section 3.3 provides analyses regarding the uncertainties of extreme flows. Finally, section 3.4 demonstrates the results of analyses carried out on the separation of uncertainties of extreme flows into uncertainties of CDs and CPs.

3.1 Annual Hydrographs

Figures 3 to 5 display the mean annual cycle of simulated and observed streamflows for 3- and 24-hour time steps. As discussed in section 2.4, for each catchment, 16 simulations are available, which is the combination of 4 sets of CP and 4 CDs resolutions. The figures show the entire period of calibration and validation. Furthermore, winter streamflow has been removed for the 3-hour time step due to a lack of observation data. The results are presented according to the catchment area: the top row shows larger catchments ($> 1000\,\mathrm{km}^2$) whereas the bottom row shows smaller catchments ($< 500\,\mathrm{km}^2$). In Figure 3, WaSiM is used to simulate streamflow. The uncertainty bounds in the figures demonstrate the sensitivity of the model to variations of the spatial resolution. Such uncertainty can be found in most of the cases, regardless of the catchment size and time step (3 hours or 24 hours). The Croche, Aux Brochets, and Boyer catchments, which show notable uncertainties, belong to the groups of large, medium and small size catchments, respectively. Thus, no clear link between the size of the catchment and the degree of uncertainty can be found in this study. By contrast, the impact of the time step on the uncertainty can be observed for the catchments mentioned above, as the simulations with a 3-hour time step show wider uncertainty bounds.

Figure 4 shows the Hydrotel simulations, when the number of HRUs are kept constant (Hydrotel1, see section 2.4). Compared to the WaSiM simulations, the model shows less sensitivity to a changing spatial resolution. The only exception is the Aux Pommes catchment, in which a large disparity between simulations can be observed. Furthermore, the uncertainty bound is visible for the Croche catchments. Regarding the impact of time steps, unlike WaSiM, no systematic pattern emerged.

Figure 5 shows the Hydrotel2 simulations, when the number of HRUs has changed (see section 2.4). In general, a slight widening of the uncertainty bounds can be observed, manifesting a higher sensitivity of the Hydrotel2 set-up to changes in spatial resolution as compared to the Hydrotel1 simulations.

3.2 General performance of the simulations

Figures 6 to 8 illustrate the performance of the simulations through calibration and validation periods for six catchments, according to the Kling Gupta criterion. Here, we split the uncertainty into two sources: a primary source, which is caused by direct changes to the Catchment Descriptors (CD resolution); and a secondary source, which is caused by any change in the Calibration Parameters (CP). However, the latter is itself caused by changing the resolution of CDs. We assign a marker and a color to each simulation. The former represents the resolution of CDs and the latter represents the resolution of CPs.

Figure 6 demonstrates the performance of the simulations by WaSiM. Although the number of optimization trials is limited (150) due to the intensive computational demand of the model, the efficiency is high (> 0.8) for most cases. Furthermore, the model shows a robust performance for both the validation and calibration periods. It is notable that, except for the Châteauguay and Chaudière catchments, the spread in the distribution of KGE values is visible, as a result of changes in resolution. In addition, no systematic pattern regarding the relationship between catchment size and uncertainty can be identified. Interestingly, the maximum spread can be seen in Boyer catchment, which is small (191 km^2). In terms of temporal resolution, for most of catchments, the simulations with a 3 hour time step display a slightly higher dispersion than those with a 24-hour time step.

Figures 7 and 8 show the KGE of simulations by the Hydrotel1 and Hydrotel2 configurations, where 500 optimization trials have been used for each case. In general, the efficiency of simulations with Hydrotel is lower than with WaSiM (> 0.7), even though the number of optimization trials for Hydrotel exceeds those of WaSiM. Nonetheless, the models demonstrate a robust performance for the calibration and validation periods. While the spread of the KGE for Hydrotel1 tends to be smaller for WaSiM, there are cases such as Croche and Boyer catchments with a 3-hour time step with a larger spread. Furthermore, the Aux Pommes catchment depicts a large dispersion in the spread of the simulations. Figures 7 and 8 reveal that a major drop in the performance often occurs when the highest resolution ($100\,\mathrm{m}^2$) of CP (or CD) is combined with the lower resolution of CD (or CP, i.e. 100, 250, 500, $1000\,\mathrm{m}^2$). Remarkably, such a pattern holds for the WaSiM simulation of the Boyer catchment with a 3-hour time step in Figure 6, where a major decline in KGE is seen in simulations (blue). This highlights the issue of compatibility between the resolution at which parameters are calibrated and the resolution at which the model is simulated. Comparing Figures 8 and 7, it can be seen that the spread of the simulations is higher for Hydrotel2 than for Hydrotel1. This is an expected outcome given the scheme used for Hydrotel2, in which the numbers of HRUs are changed in accordance with the resolution of CDs .

Looking at Figures 6 to 8, no systematic pattern can be detected in terms of the impact of uncertainties corresponding to CDs or CPs. In some cases, the CDs are dominant (the markers grouped together), while in others, CPs are dominant (colors grouped together) and for the rest of the cases there is no clear pattern. The figures, however, reveal that the best performance is not necessarily correlated with the highest possible resolutions of CDs and CPs. Indeed, the combinations of the lowest resolutions (P10 or D10), which are shown by black colors and asterisk shape markers, are among the top performing simulations. This is important for practical applications, as using a combination of lower resolution CDs for calibration and high resolution CDs for simulation could substantially reduce the computational costs while maintaining the detail of simulations. The computational time of a 1-year single execution by WaSiM is shown in Figure 9. In this figure, we use a random sampling method to produce 100 parameter sets within the boundary of parameters and run WaSiM for the Chaudière catchment. Since WaSiM is a gridded physically-based model, the time and computational power that could be saved using lower resolutions is noticeable. This might not be as significant for more conceptually-based distributed models. It is worth noting that the distribution of the run time is due to the variations of the parameters of the unsaturated zone model that controls runoff, interflow and baseflow.

3.3 Uncertainty of extreme streamflows

Figures 10 to 12 show the relative error when the models are used to simulate floods with 5-, 10-, 20-, and 50-year return periods. We fitted the Log-Pearson distribution to the annual maxima of the simulated and observed streamflows for the 2000-2017 period and extracted the flood events corresponding to the return periods mentioned above. The spread of the boxplots show the difference in relative error (Equations 3) of all simulations (i.e., for the ensemble of 16, which is combination of CDs and CPs in each case) generated by changes in spatial resolution. Given the nature of extreme events, which comprise streamflows with large magnitudes, the noticeable spread of simulations shown in these figures highlights the importance of spatial discretization for flood modeling. Figure 10 demonstrates the relative error of extreme events simulated by WaSiM. In agreement with the previous observations, a spread can be detected across different catchment sizes, (i.e. Croche, Aux Brochets, Aux Pommes) and a systematic relationship between extreme flow and catchment size cannot be identified. Moreover, there is no significant relationship between the spread and the time step of the simulations.

Figures 11 and 12 show the relative error of flood simulations produced by the Hydrotel1 and Hydrotel2 configurations. The response of Hydrotel1 to extreme flow is similar to other figures (i.e. annual hydrographs and KGE) discussed earlier. While the magnitude of error is higher as compared to WaSiM, the model shows a smaller spread of relative errors. Nonetheless, the spread of relative error is visible across different catchment sizes (Châteauguay, Aux Brochets, and Aux Pommes), which refutes the possibility of a correlation between the catchment size and the uncertainty of extreme flow. However, the time step chosen for the simulation is important, as the width of the boxplots corresponding to the 3-hour time step is larger than for the 24-hour time step. Simulations with Hydrotel2 exhibit a noticeably larger uncertainty for extreme streamflows as compared to Hydrotel1, particularly for the Châteauguay and Aux Brochets catchments. This is in line with the earlier observations discussed in Figures 7 and 8, where the uncertainties corresponding to Hydrotel2 are higher than for Hydrotel1 due to the change in the numbers of HRUs for Hydrotel2. Finally, considering Figures 10 to 12, the return period does not appear to influence the uncertainty of the simulations. Indeed, the spread of the simulations for different return periods is similar, per catchment.

3.4 Analyzing the uncertainty of extreme streamflows

Figures 13 to 15 illustrate a separation of the total uncertainty for extreme streamflows into contributions from CDs and CPs. The separation procedure is carried out following section 2.4. In these figures, RN represents the resolution of simulations and QTN represents the flood return period. The vertical and horizontal axes are the Maximum Difference of relative Errors (MDE) of CDs and CPs respectively, as defined in Equations 4 and 5.

Figure 13 depicts the results of simulations with WaSiM. For most catchments, the contribution of CPs to the total uncertainty is larger than that of CDs. For instance, the MDE of CPs in Châteauguay is between 0.1 to 0.2, while the MDE of CDs is around zero. The same pattern can be seen for Croche, Chaudière, Aux Pommes (3 hour), and Boyer (3 hour) catchments. This, however, is not the case for all the catchments. For the Aux Brochets (3 and 24 hour) and Aux Pommes (24 hour) catchments the MDE corresponding to CDs is equal to or larger than that of CPs. The dominance of MDE of CDs is evident, particularly for Aux Brochets (3 hour). Interestingly, the Aux Brochets (24 hours and 3 hours) and Aux Pommes (24 hour) catchments demonstrate the highest range of uncertainty among all catchments. This highlights the importance of accounting for the contribution of CDs to the total uncertainty of extreme streamflow simulations when dealing with catchments that are sensitive to changes in resolution.

Figures 14 and 15 display the results of simulations with Hydrotel. Figure 14 illustrates the decomposition of uncertainty for extreme streamflows simulated by Hydrotel1. The magnitude of MDE for both CDs and CPs as compared to WaSiM is limited. Likewise, the MDE of CPs is larger in most cases, except for the Aux Brochets catchment with a 3-hour time step and, the Aux Pommes catchment. In general, Hydrotel2 simulations show larger MDEs than Hydrotel1 simulations. Also, the number of cases in which the dominant source of uncertainty is CDs is increased (compared to WaSiM) as the Châteauguay and Aux Brochets catchments show larger MDEs across the vertical axis (Note that the MDEs of CDs calculated for QT50 for Aux Brochets-3 hour are larger than 1, and have been removed for the sake of consistency in comparisons). Looking at Figure 12, the range of uncertainties corresponding to these two catchments is substantially larger than for other catchments, in which the dominant source of uncertainty is CPs.

4 Discussion

As discussed in section 3.4, the dominant cause of uncertainty in the simulation of extreme streamflow relates to CPs resolution for most of the catchments. There are exceptions, in which the dominant source of uncertainty in the simulation of those extreme values can be attributed to changes in the resolution of CDs. As shown in Figures 12 to 15, catchments such as Aux Brochets, Aux Pommes, and Châteauguay, are among these cases. From this list, the Aux Brochets (3-hour) catchment demonstrates the highest level of dominance of CDs, regardless of the model or configuration used for simulations. Figure 16 shows the distribution of monthly flow maxima for the Aux Brochets (3-hour) catchment simulated by WaSiM. Here, we fitted a Generalized Extreme Values distribution to the monthly maxima of simulated and observed streamflows. The summer months (June-July-August) were selected for the figure, to minimize the effects of missing data on the analyses. For each subplot, the resolution of CDs was kept constant while the resolutions of parameters vary. By coarsening the resolution of CDs, a noticeable change in the shape of the cumulative distribution function can be observed.

To explore the reason for the observed sensitivity, we used simulations from WaSiM, as this model offers further insights regarding the changes in state variables and fluxes across the catchment. Figure 17 shows the distribution of average groundwater levels across the catchment. In each column, the resolution of CPs is constant, while the resolution of CDs is changing. By coarsening the resolution, a major increase of ground water level near the outlet of the catchment (located in the north-western part) can be observed. For instance, the distribution of groundwater across the catchment in subplots a and e is similar and it changes for subplots i and m. This change in the distribution of groundwater across the catchment can also be seen for other CP resolutions (e.g., b,f,j,n, etc.).

To explore further, we picked the groundwater distribution results for 100 and 500 m^2 CDs as representative of high and low resolution catchment descriptors and compared them with the distribution of slopes across the catchment. Figure 18 shows the average ground water level (bottom row) and slope (top row) within the catchment. Subplot c (CD 100 m^2) shows that the maximum groundwater level can be found in the middle part of the catchment. Neverthless, for subplot d (CD 500 m^2), most of the groundwater accumulates on the downstream part of the catchment. This can be explained by looking at the top row showing the slope distribution. In the subplot a (100 m^2 resolution), there are small-scale hillslopes and valleys, which spatially correlate with the maximum groundwater level in the middle of the catchment. These uneven areas that retain groundwater at specific parts of the catchment disappeared during the interpolation for 500 m^2 CDs (subplot b), resulting in an accumulation of groundwater downstream.

Figure 19 illustrates the catchment response at the outlet and at Reach1 (R1), for the spring flood of 2008. R1 is located right before the outlet in the downstream area. Here, the dashed lines depict direct runoff from the subbasins and the solid lines show the simulated streamflow at the 3-hour time step. In both subbasins, the catchment responses reproduced by the 500 m^2 resolution demonstrate considerable fluctuations, particularly for the R1 subbasin. The reason for this is that the water table is very close to the surface in this area, and this reduces the damping effect of interflow and baseflow down to near zero. As a result, any change in the meteorological forcings translates into direct flow and a corresponding rapid reaction of the catchment in the R1 subbasin.

The fluctuations further transfer and commensurately impact the streamflow at the outlet of the catchment. In fact, changes in the resolution of the CDs alter the magnitude and timing of the peak flow, regardless of the variations of CPs. Such behaviour can explain the dominance of CDs over CPs in Figures 12 to 15 for the Aux Brochets (3hr) catchment.

5 Conclusion

We have explored the impact of spatio-temporal discretization to reproduce streamflow and simulate flood events across six catchments located in Quebec (Canada) using two distributed hydrology models. We framed a hypothesis regarding the uncertainty of heterogeneity and broke it down into four main aspects reiterated as follows: Changing the spatial resolution of catchment descriptors generates uncertainty that can potentially impact flood simulations. The catchment area, the modeling time step, and the model structure are the major components used to determine the significance of such uncertainty. More precisely, we hypothesized that:

i Larger catchments are susceptible to larger uncertainties in the simulation of streamflow, when varying the spatial resolution of their physiographic characteristics.

ii Finer time steps introduce a higher degree of variability in the simulation, leading to increased uncertainty in streamflow simulation.

iii The more finely distributed and physically realistic a model is, the more sensitive to changes in spatial resolution it is.

iv The uncertainty related to model parameters is dominant (larger) than that of catchments descriptors (DEM resolution, land use, soil texture).

Based on the above results and analysis, the following conclusions can be drawn:

1. There is no systematic link between the catchment size and the uncertainty corresponding to the simulation of streamflow, so hypothesis *i* is not verified for our experiment. Regardless of the model used to reproduce streamflow, the uncertainty of heterogeneity have been observed across different catchment sizes (see Figures 3 to 5 and 6 to 8). Interestingly, smaller size catchments (Boyer and Aux Pommes) generate larger uncertainties (see Figures 6 and 8), which refutes the assumption that changing the spatial resolution mainly affects larger catchments.

2. The temporal resolution plays only a minor role in the determination of the uncertainty related to spatial resolution, so hypothesis *ii* is also not clearly verified for our experiment. WaSiM and Hydrotel2 showed that a 3-hour time step could moderately increase the uncertainty bounds of simulations for most catchments (see Figures 3 and 5).

3. The model structure is an important driver of the uncertainty related to the spatial resolution of simulations (hypothesis *iii* is verified for our experiment). WaSiM demonstrated a sensitivity to changes in the spatio-temporal resolution of the simulations (See figures 3 and 6). This was expected, given that the model solves Richards Equations for each grid cell, associated with specific catchment descriptors. Hydrotel's conceptualization of infiltration, percolation and groundwater is less physically-based. In its default setting, it cannot adequately capture the uncertainty related to spatial discretization unless change is imposed by altering the number of HRUs (see Figures 4, 5 and 7, 8).

4. Our attempt to separate the total spatio-temporal uncertainty into a portion attributable to CDs and a portion attributable to CPs showed that the latter is the dominant contributor for most of the catchments (hypothesis *iv*-see Figures 13 to 15). However, there are catchments in which the change of CD resolution is dominant (e.g., Aux Brochets and Aux Pommes catchments in Figures 13 to 15). Such catchments also demonstrate a large uncertainty in the simulation of extreme flows (see Catchment Aux Brochets and Aux Pommes in Figures 10 to 12, Figure 16). Based on section 4, this might be due to changes in the dynamic interactions of states variables and fluxes once the resolution of simulations is altered (see Figure 17). Such behavior is expected for relatively flat catchments, but that still includes multiple small hillslopes and valleys (e.g., catchment Aux Brochets). Indeed, changing the resolution can reduce the impact of an uneven topography, or even eliminate it completely (see Figure 18), which can result in an inconsistent hydrologic behaviour and response of the catchment (see Figure 19).

Given the dearth of credible publications addressing the impact of the uncertainty corresponding to the resolution of simulations, many gaps and opportunities remain to be addressed in this line of research. One major area of focus could be the adoption of more advanced physically-based distributed hydrology models to explore the degree of uncertainty, particularly for extreme streamflows. Another focus could be on identifying the key parameters and hydrological processes that are mainly affected by spatio-temporal discretization change. Finally, using a larger set of catchments with different physical characteristics could help provide a better understanding of how they react to variations of the resolution of catchment descriptors. It could also shed light on the importance of accounting for this uncertainty in streamflow simulations and in the assessment of flood events.

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Table 1: General information and characteristics of the catchments

Table 2: The submodels employed to represent the hydrological processes in Hydrotel and WaSiM.

Figure 1: Location of the catchments for this study, over the southern part of Quebec.

Figure 2: Schematic explanation for building ensemble of simulations and analyses.

Figure 3: Annual hydrographs of the selected catchments simulated by WaSiM and compared to observed data. The time steps of the modeling are 24 and 3 hours. The responses are arranged according to the size of the catchments: large catchments ($> 1000\,\mathrm{km}^2$) are on the top row; medium catchments (between 500 and $1000\,\mathrm{km}^2$) are on the middle row; large catchments ($< 500\,\mathrm{km}^2$) on the bottom row.

Figure 4: Annual hydrographs of the selected catchments simulated by Hydrotel (Hydrotel1) and compared to observed data. The time steps of the modeling are 24 and 3 hours. The responses are arranged according to the size of the catchments: large catchments ($> 1000\,\mathrm{km}^2$) are on the top row; medium catchments (between 500 and $1000\,\mathrm{km}^2$) are on the middle row; large catchments ($< 500\,\mathrm{km}^2$) on the bottom row.

Figure 5: Annual hydrographs of the selected catchments simulated by Hydrotel (Hydrotel2) and compared to observed data. The time steps of the modeling are 24 and 3 hours. The responses are arranged according to the size of the catchments: large catchments ($> 1000\,\mathrm{km}^2$) are on top row; medium catchments (between 500 and $1000\,\mathrm{km}^2$) are on the middle row; large catchments ($< 500\,\mathrm{km}^2$) on bottom row.

Figure 6: Efficiency of WaSiM in reproducing streamflow for the calibration and validation periods. Here, CP and CD represent calibration parameters and catchment descriptors respectively and the numbers assigned show the resolution divided by 100 for brevity.

Figure 7: Efficiency of Hydrotel (Hydrotel1) in reproducing streamflow for the calibration and validation periods. Here, CP and CD represent calibration parameters and catchment descriptors respectively and the numbers assigned show the resolution divided by 100 for brevity.

Figure 8: The efficiency of Hydrotel (Hydrotel2) in reproducing streamflow for the calibration and validation periods. Here, CP and CD represent calibration parameters and catchment descriptors respectively and the numbers assigned show the resolution divided by 100 for brevity.

Figure 9: Model run-time for different resolutions (R100 = resolution of 100 km^2, ... R1000 = resolution of 1000 km^2) and different time steps (3 hour versus 24 hour) for a one-year simulation with WaSiM for Chaudière catchment.

Figure 10: Relative error of reproducing summer-fall flood with 5-, 10-, 20-, and 50-year return periods using WaSiM. QT represents a flood event with the specific return periods.

Figure 11: Relative error for the simulation of summer-fall floods with 5-, 10-, 20-, and 50-year return periods using the Hydrotel1 configuration. QT represents a flood event with a specific return period. For instance, QT5 is the 5-year return period flood.

Figure 12: Relative error for the simulation of summer-fall floods with 5-, 10-, 20-, and 50-year return periods using the Hydrotel2 configuration. QT represents a flood event with a specific return period. For instance, QT5 is the 5-year return period flood.

Figure 13: Relative error for the simulation of summer-fall floods with 5-, 10-, 20-, and 50-year return periods using WaSiM. QT represents a flood with a specific return period. For instance, QT5 is the flood magnitude corresponding to a 5-year return period. R represents the resolution (divided by 100) of CDs or CPs, in which the Maximum Error Difference (MDE) is calculated.

Figure 14: Relative error for the simulation of summer-fall floods with 5-, 10-, 20-, and 50-year return periods using the Hydrotel1 configuration. QT represents a flood with a specific return period. For instance, QT5 is the flood magnitude corresponding to a 5-year return period. R represents the resolution (divided by 100) of CDs or CPs, in which the Maximum Error Difference (MDE) is calculated.

Figure 15: The relative error for the simulation of summer-fall floods with 5-, 10-, 20-, and 50-year return periods using Hydrotel2 Configuration. QT represents a flood with a specific return period. For instance, QT5 is the flood magnitude corresponding to a 5-year return period. R represent the resolution (divided by 100) of CDs or CPs, in which the Maximum Error Difference (MDE) is calculated.

Figure 16: Cumulative distribution function of monthly maximum values for 3-hour streamflow simulated by WaSiM in summer months, for the Aux Brochets catchment (CD_{100}: the resolution of CDs is $100\,m^2$, etc).

Figure 17: Distribution of groundwater elevation across the Aux Brochets catchment for different resolutions for a 3-hour time step.

Figure 18: Comparison of slope (top) and groundwater elevation (bottom) for Aux Brochets (3 hr) simulated by WaSiM.

Figure 19: Routed discharge (Q100, Q500) and direct runoff (R100, R500) of 100 and $500\,m^2$ CD resolutions simulated by WaSiM for the outlet and Reach 1 (R1 is the reach located in downstream area next to the outlet of the catchment) of Aux Brochets catchment for 3-hour time step.