Impacts of Climate Change on the Hydrology of Extreme Summer Floods

by

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Impacts du changement climatique sur l'hydrologie des crues estivales extrêmes

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RÉSUMÉ

L'examen des impacts du changement climatique sur les événements hydroclimatiques extrêmes a suscité un grand intérêt, car une augmentation de ces événements aura un impact sur les inondations et les sécheresses. Ces événements peuvent nuire aux humains et aux animaux et causer des dommages aux biens et aux infrastructures. Il est essentiel d'avoir une compréhension approfondie des caractéristiques et de la distribution des précipitations extrêmes, ainsi que du moment, de l'ampleur et de la fréquence des débits extrêmes, afin de planifier et de gérer efficacement nos systèmes de ressources en eau, notamment les barrages, les réservoirs et les systèmes d'irrigation.

Des études récentes ont indiqué qu'il pourrait y avoir une augmentation de l'intensité des événements de précipitations extrêmes, tels que les précipitations convectives, à l'avenir en raison des effets du changement climatique. Cela pourrait se traduire par des quantités plus importantes de pluie ou de neige sur une période de temps plus courte, ce qui pourrait potentiellement entraîner une augmentation des inondations et d'autres problèmes liés aux conditions météorologiques.

Cette étude vise à examiner les variations d'intensité et de fréquence de la variabilité hydroclimatique à court et à long terme, en mettant l'accent sur les précipitations et les débits extrêmes dans les régions de l'est et du nord-est des États-Unis. En outre, l'étude examine l'incertitude associée aux biais du cycle diurne et à la variabilité climatique interne pour la variabilité hydroclimatique future. L'objectif global de cette recherche est d'améliorer notre compréhension de la façon dont les événements extrêmes futurs se développeront, en mettant l'accent sur leur relation avec la taille du bassin versant, afin de mieux se préparer au changement climatique.

Cette étude a utilisé l'ensemble de données ClimEx comprenant 50 membres. ClimEx est un ensemble de données de grande envergure à conditions initiales uniques (Single Model Initial condition Large Ensemble ou SMILE) opérant sous le scénario du Chemin de Concentration Représentative 8.5. ClimEx offre une haute résolution spatiale (0,11º) et temporelle (1 heure) et a été dérivé par une réduction dynamique de l'échelle à partir de 50 membres du Modèle Système Terrestre Canadien (CanESM2) à travers un domaine de l'Amérique du Nord-Est

Comme la modélisation hydrométéorologique effectuée dans cette étude se fait au pas de temps infra-journalier, une première étape a consisté à étudier la nécessité et l'impact d'une méthode de correction du biais du cycle diurne sur les variables climatiques, telles que la température et les précipitations, et son effet sur le débit simulé.

Dans la deuxième étape de l'étude, la progression des extrêmes hydrologiques dans 133 bassins versants a été examinée en étudiant la relation entre la taille du bassin versant, la durée des précipitations (allant de 1 à 72 heures), les périodes de retour (entre 2 et 300 ans) et le débit.

Enfin, l'étude a cherché à comprendre l'importance de la variabilité climatique interne pour l'identification des changements de débit en analysant le moment de l'émergence. Cette analyse visait à mettre en lumière la façon dont la variabilité climatique interne peut influencer la détection des changements de débit et la fiabilité des résultats.

L'étude a révélé que l'utilisation de méthodes multivariées de correction des biais du cycle diurne peut efficacement ajuster les biais infra-quotidiens de la température et des précipitations, en termes de moment et d'ampleur, par rapport aux observations réelles. Ces corrections entraînent des améliorations légères mais systématiques de la simulation des quantiles de débit, en particulier dans les petits bassins versants.

Avec le changement climatique, l'étude a également révélé une augmentation des précipitations extrêmes pour toutes les durées et périodes de retour. L'augmentation prévue des précipitations extrêmes est étroitement liée à la durée, à la fréquence et à la taille du bassin versant. Les zones qui devraient connaître les plus fortes augmentations relatives de précipitations sont celles qui ont les durées les plus courtes, les plus grandes périodes de retour et les plus petits bassins versants.

L'étude a déterminé que le moment de l'émergence du changement climatique sur les inondations et les sécheresses extrêmes se produit plus tard que ceux sur les niveaux de débit moyens, mais les changements dans les inondations et les sécheresses sont plus prononcés. Le moment de ces changements est lié à la taille du bassin versant, les petits bassins versants affichant une émergence plus précoce pour les inondations et plus tardive pour les sécheresses.

Les résultats de cette étude impliquent qu'à l'avenir, les petits bassins versants seront affectés de manière disproportionnée par l'augmentation des précipitations extrêmes. Cela souligne la nécessité de poursuivre les recherches sur les impacts du changement climatique sur les inondations et les sécheresses extrêmes, en particulier en ce qui concerne le moment de ces effets et la façon dont il est influencé par la taille du bassin versant.

Mots-clés: Changement climatique; correction de biais ; Cycle diurne ; étude d'impact ; Événements extrêmes ; grand ensemble ClimEx; variabilité climatique interne; moment de l'émergence ; Modélisation hydrologique.

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ABSTRACT

The examination of the impacts of climate change on extreme hydroclimate events has received a great deal of interest, as a rise in these events will impact floods and droughts. These events can harm human and animal and also cause damage to property and infrastructure. It is essential to have a thorough comprehension of the characteristics and distribution of extreme precipitation, as well as the timing, magnitude, and frequency of extreme flow, in order to effectively plan and manage our water resources systems, including dams, reservoirs, and irrigation systems.

Recent studies have indicated that there may be an increase in the intensity of extreme precipitation events, such as convective precipitation, in the future due to the effects of climate change. This could result in higher amounts of rain or snowfall within a shorter period of time, which could potentially bring about an increase in flooding and other weather-related challenges.

This study endeavors to examine the variations in the intensity and frequency of short and long-term hydroclimatic variability, with a specific focus on extreme precipitation and streamflow in the Eastern and Northeastern regions of the United States. Additionally, the study delves into the uncertainty associated with diurnal cycle biases and internal climate variability for future hydroclimatic variability. The overall aim of this research is to enhance our understanding of how future extreme events will develop with a focus on their relationship to catchment size, in order to better prepare for the changing climate.

This study utilized the 50-member ClimEx large ensemble, which is a Single Model Initial condition Large Ensemble (SMILE) operating under the Representative Concentration Pathway 8.5 scenario. ClimEx offers high spatial resolution (0.11º) and temporal resolution (1-hour) and was derived by dynamically downscaling the 50-member Canadian Earth System Model (CanESM2) across a northeastern America domain.

As the hydrometeorological modeling done in this study was at the sub-daily time step, a first step was to investigate the need and impact of a diurnal cycle bias correction method on climate variables, such as temperature and precipitation, and its effect on simulated streamflow.

In the second step of the study, the progression of hydrological extremes across 133 catchments was examined by investigating the relationship between catchment size, rainfall duration (ranging from 1 to 72 hours), return periods (between 2 and 300 years) and streamflow.

Finally, the study sought to understand the significance of internal climate variability for identifying changes in streamflow by analyzing the timing of emergence This analysis aimed to shed light on how internal climate variability can influence the detection of changes in streamflow and the reliability of the results.

The study revealed that the utilization of multivariate diurnal cycle bias correction methods can effectively adjust sub-daily biases in temperature and precipitation, in terms of both timing and magnitude, when compared to actual observations. These corrections lead to small yet systematic improvements in the simulation of streamflow quantiles, particularly in smaller catchment areas.

As the climate changes, the study also found an increase in extreme precipitation across all durations and return periods. The projected increase in extreme precipitation is closely correlated with the duration, frequency, and size of the catchment area. The areas that are expected to experience the largest relative increases in rainfall are those with the shortest durations, largest return periods, and smaller catchment areas.

The study determined that the time of emergence of climate change on extreme floods and droughts occurs later than those on average flow levels, but the changes in floods and droughts are more pronounced. The timing of these changes is related to the size of the catchment area, with smaller catchments displaying an earlier emergence for floods and a later one for droughts.

The findings of this study imply that in the future, smaller catchments will be disproportionately affected by the increases in extreme rainfall. This emphasizes the need for further research on the impacts of climate change on extreme floods and droughts, particularly in relation to the timing of these effects and how it is influenced by the size of the catchment area.

Keywords: Climate change; Bias correction; Diurnal cycle; Impact study; Extreme events; ClimEx large ensemble; Internal climate variability; Time of emergence; Hydrological modeling.

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LIST OF ABREVIATIONS

ACC	Anthropogenic Climate Change
AE	Actual Evapotranspiration
AGCM	Atmospheric General Circulation Model
ARF	Areal Reduction Factor
C3S	Copernicus Climate Change Service
CANESM2-LE	Canadian Earth System Model- Large Ensemble
CC	Clausius Clapeyron
CCCMA	Canadian Centre for Climate Modelling and Analysis
CCSM3	Community Climate System Model Version 3
CESM2	Community Earth System Model 2
CLIMEX	Climate Change and Hydrological Extremes
CMIP5/6	Coupled Model Intercomparison Project Phase 5/6
CAPE	Convective Available Potential Energy
CORDEX	Coordinated Regional Downscaling Experiment
CRCM5	Canadian Regional Climate Model
DBC	Diurnal Bias Correction
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF Reanalysis 5th Generation

ESMS	Earth System Models
GCM	Global Climate Model
GCS	Gauss Centre For Supercomputing
GHGES	Greenhouse Emission Scenario
GR4H	Modèle Du Génie Rural A 4 Paramètres Horaire
GR4J	Modèle Du Génie Rural A 4 Paramètres Jour
ICV	Internal Climate Variability
IPCC	Intergovernmental Panel on Climate Change
KS	Kolmogorov-Smirnov Test
LRZ	Leibniz Supercomputing 723 Centre
MBCN	N-Dimension Multivariate Bias Correction
MOPEX	Model Parameter Estimation Experiment
NNA	Northeastern North America
NSE	Nash–Sutcliffe Efficiency
P	Precipitation
PET	Potential evapotranspiration
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RMSE	Root-mean-square deviation
SBC	Standard Bias Correction
SCE-UA	Shuffled Complex Evolution

SEM	Standard Error of the Mean
SMILE	Single Model Initial Condition Large Ensemble
SNR	Signal-To-Noise Ratio
T	Temperature
TOE	Time Of Emergence
USGS	United States Geological Survey

LIST OF SYMBOLS

%	Percent
°C	Degree Celsius
H	Hour
M	Meters
Km	Kilometer
S	Second
W	Watt

INTRODUCTION

Extreme hydro-meteorological events (such as storms, flash floods, and droughts) can cause severe damage in terms of injuries, deaths, and socio-economic losses. These events are becoming increasingly frequent around the world and pose a threat at local, regional and global scales. These types of events typically have a cascading impact, ranging from slope instability, creating disruptions in infrastructure and services, to natural disasters, such as water scarcity, loss of agricultural yield, and increased food costs (Almazroui et al., 2021b; Field et al., 2012; Lawrence, Blackett et Cradock-Henry, 2020). By the end of the 21st century, the Intergovernmental Panel on Climate Change (IPCC., Pachauri et Meyer, 2014) predicts that successive changes in temperature and precipitation will have a wide range of environmental and socioeconomic impacts . For this reason, the IPCC emphasized the importance of focusing on changes in extreme climate and hydrological events in its Fifth Assessment Report (AR5).

Increasing temperatures have various impacts on the hydrological cycle (Allan et al., 2020; Held et Soden, 2006; Markonis et al., 2019; Tabari, 2020) such as increased frequency of extreme precipitation events and earlier melting of snowpack leading to more frequent and larger magnitude floods (Cho, McCrary et Jacobs, 2021; Huang et Swain, 2022; Musselman et al., 2018). Many water infrastructures such as bridges, culverts, and dams are designed for a long-lifespan, so it is critical to consider the potential increase in extreme events (e.g., events with a 100-year return period) in order to ensure public safety and reduce damages associated with these events. Extreme precipitation, for example, is often part of the design criteria for a variety of urban infrastructure such as wastewater collection systems, and extreme flows can be used to design major structures (e.g., dams) or for floodplain delineation (Bornemann et al., 2019; Martel et al., 2021; Swanson et al., 2021).

Floods are one of the most impactful natural disasters for our civilization (Huppert et Sparks, 2006; Leroy, 2020). According to research conducted globally between 1995 and 2005, 43% of natural disasters are related to floods (Guha-Sapir et Hoyois, 2015). The impacts and costs of extreme flooding have increased significantly in recent years in many parts of the world (Mirza, 2003; Mitchell, 2003). The cost of flood damage worldwide between 2000 and 2019 has been estimated at US$651 billion by the Center for Research on the Epidemiology of Disasters (CRED) and the United Nations Disaster Risk Reduction (UNDRR) (CRED, 2020). Floods can result from a variety of causes, including continuous rainfall of long duration, snowmelt runoff, flash floods caused by extreme precipitation of short duration, coastal flooding, and flooding caused by dam failure (Kundzewicz et al., 2014; Whitfield, 2012). In Nordic watersheds, snowmelt flooding is common in the spring, but many watersheds are also susceptible to summer/fall storm precipitation (Buttle et al., 2016). The number of extreme summer floods due to global warming has increased over the past decade (Alipour, Ahmadalipour et Moradkhani, 2020; Sassi et al., 2019; Wang et al., 2021). Flooding occurs on a wide range of spatial and temporal scales, and that vary with the size of the affected watersheds (Kundzewicz, Szwed et Pińskwar, 2019).

In a warmer future climate where extremes are more frequent, urban infrastructure design decisions based on climate stationarity will result in underestimated damage costs, driving up total expenditures over the life of the infrastructure (François et al., 2019; Stern et Stiglitz, 2021). Therefore, traditional flood control strategies that rely on historical information are very likely to be inadequate and inappropriate. Therefore, in light of the increasing frequency of extreme hydrometeorological events, the conventional assumption of stationarity employed in frequency analysis must be reconsidered (Martel, 2019).

It is now clear that a better understanding of how climate change affects the likelihood of extreme hydro-meteorological events (HMEs) is essential (IPCC, 2021). The increase in their frequency and intensity has an immediate impact on the economy, the environment and public safety. Changes in internal and external climate forcings affect the regional climate on all time scales (Deser et al., 2012c; Wu et al., 2019). The two changes that affect the climate on decadal and multi-decadal scales are anthropogenic forcing and internal variability (Deser et al., 2012a; Höök et Tang, 2013; Swanson, Sugihara et Tsonis, 2009). Anthropogenic forcing is related to increases in greenhouse gases and land use change, while internal forcing, also known as internal climate variability, is a natural result of non-linear interactions between the ocean and atmosphere within the climate system. It is crucial to understand the dynamics of these forcings, to estimate the spatiotemporal scales on which they are expressed, and to understand their impact on global and regional climate (IPCC, 2014). A better understanding will allow us to strengthen warning systems, mitigate disaster risks, and thus reduce vulnerability and increase the resilience of society to natural disasters.

Internal natural variability, especially in the short term, can mask or amplify the consequences of climate change (i.e., the trend or signal) at local and regional scales (e.g., Dai et Bloecker, 2019b; Deser et al., 2012c; Fatichi et al., 2014; Gu et al., 2019; McKinnon et Deser, 2018; Thompson et al., 2015) Although meaningful trends can currently be detected in global average temperature data (IPCC, 2013), it is much more difficult to discern such changes in precipitation and streamflow, and particularly with respect to extremes, because they are much more affected by internal variability (Westra, Alexander et Zwiers, 2013). The study of trends present in recent hydroclimatic data is an important area of research that is strongly affected by internal variability. This is particularly true for precipitation and streamflow originating from short-term convective storms. The uncertainty associated with internal climate variability in climate change impact studies poses a significant challenge for the design of efficient adaptation measures (Seiller et Anctil, 2014).

The increasing frequency of extreme events, such as summer and fall flooding, will particularly affect small watersheds since they are commensurate with the size of convective storms. Therefore, these types of watersheds may be more vulnerable to the impacts of climate change. A better understanding of how the increased frequency of these events will manifest itself in the future, as well as the role of internal variability in detecting these changes is important to help decision makers guide adaptation efforts.

CHAPTER 1

LITERATURE REVIEW

1.1 Climate change

According to the World Meteorological Organization the *climate* is defined as:

'The climate, sometimes understood as the "average weather," is defined as the measurement of the mean and variability of relevant quantities of certain variables (such as temperature, precipitation or wind over a period of time, ranging from months to thousands or millions of years. The classical period is 30 years. Climate in a wider sense is the state, including a statistical description, of the climate system.'

In its most general definition, climate change refers to a shift in the climate's state that may be identified by variations in its mean and/or variability (IPCC; Solomon, 2007). Climate change is the result of both anthropogenic and natural forcing.

1.1.1 Anthropogenic Climate Change (ACC)

Anthropogenic climate change (ACC), also known as "human-induced climate change," refers to how the climate system responds to an increase in greenhouse gas concentrations caused by human activity, as well as an increase in tropospheric ozone and aerosol concentrations (IPCC.; Stocker, 2013a). The increase in greenhouse concentration impacts the climate and leads to a rise in the frequency and severity of many weather events such as floods, droughts, heatwaves, and extreme precipitation (Ebi et al., 2021; Goodess, 2013; Ripple et al., 2022; Trenberth, 2005; Van Aalst, 2006).

1.1.2 Natural variability

The natural forcing of the climate system includes both external and internal variability (IPCC; Houghton, 2001). Natural variability develops in response to numerous modifications in external forcing and through interactions between the internal elements of the climate system (i.e.: the atmosphere, hydrosphere, cryosphere, lithosphere and biosphere) (Bersch, Yashayaev et Koltermann, 2007; Deser et al., 2012a; Hegerl et al., 2019; Shepherd, 2014). In fact, the findings of some research suggest that this natural variability may be able to obscure the signal of local and regional anthropogenic climate change in temperature and precipitation (Abatzoglou, Williams et Barbero, 2019; Bass et al., 2022; Christidis et Stott, 2021; Deser et al., 2012a; Sarojini, Stott et Black, 2016). Consequently, the chaotic nature of the climate system requires special consideration.

External natural forcing variability mostly results from astronomical and terrestrial variations (Crespin et al., 2013; Woodworth et al., 2019). The Milankovitch cycles and fluctuations in solar activity are the two fundamental astronomical influences (Mcguffie et Henderson-Sellers, 2005). The variations in the eccentricity of the Earth's orbit, the Earth's obliquity, and the Earth's precession, which change over thousands of years, provide a description of the Milankovitch cycles. Earth's orbit fluctuates between elliptical and circular in periods that last about 110,000 years. The angle between the axis of rotation and the axis parallel to its orbital plane is known as obliquity, or terrestrial inclination. This fluctuates between 22° and 24.5° in cycles that span around 41,000 years (Berger, 1988). The terrestrial precession causes fluctuations in the synchronisation of the equinoxes due to the gravitational influence of the other planets. The Earth's two primary precessional cycles have a combined age of around 23,000 years (Hays, Imbrie et Shackleton, 1976; Short et al., 1991). In addition, fluctuations in solar activity occur in cycles that last between 80 and 100 years (Tsiropoula, 2003).

Changes in land use (such as deforestation and desertification), tectonic forces that cause continents to shift or even produce mountains, and fluctuations of gases and aerosols constituting the atmosphere via volcanic eruptions can be mentioned as examples of terrestrial changes influencing the climate (Baede, 2001; Owen, Pickering et Pickering, 2006). Typically, these external forcing mechanisms have an impact on the climate over timescales that are either too short or too long to be considered in anthropogenic climate change impact studies, such as less than ten years for volcanic eruptions, tens of thousands of years for the Milankovitch cycles, and tens to hundreds of millions of years for continental shifts due to plate tectonics (Frankcombe et al., 2015; Hall, 2004; Meehl et al., 2009; Mitchell, 1976). Since the majority of impact research is focused on how the climate will change over the next several decades or centuries, climate change impact studies typically do not take external natural forcing variability into account (Chen et Brissette, 2019).

Internal climate variability (ICV), which may be studied via cycles of changes in the states of the atmosphere and oceans at various time scales ranging from interannual to multidecadal, is the nonlinear variation of the earth's climate at time scales of interest to researchers (Dai et Bloecker, 2019b; Dai et al., 2015; Gu et al., 2019; Sérazin et al., 2016; Zhuan et al., 2018). Some components of internal variability are often measured using differences in pressure or temperature between two places or over specific areas. These components are called teleconnection indices or oscillations (Criado-Aldeanueva et Soto-Navarro, 2013; Domeisen, Garfinkel et Butler, 2019; Khokhlov, Glushkov et Loboda, 2006). For example, Table 1.1 lists six major teleconnection indices which are known to be related to climate anomalies in North America.

The El Niño-Southern Oscillation (Otto-Bliesner et al., 2016) is primarily thought to affect interannual hydroclimatic variability and is linked to the frequency of extreme events such as storms and floods (Martel et al., 2018). The variability of the Pacific Decadal Oscillation (PDO) extends on interannual and decadal time scales, with the latter resulting from oceanic thermal inertia related to the Kuroshio and Oyashio ocean currents (Mantua et Hare, 2002; Newman et al., 2016). The North Atlantic Oscillation (NAO) and the exhibit both long-term changes and interannual variability which is defined as changes in sea level pressure variations (Deser, 2000; He et al., 2017; Hurrell et al., 2003; Wanner et al., 2001).

Table 1.1 Teleconnection indices used to characterize internal climate variability (Martel, 2019)

Index	Type of phenomenon	Periodicity of the signal	Description	Location of the phenomenon
Atlantic Multidecadal Oscillation (AMO)	Oceanic	Interdecadal	Mean SST in the Atlantic, north of the Equator between 0°N -60°N and 75°W-7.5°W	North Atlantic Ocean
Pacific Decadal Oscillation (PDO)	Oceanic	Interdecadal	The leading principal component of monthly SST anomalies in the North Pacific Ocean, poleward of 20°N	North Pacific Ocean
Arctic Oscillation (AO)	Atmospheric	Decadal	Difference in SLP between the North Pole and the 45°N parallel	Extratropical Northern Hemisphere
North Atlantic Oscillation (NAO)	Atmospheric	Decadal	Difference in SLP between the north (Reykjavik, Iceland) and the south (Ponta Deldaga, Spain) of the North Atlantic Basin	Extratropical North Atlantic zone
Pacific North American (PNA) pattern	Atmospheric	Interannual	Quadrupole atmospheric model of anomalies in the geopotential height fields (low pressure)	From the subtropical west Pacific to the east coast of North America
El Niño and Southern Oscillation (ENSO)	Oceanic-Atmospheric	Interannual	Difference in SLP anomalies between Tahiti and Darwin (known as the Southern Oscillation Index) and SST in the equatorial Pacific	Tropical South Pacific

The Atlantic Multidecadal Oscillation (AMO) is a multidecadal variability of sea surface temperature fin the North Atlantic Ocean between latitudes 0° and 70°N. AMO has a 65-70 year cycle with a difference of 0.4°C between extremes (Knight, Folland et Scaife, 2006; Knudsen et al., 2011).

1.2 Potential impacts of climate change

Climate change is among the most important problems the world is currently experiencing (Hardy, 2003; Hoegh-Guldberg et Bruno, 2010; Urry, 2015). It is predicted to have an effect on every aspect of society and human life, with both global and regional consequences (IPCC., Pachauri et Meyer, 2014; Masson-Delmotte et al., 2021). Given the interaction between the climate system and the hydrologic cycle, variations in local and regional water availability would be one of the most significant and immediate consequences of global warming (Barnett, Adam et Lettenmaier, 2005; Sheffield et Wood, 2008; Trenberth, 2011; Xu et Singh, 2004). If climate change consequences are not considered, they will have severe, damaging, and potentially irreversible impacts on people and ecosystems. These effects may be seen in the precipitation patterns, quantity and timing of runoff, the frequency and intensity of floods and droughts, extreme weather events, and the quality and quantity of water available (IPCC., 2013; Jiang et al., 2007). Of the many potential negative impacts, changes in precipitation extremes (and consequently hydrological extremes) are amongst the most critical to engineers since the design of many infrastructures is directly based on the probability of occurrence of extreme events, therefore having a direct impact on public safety (Romanowicz et al., 2016; Westra, Alexander et Zwiers, 2013; Zhang et Zhou, 2019).

1.2.1 Climate change impact on extreme rainfall

In recent decades, many extreme weather events have increased in frequency and intensity (Howe et al., 2014; Zwiers et al., 2013). Due to global warming, the hydrologic cycle is expected to intensify, resulting in an increase in the intensity and frequency of extreme precipitation events and, consequently, potentially increasing the risk of flooding (Tabari, 2020). Recent changes in extreme precipitation across the United States have been the subject of several studies (Akinsanola et al., 2020; Howarth, Thorncroft et Bosart, 2019; Huang et al., 2017; Zhu, 2013). Over the past century, average precipitation has increased by 5-7% nationwide (Westra et al., 2014a). Numerous studies have found that the majority of this increase is in the higher quantiles of the precipitation distribution (Dhakal, 2019; Lopez-Cantu, Prein et Samaras, 2020; Markonis et al., 2019). In the northeastern United States, annual precipitation extremes have increased more than total precipitation, with precipitation extremes during the 1996-2014 period being 53% higher than during the 1901-1995 period (Huang et al., 2019).

Since 1950, temperatures have risen by an unprecedented amount compared to the increases recorded over the past several thousand years. Between 1880 and 2012, the average increase in land and ocean surface temperatures was 0.85°C [0.65 to 1.06°C] (IPCC., 2013). As a result of global warming, the atmosphere is warming, leading to more evaporation and an increase in the amount of water vapor in the troposphere. This can result in increased precipitation and precipitation extremes (Trenberth, 2011). Precipitation extremes are typically described using a threshold in the cumulative precipitation distribution function, such as the 99th percentile (Coles et al., 2001), or other appropriate thresholds depending on the regions and use of the precipitation data (Westra et al., 2014a). Changes in precipitation extremes, however, are not spatially uniform due to the interaction of a number of variables, including moisture availability, evapotranspiration, and the location of the study area (Tabari et al., 2019). For example, evaporation may reduce the increase in precipitation in dry locations, while greater convergence of atmospheric moisture could exacerbate extreme precipitation in wet areas (Held et Soden, 2006).

The growth rate of the air's saturation humidity, which generates extreme precipitation intensity, has been estimated to be 7% per degree increase in the average near-surface atmospheric temperature (Molnar et al., 2015; Westra, Alexander et Zwiers, 2013). This estimate is based on thermodynamics, the dynamics of convective air currents, and the Clausius-Clapyron (CC) equation, which allows us to calculate vapour pressure, heat of vaporisation, and the air's capacity to keep moisture (Capek, 2021).

There are considerable differences in the increase rate of extreme precipitation by latitude (Westra et al., 2014a). Precipitation intensity is projected to increase largely by the end of the current century over mid- and high-latitudes and the humid tropics (Stocker et al., 2013).
The rate of increase in extreme precipitation is not uniform for stratiform and convective precipitation (Ghosh et al., 2016; Norris, Chen et Neelin, 2019). Extreme stratiform precipitation is expected to increase following the Clausius-Clapeyron equation. In contrast, the intensity of extreme convective precipitation in response to warming may exceed (and possibly greatly exceed) the Clausius-Clapeyron rate, a phenomenon called super Clausius-Clapeyron scaling (Molnar et al., 2015).

A substantial scientific consensus exists about the possibility that a warmer climate might enhance the availability of moisture and deep convection, which would result in more intense rainfall, especially for short-term duration and longer return periods (Cannon et Innocenti, 2019; Martel et al., 2021; Pendergrass, 2020).

Based on the dependency between temperature and the air's ability to contain water vapor, convective precipitation shows spatial and temporal characteristics such as being short-duration (1-4 hours) and spatially localized (Chan et al., 2014). The diurnal cycle of solar radiation alters the surface temperature, which alters the patterns of convection and cloud formation and, ultimately, precipitation (Trenberth, 1999). On continental surfaces, convection typically causes rainfall to be at its highest in the afternoon and at its lowest in the morning, but over the ocean, sea/land breeze mesoscale circulation causes the opposite to happen (Bowman et al., 2005; Dai, 2001; Meredith, Ulbrich et Rust, 2019). As a result, studying the diurnal cycle of precipitation is crucial for comprehending rainfall variability as well as the physical processes involved in precipitation creation. It also helps to assess how well weather, climate, and hydrology models work. Convective precipitation typically occurs in small, localised areas and over a relatively short duration (typically 1-4 hours). Convective precipitation dominates hourly extremes, especially those that occur in the summer (Blenkinsop et al., 2017; Lee et al., 2022; Schroeer, Kirchengast et O, 2018). Extreme rainfall at sub-daily time intervals (short duration) is linked to a variety of socioeconomic risks (Fowler, Wasko et Prein, 2021; Gill et Malamud, 2014; Poschlod, Ludwig et Sillmann, 2021).

There is growing evidence, at least across small catchments, that increased sub-daily rainfall is associated with increased flooding risk, as will be further discussed in the next section. Short-duration rainfall extremes can cause landslides, debris flows, and water quality issues, in addition to flooding, all of which can threaten infrastructures, the economy, and population safety (Bruni et al., 2015; Dale, 2021; Ochoa-Rodriguez et al., 2015; Panagos et al., 2017; Poschlod, Ludwig et Sillmann, 2021). It is therefore essential to better understand how variations in the frequency and severity of intense precipitation will affect streamflow discharge. This is particularly critical for sub-daily precipitation where a lot of the projected future increases will take place (Beranová, Kyselý et Hanel, 2018a; Dale, 2021; Förster et Thiele, 2020; Marchi et al., 2010; Yuan, Liu et Wan, 2019). However, due to a lack of subdaily observations as well as the coarse-resolution of global and regional climate models, only a small number of research work has looked at the impact of climate change on subdaily precipitation and streamflow (Bajracharya et al., 2018; Fatichi et al., 2014).

1.2.2 Climate change impact on hydrological extreme

The distribution of streamflow will potentially be strongly influenced by the projected effects of rising temperatures, such as increased convective precipitation, glacier melt, and changes in snowpack (Berghuijs, Woods et Hrachowitz, 2014; Muelchi et al., 2021). According to the Intergovernmental Panel on Climate Change (IPCC., 2013) reports, changes in precipitation variability are likely to result in an increase in extreme events such as flash floods and droughts. The impacts of climate change on extreme events tend to be more significant for society as a whole compared to changes in average conditions, however, the scientific challenges in determining these impacts are also greater (Bruni et al., 2015; Leng et al., 2016; Panagos et al., 2017).

Global studies of precipitation extremes show systematically increasing trends. In contrast, regional studies of flood magnitude show mixed trends (Archfield et al., 2016; Blöschl et al., 2019; Gudmundsson et al., 2021; Sharma, Wasko et Lettenmaier, 2018; Wasko et al., 2021a). The overall magnitude and/or frequency of flooding would be likely to increase with larger or more frequent extreme precipitation events (Collins, 2019; Morante-Carballo et al., 2022; Swain et al., 2020). However, it is also recognized that the hydrologic response to increased extreme precipitation depends on regional climate, individual storm characteristics (such as the existence or absence of hurricanes and atmospheric rivers), and characteristics of surface and subsurface features, such as, for example, topographic features, vegetation, and geology (Devia, Ganasri et Dwarakish, 2015; Lucas-Picher, Laprise et Winger, 2017b). These features can exacerbate or weaken the hydrologic response to extreme precipitation increases. If extreme precipitation intensifies in the future, the risk of flash flooding is expected to increase. Flash floods are generally defined by rapid flooding in small watersheds in response to extreme precipitation events caused by a severe thunderstorm, usually within six hours of the rain event (Hong, Adhikari et Gourley, 2013; Saharia et al., 2017). Flash floods are one of the most serious hydrometeorological hazards and a major cause of property damage and loss of life (Hong, Adhikari et Gourley, 2013). Ashley et Ashley (2008) developed a comprehensive record of flood fatalities across the United States between 1959 and 2005. They report that the majority of deaths were related to flash floods. In 2014 alone, a total of 55 flood deaths were reported, 39 of which were due to flash floods (NWS, Clark et al., 2014). In China, flash floods were responsible for nearly 16,000 deaths between 2000 and 2017. The frequency and severity of flash floods are expected to increase due to an increasing trend in extreme precipitation at continental (Groisman et al., 2004; Howarth, Thorncroft et Bosart, 2019) and global scales (Groisman et al., 2005; Gudmundsson et al., 2019), exacerbated by increasing urbanization. Therefore, assessments of the effects of climate change on streamflow, particularly those related to short-term precipitation extremes, are essential for planners to design adequate adaptation measures and can also serve as a basis for mitigation efforts (Arheimer et Lindström, 2015; Fowler et al., 2021a; Willems et Olsson, 2012).

1.2.3 Flooding sensitivity of small catchments to extreme precipitation

Small watersheds are more sensitive to convective precipitation since their size is of the same order of magnitude as that of the thunderstorm cells (Sharma, Wasko et Lettenmaier, 2018). A convective storm is therefore more likely to cover a large proportion of the size of small watersheds, resulting in rapid saturation of soil moisture and a greater contribution of precipitation to rapid runoff, which translates into heavier and more rapid flooding (Do, Westra et Leonard, 2017). In other words, the duration of precipitation and the size of the watershed must be simultaneously considered in order to properly assess the impact of changing precipitation intensity on future flows (Li et al., 2018; Panthou et al., 2014; Prein et al., 2017a; Wasko, Sharma et Johnson, 2015).

Extreme flows are more likely to be maximized when the duration of precipitation is proportional to the watershed response time, also know as the time of concentration. Therefore, smaller watersheds are more likely to see an increase in flood hazard from convective storm cells, while watersheds larger than storm cells may be less affected due to attenuation of flood waves throughout the watershed (Prein et al., 2017a).

Generally, a flash flood is considered to be a high-intensity rainfall event with rapid peak flows where the catchment area is typically less than 1000 km^2. According to Do, Westra et Leonard (2017), smaller watersheds are more likely to experience increases in flood magnitude while larger watersheds are more likely to experience decreases in peak flooding. In larger watersheds, evaporative losses and changes in soil moisture storage have a greater impact (Ivancic et Shaw, 2015). This implies that future changes in flooding will depend on the watershed scale. Summer-fall flooding in small watersheds will be significantly affected by the transition to more frequent, larger amplitude and shorter duration convective events (Kundzewicz et al., 2014; Oubennaceur et al., 2021; Roy et al., 2001; Špitalar et al., 2014; Westra et al., 2014b).

1.3 Climate change impact studies

Policy makers and planners need to be aware of the potential impacts of climate change on future flows, as these have a significant impact on infrastructure and land management. Many infrastructures have long enough life spans that future climate should be part of the design criteria. Land use decisions are difficult to reverse in the future, and must therefore also be based on future climate and hydrology (Hurlimann, Moosavi et Browne, 2021; Kumar et Geneletti, 2015; Lawrence, Blackett et Cradock-Henry, 2020; Weaver et al., 2013).

A first solution to projecting future climate and hydrology is to examine past trends and extrapolate them (Willems et Olsson, 2012). However, it is extremely difficult to properly analyze extreme events due to the scarcity of observations and limited durations of observed data (Lewis et al., 2019). Most of the time, information on the magnitude and frequency of historical extreme hydrological events is insufficient to properly assess the historical period, let alone to project them into the future (Knox et Kundzewicz, 1997; Mandal et Simonovic, 2017; Merz et Blöschl, 2008; Shrestha et al., 2017a).

The study of past climatic conditions can also be done via several indirect environmental observations made by the geological, botanical and geographical sciences. Paleoclimate archives, such as tree rings and ice cores from Antarctica and ocean sediments, have provided a better understanding of climate variability and sensitivity. Although paleoclimate series provide information on climate sensitivity and the links between certain gases (e.g. CO2) and temperature, they are of limited use in view of the extremely rapid changes observed and the exponential increase in anthropogenic greenhouse gases (IPCC, 2013).

The best knowledge of future climate comes from climate models (Löllgen, Erdmann et Gitt, 2009). Climate models are numerical models that use mathematical equations to simulate how the climate system responds to greenhouse gases forcing and how the world's oceans and atmosphere interact dynamically (Flato et al., 2014; Schneider et Dickinson, 1974; Solomon et al., 2007). Climate models are the best available alternative to the real world. More details on climate models are presented in Section 1.3.2.

To project the impacts of climate change on future streamflow and to estimate the uncertainties, a hydroclimatic modeling chain is typically used, as shown in Figure 1.1. This chain begins with a selection of future radiative forcing scenarios (Hakala et al., 2019). These scenarios are used by climate models to generate projections of future climate variables, such as precipitation and temperature. Since the latter are generally biased, bias correction methods are applied to ensure that the response of the impact models (e.g., hydrological model) is accurate over a historical reference period. Once corrected, the climate model outputs are fed into the impact models to assess future impacts on various variables of interest (e.g., streamflow). To assess the uncertainty in these projections, ensembles of climate models and impact models are frequently used (e.g., Gao, Booij et Xu, 2020; Givati et al., 2019; Gosling et al., 2017; Haddeland et al., 2014; Kay et al., 2020; Vetter et al., 2017).

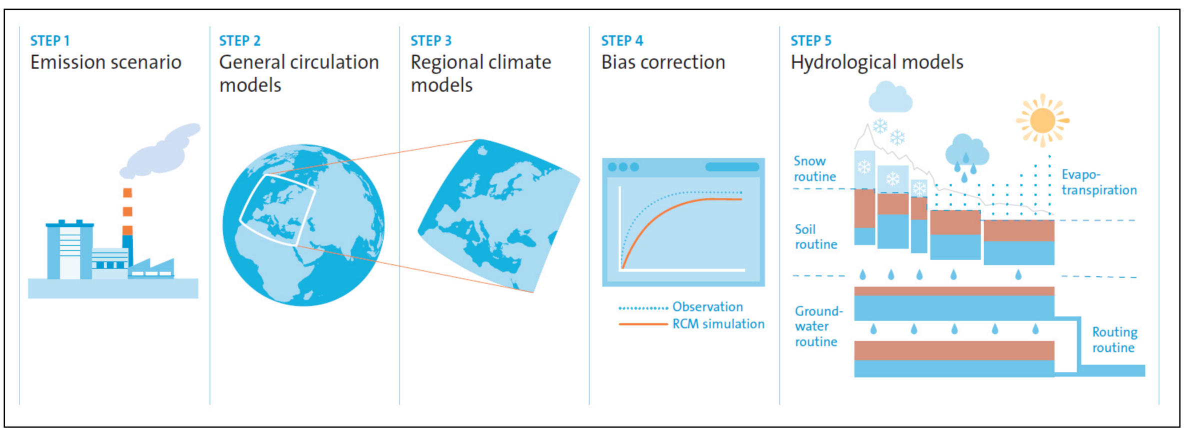

Figure 1.1 Schematic of a model chain used for evaluation the hydro-climatic change impact studies (Based on Hakala et al., 2019).

1.3.1 Greenhouse gases emission scenarios

There are several climate modeling centers in several countries (IPCC., 2013). To facilitate comparison of the results produced by the different climate modeling centers, the research community has come together to define a set of plausible scenarios of future changes in the concentration of future greenhouse gases. The Intergovernmental Panel on Climate Change (IPCC; Solomon, 2007) published its first set of climate change scenarios in 1992.

The scenarios come from energy system modelers and use integrated assessment models to forecast future energy technologies and demands to provide a range of likely future emissions (IPCC., 2013). These models generate future emission trajectories with a range of scenarios that can be described as optimistic to pessimistic. These scenarios are used by climate modeling centers to generate future climate projections. The emission scenarios are updated periodically to better reflect the state of knowledge. These include the six 1992 IPCC scenarios (IS92), the six Special Report on Emissions Scenarios (SRES), the four Representative Concentration Pathway (RCP) scenarios used for the IPCC Fifth Assessment Report (AR5), and the nine Shared Socioeconomic Pathways (SSP) used for the IPCC Sixth Assessment Report (AR6) (Nakicenovic et al., 2000).

In this thesis the RCP scenarios were the ones used. Each RCP specifies a certain emission pathway and its associated radiative forcing. The radiative forcing expresses the additional energy reaching the earth's surface (in watts/m^2) as a result of anthropogenic emissions of greenhouse gases. For example, the RCP8.5 pathway stipulates an additional global mean forcing of 8.5 watts/m^2 , in addition to the natural average pre-industrial forcing (Meinshausen et al., 2011).

1.3.1.1 Representative Concentration Pathway (RCP) Scenarios

There are four RCP scenarios labeled 2.6, 4.5, 6.0 and 8.5. The RCP2.6 scenario corresponds to the path of lowest increases in greenhouse gas concentrations. This scenario is considered a "peak and decline" scenario because its radiative forcing level increases to about 3.1 W/m^2 by mid-century and then declines to 2.6 W/m^2 by 2100 (Van Vuuren et al., 2011b). To achieve this level of radiative forcing, greenhouse gas emissions (and therefore air pollution emissions) must be reduced significantly over time (Nazarenko et al., 2015). RCP 4.5 is characterized as a stability scenario. In this case, global radiative forcing stabilizes at 4.5 W/m2 at the beginning of 2100, without exceeding the target long-term radiative forcing threshold (Thomson et al., 2011). According to the IPCC, RCP 4.5 is a moderate scenario in which emissions peak around 2040 and decline thereafter (Knutson et al., 2015). RCP 6.0 uses a higher rate of greenhouse gas emissions, and is a stabilization scenario in which total radiative forcing is stabilized after 2100 through the implementation of various greenhouse gas emission reduction technologies and tactics. The radiative forcing achieved in 2100 is 6.0 W/m^2. According to RCP 6.0, emissions are expected to double by 2060 and then decline sharply (Dhomse et al., 2018). However, it is crucial to remember that even with this huge reduction, emissions would still be higher than today. Carbon dioxide emissions are expected to continue to increase, albeit at a slower rate, as the century progresses. RCP 8.5 is the most pessimistic scenario for future emissions. RCP 8.5 is characterized by a very significant increase in greenhouse gas emissions over the course of the century, with the largest increase occurring in the early to mid-century of this century. In this scenario, the concentration of carbon dioxide in the atmosphere will continue to increase throughout the next century (Hausfather, 2019).

The RCP8.5 scenario is considered increasingly unlikely. However, climate modeling with high forcing scenarios such as RCP8.5 is extremely useful since it results in higher impacts and thus more easily discernible from natural internal variability (Hausfather, 2019). These scenarios thus provide climate projections with a higher signal-to-noise ratio. This is particularly important for climate change attribution studies, which seek to determine the contribution of anthropogenic climate change to natural climate variability.

1.3.2 Climate models

All climate models (GCMs) consist of a "dynamical core" that uses classical equations to model large-scale fluid motion and a "physical model" that simulates physical processes important to climate science, such as radiative transfer, cloud formation, and convection. These interactions typically occur in the real environment at scales smaller than the numerical grid of the models. The impact of aerosols, heat fluxes between the ocean and atmosphere, friction between land or ocean surfaces and air, and many other processes are also included in the physics of the models (Edwards, 2011; Palmer, 2019). By using "parameters," i.e., mathematical functions and constants, modelers can capture the impact of small-scale processes on a larger scale without explicitly modeling those small-scale processes. The most critical part of climate modeling and the cause of significant scientific and political debate is the precise parameterization of these physical processes (Berner et al., 2017; Coakley Jr, Cess et Yurevich, 1983; Dickinson, 1995).

The goal of climate models is to represent long-term changes in the atmospheric system at global and regional scales. Because simulated climate data are based on the fundamental conservation laws of mass, energy, and momentum, climate models produce physically consistent data (Caya et Laprise, 1999; IPCC; Solomon, 2007). By modeling and predicting the behavior of various variables in a future climate, they help improve our understanding of the climate system. To project climate in terms of changing greenhouse gas concentrations, climate models are run in a model chain, with emissions scenarios serving as the radiative forcing for the future period, whereas measured gas concentration are used for modeling the historical period.

The Earth's climate has fluctuated over time, as shown by climate reconstructions from ice cores, sediments, tree rings, etc. The evidence indicates that the Earth's climate occurs in cycles of known duration. Insofar as they are created to simulate the mechanisms behind these oscillations, climate models are a state-of-the-art tool that allows modelers to explore and understand the behavior of past, present, and future climate (Giorgi, 2006; Randall et al., 2007; Rummukainen, 2010).

Producing climate simulations in an acceptable time frame requires considerable computing time and the use of supercomputers. Despite the power of modern supercomputers, the numerical mesh scale of global climate models remains coarse (80 to 350 km) (Palmer, 2015; Palmer, 2019; Washington, Buja et Craig, 2009). This coarse scale and the need to parameterize many physical processes results in simulations of the current climate that may differ from observed data at the regional scale. Despite this, climate models are able to produce spatially and physically realistic simulations of the present climate as well as plausible future projections consistent with the climate sensitivity estimated by various paleoclimate studies (Randall et al., 2007).

1.3.3 Downscaling

GCMs are now being used in the majority of climate change research. However, the ability of GCMs to produce accurate information at local and regional scales is limited by their coarse spatial resolution, which limits the direct use of their data to continental and global scale climate change studies (Kitchin et Thrift, 2009; Liang et al., 2006). Assessing the impact of climate change on hydrology has several limitations due to the coarse geographic resolution of GCM results (Chen et al., 2011b; Chokkavarapu et Mandla, 2019; Teutschbein, Wetterhall et Seibert, 2011). For example, GCMs are unable to provide elevation-dependent information such as temperature and precipitation in mountainous regions, yet this information plays a key role in hydrological modeling (Seager, Naik et Vecchi, 2010). In addition, because GCM data typically contain daily or coarser temporal scale information, they are not suitable for studies of processes that depend on sub-daily processes, such as small watershed hydrology (Fowler et al., 2021b; Trzaska et Schnarr, 2014b). The spatial and temporal resolutions of GCMs are still limited by the high computational cost from these simulations (Benedict et al., 2019; Li et al., 2019b; Prudhomme, Reynard et Crooks, 2002; Rummukainen, 2010). In general, increasing the resolution by a factor of 2 (e.g., from a 200km grid to a 100km grid) results in an increase in computational cost by a factor of 16 (2^4) since refinement must be performed on the X, Y, Z spatial grid as well as in time to meet the numerical stability criteria for solving the differential equations of the dynamic part of the climate model.

To solve this problem, researchers use downscaling approaches to post-process and recalibrate the raw GCM forecasts. Downscaling methods were established to bridge the gap between the coarse resolution (spatial and temporal) of GCMs and the finer resolution needed to study climate and hydrology at a regional or local spatial scale. To obtain finer scale climate information, the interaction between GCM outputs and local features (water bodies, mountain ranges, land cover/land use, etc.) is used and modeled by downscaling methods (Bhuvandas et al., 2014; Chokkavarapu et Mandla, 2019; Smid et Costa, 2018; Trzaska et Schnarr, 2014b). Depending on the conceptual and mathematical structures employed in these approaches, there are two main downscaling methods: statistical downscaling and dynamic downscaling (Boé et al., 2007; Hellström et al., 2001; Schmidli, Frei et Vidale, 2006; Tang et al., 2016; Tiwari et al., 2019; Walton et al., 2020), which have different characteristics with competitive advantages and clear disadvantages.

1.3.3.1 Dynamic downscaling methods

Dynamic downscaling uses finer-grid climate models, called regional climate models (RCMs), to provide climate data at a higher spatiotemporal resolution (e.g., Adachi et Tomita, 2020; Tang et al., 2016; Tapiador et al., 2020; Xu, Han et Yang, 2019; Xue et al., 2014). RCMs allow for simulations to be made at a higher-resolution at the expense of foregoing the global scale and focusing on specific regions (such as North America or Europe). RCMs, on the other hand, must still use GCM/ESM outputs or meteorological reanalysis data at the boundaries of the sub-domain over which the high-resolution simulations will be performed. RCMs produce high resolution data, which can be very useful in some cases such as in regions with complex topography (Feldmann et al., 2013; Gao, Pal et Giorgi, 2006; Li et al., 2017b; PaiMazumder et al., 2013; Poschlod, 2021; Yu et al., 2020).

Since precipitation is spatially highly variable and has a strong correlation with surface topography and physiography, using RCMs to project hydroclimatic variables such as precipitation and flash floods is therefore a useful approach (Erler, Peltier et d'Orgeville, 2015; Gorguner, Kavvas et Ishida, 2019; Music et al., 2015; Samuelsson et al., 2011; Wi et al., 2012).

Compared to GCMs and ESMs, downscaling using high-resolution RCMs has typically improved projections of mean and extreme precipitation at local and regional scales (Buonomo et al., 2007; Gao, Pal et Giorgi, 2006; Nishant et Sherwood, 2021; Pinto et al., 2016). The accuracy of RCM results depends on the quality of the GCM used at the domain boundary, as well as on the quality of the climate model structure on which they are based (Chomé, Vannitsem et Nicolis, 2002; Rummukainen, 2010; Vannitsem et Chomé, 2005; Yhang et Hong, 2008). Like GCMs, RCMs also often tend to underestimate the probability of extreme precipitation while overestimating the frequency of light precipitation (Barrow et Sauchyn, 2017; Buonomo et al., 2007; Dong et al., 2022; Fowler, Blenkinsop et Tebaldi, 2007; Haylock et al., 2006; Rajczak, Pall et Schär, 2013; Sunyer, Madsen et Ang, 2012). Despite the improved resolution of RCMs (typically greater than 12km) many physical processes still require parameterization. Recently, several studies have used convection-permitting regional climate models (e.g., Chan et al., 2013; Fumière et al., 2020; Kendon et al., 2017; Prein et al., 2015; Vanden Broucke et al., 2019; Yun et al., 2020). These models can resolve the convection directly in the physical part of the model, which improves the quality of extreme precipitation (e.g. Lucas-Picher et al., 2021b). However, these models require a very fine spatial grid (<3km). To compensate for the exponentially increasing computational costs at such scales, these models are only used over small spatial regions.

1.3.3.2 Statistical downscaling methods

Statistical downscaling methods consist of developing numerical relationships between large-scale (e.g., outputs of GCMs/ESMs and RCMs) and local/regional-scale variables (Benestad, Hanssen-Bauer et Chen, 2008; Schmidli, Frei et Vidale, 2006; Wilby et al., 1998). A statistical relationship is established over a reference period and then extrapolated to the local variable at a future time. Although statistical downscaling methods have some weaknesses, such as the validity of the statistical relationship in a changed climate, they are a simple and inexpensive option compared to dynamic downscaling. For these reasons, they have been widely used in impact studies (Benestad, Chen et Hanssen-Bauer, 2008; Diaz-Nieto et Wilby, 2005; Schmidli et al., 2007; Zhang et al., 2020).

In general, there are three main classes of statistical downscaling techniques: perfect prognosis (Pinto et al., 2010), weather generators (Wilby, Dawson et Barrow, 2002), and model output statistics. In the perfect prognosis approach, observed data is used to calibrate a statistical model that relates large-scale predictors to local-scale predictands. Then, the statistical model is used to simulate the predictand in a future period. The predictors are typically based on synoptic meteorology and climatology, which are well-reproduced by GCM/ESM (Wilks, 2011). However, typically, synoptic-scale predictors only explain a moderate fraction of the variance of local variables, and in particular for precipitation, which limits the effectiveness on the method (Murphy, 1999).

Weather generators are mathematical tools that have been developed to generate time series of climate data such as precipitation and temperature (e.g. Richardson et Wright, 1984) (e.g. Richardson and Wright 1984). Weather generator parameters are generally based on basic climate data (e.g., monthly mean precipitation) that are relatively well simulated by GCM/ESMs. By modifying the parameters of a climate generator, it is relatively simple to produce future climate series (Ailliot et al., 2015). Climate generators, however, are generally not very good at reproducing extremes and simulating internal climate variability (Fowler, Blenkinsop et Tebaldi, 2007; Kilsby et al., 2007).

Model output statistics (MOS) involve correction methods to directly correct the bias of key outputs (e.g. precipitation) from climate models using time series of observations (Glahn et Lowry, 1972; Gutiérrez et al., 2019). In the following section, this approach is explored in more detail.

1.3.4 Bias correction

Although the structure and resolution of climate model outputs are constantly being improved, model outputs nevertheless remain too biased to be used directly within hydrological models to assess the impacts of climate change on hydrology (Chen et al., 2013a; Chen et al., 2019; Hagemann et al., 2013; Muerth et al., 2013; Piani et al., 2010; Potter et al., 2020). For example, the majority of climate models tend to overestimate the frequency of precipitation and the incidence of light precipitation, while underestimating the intensity of heavy precipitation (Klutse et al., 2021; Olmo et Bettolli, 2021; Tang et al., 2022). In addition, the biases depend on the seasons and regions considered (Kotlarski et al., 2005; 2019; Liang et al., 2008; Timm et al., 2008). Because of the challenges of simulating convective precipitation, climate models are generally less accurate when describing convective summer precipitation than for fall and winter synoptic precipitation (Fosser, Khodayar et Berg, 2015; Kendon et al., 2017; Maraun et al., 2010). Climate models perform better in temperate climate regions compared to tropical regions since tropical precipitation often has a predominantly convective structure and occurs on a sub-daily time scale (Lenderink et Van Meijgaard, 2008a). Although regional models generally reduce the magnitude of biases, data used at boundary conditions can also introduce biases, as can model systemic errors, such as those caused by imprecision in the parameterization of some climate processes (Rocheta, Evans et Sharma, 2020; Teutschbein et Seibert, 2013).

Therefore, post-processing of climate model data is generally considered an essential step in climate change impact studies (Chen et al., 2021a; Luo, 2016). Different numerical algorithms are used in the bias correction of climate model outputs. In the last decade, various bias correction approaches have been developed, ranging from simple scaling to complex distribution mapping (Chen et al., 2013a; Cho et al., 2020; Durai et Bhradwaj, 2014; Fang et al., 2015; Goshime, Absi et Ledésert, 2019; Luo et al., 2018; Mendez et al., 2020; Mpelasoka et Chiew, 2009; Terink et al., 2010; Teutschbein et Seibert, 2013). Bias correction remains a controversial topic (Muerth et al., 2013), especially within the climate modeling community. Indeed, the application of bias correction to climate simulations can reduce the range of inter-model uncertainty, some approaches destroy existing relationships within the variables from the climate models and do not respect the climate change signal from the climate model (Vrac, 2018; Yang et al., 2015). In addition, the approach relies on the assumption of stationarity of biases over time, which has been shown to be an incorrect assumption (e.g., Chen, Brissette et Caya, 2020).

Since they affect the quality of the corrected data from the climate models, bias correction techniques also affect the data from the hydrological models (Chen et al., 2013a; Chen et al., 2019; Ghimire, Srinivasan et Agarwal, 2019; Rojas et al., 2011; Zalachori et al., 2012). The characteristics of the simulated streamflow are considerably improved following the correction of biases, but these depend in part on the correction method used (Crochemore, Ramos et Pappenberger, 2016; Fang et al., 2015; Hashino, Bradley et Schwartz, 2007; Meyer et al., 2019; Teutschbein et Seibert, 2012; Worako, Haile et Taye, 2022). It is therefore important to evaluate and contrast the performance of different bias correction techniques.

The linear scaling technique (Lenderink, Buishand et Van Deursen, 2007) uses correction values that are determined by the differences between the average values simulated from observations and the corrected values over a historical reference period. Following bias correction, the corrected monthly values will be identical to the observed ones. While linear scaling can account for a bias in the mean, it cannot correct for changes in variance and biases in the frequency or intensity of wet days, because every precipitation event during a given month receives the same adjustment (Serinaldi, Kilsby et Lombardo, 2018). Therefore, the bias-corrected data have variability that is more consistent with the original climate model data rather than the observed data (Graham, Andréasson et Carlsson, 2007). The local intensity scale (LOCI), introduced by Schmidli, Frei et Vidale (2006) extends the linear scaling by individually adjusting the mean and the frequency and intensity of wet days. In order to explicitly modify the variance statistics of a precipitation time series, a non-linear fit in exponential form can be applied (Leander et al., 2008). The variance and mean of the raw climatic model data are modified by a power transformation and variance scaling. This results in a better performance in terms of variability and a number of other statistical features (Chen et al., 2011b; Leander et Buishand, 2007).

There are several available bias correction techniques, but those using the quantile distribution mapping (QM) technique are the most commonly used (Cannon, Sobie et Murdock, 2015; Grillakis et al., 2017; Heo et al., 2019; Ngai, Tangang et Juneng, 2017; Yang et al., 2018). Quantile mapping allows for the distribution function of climate model variables to be matched (mapped) onto the observed distribution function. This can be accomplished by developing a transfer function to modify the distributions of temperature and precipitation, including magnitude and frequency in the latter case (Enayati et al., 2021; Maurer et Pierce, 2014; Sennikovs et Bethers, 2009). Quantile mapping successfully removes model biases for extreme events as well as mean and interannual variability (Cannon, Sobie et Murdock, 2015; Enayati et al., 2021; Maraun, 2013a; Piani et al., 2010; Teutschbein et Seibert, 2012; Thrasher et al., 2012). In order to correct daily precipitation simulated over Europe by a climate model, Piani et al. (2010) validated a bias correction method that was based on distribution mapping (gamma distribution). The results showed that this method worked largely satisfactorily, not only for the mean values but also for the distribution of precipitation intensity and for derived variables such as drought indices. Teutschbein et Seibert (2012) evaluated the hydrological effects of climate change for five catchments in Sweden, ranging in size from 147 to 293 km^2. They examined four bias correction techniques for precipitation and three bias correction techniques

for temperature. The results showed that all bias correction techniques improved the results. However, the performance of the modified temperature and precipitation depended on the correction technique chosen. Quantile mapping performed very well in predicting hydrological extremes, making it the best correction technique (Ayugi et al., 2020; Cannon, Sobie et Murdock, 2015; Park, Kang et Song, 2012).
Given the good performance of quantile mapping, many variants of the method have been proposed (e.g., Enayati et al., 2021; Gudmundsson et al., 2012; Verfaillie et al., 2017). The majority of the proposed variants are univariate, i.e., they are designed to correct climate model variables one at a time. Even if the characteristics of the univariate distribution are successfully modified according to the observed reference dataset, the statistical relationship between the different variables from the climate model are generally not respected (Maraun, 2013a). Impact study results can therefore be biased if the correction technique ignores the observed inter-variable and inter-site relationships, leading to corrected outputs which do not respect some physical constraints (Zscheischler, Fischer et Lange, 2019). Because of these problems, multivariate bias correction techniques have recently been developed. These techniques attempt to preserve the dependence structure of the climate simulations in addition to adjusting the properties of the univariate distribution (Alidoost et al., 2021; Cannon, 2018; 2016; Meyer et al., 2019).

As mentioned earlier, mesoscale convective systems, which form mainly in the afternoon and early evening, have a significant impact on the overall pattern of the diurnal precipitation cycle. Summer precipitation has considerable regional disparities and large diurnal fluctuations due to monsoon, topography and other reasons (Chen, Sha et Iwasaki, 2009; Li et al., 2015; Liu et al., 2022; Mao et Wu, 2012; Singh et Nakamura, 2009; Vondou et al., 2010; Wang, Hou et Wang, 2017; Yu et al., 2014). Climate model outputs are now more and more frequently available at sub-daily time scales. Analysis of sub-daily climate data show that the diurnal cycle predicted by these models is generally also biased. A very small number of studies has examined the issue of correcting the diurnal cycle bias of sub-daily outputs of climate models

(Li et al., 2017a; Requena et al., 2021). Whether or not we should account for the diurnal cycle bias of climate model outputs remains an unresolved question today.

1.3.5 Hydrological model

One of the key steps in the hydroclimatic modelling chain is hydrological modelling, which allows the creation of streamflow simulations for basin-scale impact evaluations. A hydrological model can be defined as a simplified representation of a real-world system for understanding and forecasting the processes of hydrological systems and their behaviors (North, Pyle et Zhang, 2014). The complexity of the governing equations used to calculate runoff determines the structure of a rainfall-runoff model (Haddeland et al., 2011). The three structural types of the hydrological model are empirical, conceptual, and physical, which increase in complexity in that order.

1.3.5.1 Empirical models (metric model)

Empirical models are observation-oriented and rely solely on information from available data, without taking into account the characteristics and processes of the hydrological system; as such, they are also referred to as "data-driven". These models use non-linear statistical equations derived from contemporaneous input and output time series, rather than the catchment's physical processes. They can be used when other outputs, such as the distribution of runoff values between upstream and downstream, are not needed (Devia, Ganasri et Dwarakish, 2015). Examples of techniques employed to determine the functional relationship between inputs and outputs include the SCS-Curve Number, used in the Soil and Water Assessment Tool (SWAT) (Douglas-Mankin, Srinivasan et Arnold, 2010), fuzzy regression equations(Chang et Ayyub, 2001), and artificial and deep neural networks. Empirical models are often selected for modelling due to their simplicity of use, efficient calculation speeds, and affordability (Abdulkareem et al., 2018; Devia, Ganasri et Dwarakish, 2015; Holmgren, 1994).

1.3.5.2 Conceptual models (parametric models)

Conceptual models are sets of assumptions that represent how we interpret surface and groundwater systems and the individual hydrological processes that make them up. They are composed of several linked reservoirs that offer a representation of the physical components of a watershed, which are fed by precipitation, infiltration, and percolation and drained by evaporation, runoff, drainage, etc. These models require a variety of input parameters and meteorological data in order to provide a conceptual understanding of the behaviours in a catchment. This approach employs semi-empirical equations, and the model parameters are evaluated through calibration and field data (Abdelmegid et al., 2020; Aghakouchak et Habib, 2010; Kavetski, Kuczera et Franks, 2006; Liu et al., 2019).

Due to their simplicity of use and calibration, conceptual models have become extremely common in the modelling field. However, their main restriction is a general lack of physical meaning in the equation and its parameters (Mudashiru et al., 2021; Robinson et al., 2015). When computing time is constrained and detailed catchment information is not available, conceptual models work well. The Stanford Watershed Model IV of Crawford et Linsley (1966), which included up to 20 parameters, was the first significant conceptual model. Some examples of conceptual models are the Topography-based Hydrological Model (TOPMODEL) (Beven, 1997; Beven et Freer, 2001), Hydrologica Byrns Vattenbalansavdelning (HBV) (Bergström, 1995), and Génie Rural à 4 paramètres Journalier (GR4J) (Perrin, Michel et Andréassian, 2003).

1.3.5.3 Physically based model

Physical models are founded on knowledge of the physics pertaining to hydrological processes (Coron et al., 2012). These models are driven by physically based equations. Physical models employ quantifiable state variables which can vary in time and space within the catchment. Conservation of mass, energy and momentum constitute the base of physical models (Abbott et al., 1986). For their calibration, they do not require considerable hydrological and meteorological data, but instead they demand a substantial number of information describing the catchment's physical features (Devia, Ganasri et Dwarakish, 2015). The relationship between model parameters and actual physical catchment features is a physical model's greatest strength. Physical models are normally spatially distributed, so that they represent physical processes based on the spatial distribution of land surface, vegetation, soil and bedrock. Physical processes are therefore spatially modelled. This is in opposition to lumped models which consider the catchment as a single, uniform entity with no spatial variability. A lumped model is designed with the single goal of simulating total runoff and streamflow at the catchment outlet. Conceptual and empirical models are usually run as lumped models. Semi-distributed models take into account some amount of spatial variability without a complex model framework (Jajarmizadeh, Harun et Salarpour, 2012; Paniconi et Putti, 2015; Trinh et al., 2016).

As mentioned above, physically-based models are generally fully-distributed models. They divide the modelling process into discrete grid cells or small pieces. Each small component (or cell) has a unique hydrological response that is computed independently without taking into account connections with neighboring cells (Paniconi et Putti, 2015; Rinsema, 2014). They provide comprehensive runoff data from different points within the catchment by calculating runoff for each grid cell. The requirement for distributed data and parameter value for each grid cell is the main drawback of distributed models (Devia, Ganasri et Dwarakish, 2015).

Whereas in theory, distributed models should perform better than their lumped counterparts, the reality has had mixed results. According to Beven (1989) and Grayson, Moore et McMahon (1992), physically based distributed models, as compared to lumped models, often give only marginally better, if not equal, or even poorer simulated flows. When Reed et al. (2004) reported the findings of a comprehensive inter-comparison analysis of a number of physically based and conceptual distributed models, they came to a similar conclusion and noted that, in more cases than not, the lumped model performed better than the distributed model when the goal was simulating outflows at the catchment outlet. Given these findings and the significant amount of work, computation time, and cost required to parameterize and test distributed hydrological models, it makes sense that most climate change impact studies tend to use the lumped model to simulate the discharge of a large number of catchments.

1.3.6 Hydrological Model Calibration

There are still physical processes characterizing the hydrological cycle that are not completely understood. Additionally, there is a dearth of data that prevents the use of the most comprehensive physical equations. Therefore, it generally necessary to calibrate hydrological models in an attempt to get the optimum parameter set for the catchment under investigation (Bárdossy, 2007; Pechlivanidis et al., 2011). Typically, optimization procedures are used to calibrate the parameters such that the simulated flow matches up with historical observations. The matching performance is assessed using an objective function. The most commonly used objective function in hydrology is that of Nash and Sutcliffe (NSE Nash, 1970) . Equation (1.1) is used to compute the NSE:

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_{Sim}^{t} - Q_{Obs}^{t})^2}{\sum_{t=1}^{T}(Q_{Obs}^{t} - \overline{Q}_{Obs})^2} \tag{1.1}$$

where, Q_{Obs} stands for observed flows and Q_{Sim} for modeled flows at time t, and $\overline{Q}_{Obs}$ is for the mean of the observed discharge.

The Kling and Gupta objective function (KGE; et al., 2009) is another objective function which has recently been used more frequently in hydrological studies and is described as Equation (1.2):

$$KGE = 1 - (\sqrt{(r-1)^2} + (\alpha - 1)^2 + (\beta - 1)^2\ ) \tag{1.2}$$

where α represents the standard deviation, r represents the correlation coefficient, and β represents the bias between the simulated and observed flows. Although KGE and NSE are comparable, KGE has been employed more frequently because of its multi-objective structure, which aims to minimise errors related to bias, variability, and correlation (Pechlivanidis et al., 2014; Santos, Thirel et Perrin, 2018).

1.4 Uncertainty in climate change impact studies

When assessing the impact of climate change, there are many methodological choices to be made, for example the choice of a climate model and greenhouse gases emission scenario and bias correction method. Different choices will likely result in different future impacts. It is therefore important to use many different choices to assess how they affect the future, and hence generate uncertainty (Bastola, Murphy et Sweeney, 2011; Lee, Galavi et Huang, 2014; Ludwig et al., 2009; Viner, 2002). However, because there are so many options at each step of the hydroclimatic modelling chain, it is getting increasingly difficult to evaluate the uncertainties that come from the combinations of those options (Wilby et Harris, 2006). The uncertainty cascade is divided into the components of the hydroclimatic modeling chain, as described in Section 1.3. The main elements are described below.

1.4.1 Uncertainty of Greenhouse Gas Emissions Scenario (GGES)

The primary source of uncertainty in climate models is the change in greenhouse gas emissions due to human activity (Kundzewicz et al., 2018). This uncertainty is distinct from other sources of uncertainty, as it is primarily influenced by political and socio-economic factors, rather than a lack of knowledge about the natural environment. The Intergovernmental Panel on Climate Change (IPCC; Solomon, 2007) has identified several factors that can affect greenhouse gas emissions, including socio-economic development, the use of carbon-free energy, and population growth. These factors can lead to different scenarios, which can produce a range of outcomes when used in simulations. The uncertainties associated with climate change modeling increase with a longer time horizon. To account for these uncertainties, various emissions scenarios have been developed. These scenarios may not differ significantly in the first half of the 21st century, but can become more important in the second half (Hawkins et Sutton, 2009a; IPCC., Pachauri et Meyer, 2014).

1.4.2 Uncertainty related to climate models

There are two main sources of uncertainty in climate models: the parameterization and structure of the models themselves, and natural variability (Hakala et al., 2019). The way in which different organizations construct their models can lead to different projections, even when using the same data. For example, different groups may use different approaches to parameterizing convection, leading to differing projections of extreme rainfall events. The coarseness of the models also limits their ability to represent certain processes (Hakala et al., 2019). Additionally, natural variability in the climate system makes it difficult to accurately predict weather and future climate conditions (Cayan et al., 2016). Even when using the same model with only slight variations in initial conditions, different projections can result due to the inherent variability of the climate system (Knutti et Sedláček, 2013) (e.g. This natural variability is irreducible and is unlikely to be reduced in future generations of climate models (Lorenz, 1963; Schirmer et al., 2022).

1.4.3 Uncertainty of downscaling

Statistical downscaling is a technique that is used to incorporate the effects of climate change into smaller scale models. This technique relies on statistical correlations between observed and climate model data, and therefore is impacted by uncertainties in these datasets (Benestad, Hanssen-Bauer et Chen, 2008; Wilby et al., 1998). Additionally, the assumption that the signal of climate change can be detected by large-scale predictors introduces further uncertainty. There are various SD methods available, each with their own sources of uncertainty (Wilby et Dawson, 2013). Dynamic downscaling, which involves using high-resolution regional climate models (RCMs) to refine the projections of large-scale global climate models (GCMs), is also subject to uncertainties related to model structure and parameterization and natural variability (Schoetter et al., 2020; Xue et al., 2014). These uncertainties can lead to consistent errors in the model projections, which highlights the need for bias correction and the use of an ensemble approach when using RCM predictions to model future streamflow (Gutiérrez et al., 2019; Ivanov et Kotlarski, 2017; Teutschbein et Seibert, 2013).

1.4.4 Uncertainty of bias correction

According to research, the choice of bias correction technique can affect the overall uncertainty of the modeling process (Iizumi et al., 2017). For example, a study by Sunyer et al. (2017) found that different techniques for bias correction resulted in varying levels of uncertainty, depending on the catchment area and season being considered. The statistical correlations established through bias correction are also influenced by uncertainties in the observed datasets (Chen et al., 2011a; Piani et al., 2010; Song, Chung et Shiru, 2020).

1.4.5 Uncertainty of hydrological model

There are several factors that contribute to uncertainty in hydrological models, including model parameters, observational data, and hydrological model structure (Liu et Gupta, 2007). Uncertainty in model parameters can arise from the assumption that parameter values will remain constant in changing climate conditions and the difficulty in constraining parameters with available data and information. The structure of the hydrological model can also impact how the hydrological system responds to climate change (Hrachowitz et Clark, 2017; Seiller, Anctil et Roy, 2017). Simple models may perform equally well as more complex models in terms of catchment discharge, but increasing model complexity without sufficient data may lead to higher uncertainty and longer run times (Breuer et al., 2009; Hakala et al., 2019; Seibert et van Meerveld, 2016).

Observational data is important for driving and calibrating hydrological model simulations, but there may be uncertainty in the data due to instrument problems, spatial heterogeneities, and temporal variability (Refsgaard et al., 2006).

In general, the uncertainty associated with global climate models (GCMs) is the greatest for both climate forecasts and hydrological impacts (Chen et al., 2011b; Dobler et al., 2012; Her et al., 2019; Shen et al., 2018), but other sources of uncertainty, such as the downscaling method and GCM initial conditions, can also be significant. Some studies have found that natural variability is the second or third most important source of uncertainty, after GCMs (Chen et al., 2011b; Garcia-Menendez, Monier et Selin, 2017; Schwarzwald et Lenssen, 2022; Seiller et Anctil, 2014).

1.5 Role and importance of natural variability analysis

Internal climate variability can have significant impacts on local and regional scales, potentially even rivaling the effects of anthropogenic climate change (Fyfe et al., 2016; Gu et al., 2019; Martel et al., 2018; Swart et al., 2015). This is particularly true in polar and extra-tropical latitudes in the near future (Bengtsson et Hodges, 2019; Deser et al., 2012c; Hallegatte, 2014; Wallace et al., 2014). Multidecadal to decadal internal climate variability significantly affects hydro-climatological variables by influencing local and regional trends (Franks, 2004; Massei et al., 2017; Shrestha et al., 2017b). The response time of different components of the climate system to internal natural variability is not consistent. The detection of climate change signals on the hydrologic cycle may be delayed or accelerated due to the interaction between the atmosphere and ocean, as well as other processes of natural climatic variability, particularly at local and regional scales (Deser et al., 2012b; Ficchì et Stephens, 2019; Fischer et Knutti, 2014; Satoh et al., 2022; Screen et Deser, 2019; Zhuan et al., 2018). It has been shown that anthropogenic climate variability can eventually overcome climate trends on large spatial scales and in the long term (Frankcombe et al., 2015) but is dominated by internal variability on shorter time scales and smaller spatial scales (Deser et al., 2012a; Fischer, Beyerle et Knutti, 2013; Fischer et Knutti, 2014). There is also evidence that the signal of precipitation with different durations at local and regional scales can be masked by natural variability. Analysis of the Coupled Model Intercomparison Project Phase 3 (CMIP3) database found that internal climate variability had a significant impact on interdecadal temperature uncertainty before 2010 and was the main factor influencing decadal fluctuations in regional scale precipitation during the early decades of the 21st century (Hawkins et Sutton, 2009a).

With respect to runoff, Gelfan et al. (2015) studied the impact of internal atmospheric variability on runoff and found a strong seasonal dependence that peaked during the summer and autumn rainfall floods. Zhuan et al. (2018) studied the impacts of natural variability on streamflow in the Hanjiang river in China and found that the signal for streamflow emerges a decade later than the emergence of precipitation due to natural variability. It is essential to understand whether and how flood intensity and frequency are changing in order to manage flood risk in the future (Bronstert, 2003; Lu, Tighe et Xie, 2020; Rogger et al., 2012; Tabari, 2020; Wasko et al., 2021b), and this requires examining the role and impact of internal natural variability. Natural climate variability will influence the detection of climate change signals for mean and extreme precipitation as well as for streamflow discharge, and therefore should be carefully examined. However, there are few studies on the impact of internal natural variability on floods, and particularly so for extreme floods (Arnell, 2003; Fatichi et al., 2014; Mallakpour et Villarini, 2017; National Academies of Sciences et Medicine, 2016).

1.6 Importance of Single Model Initial- Condition Large Ensembles (SMILE) to examine internal natural variability

A Single Initial Model Condition Large Ensemble (SMILE) is a collection of model simulations that all use the same climate model and the same external forcing, but start from different initial conditions. SMILEs have gained popularity in recent years as useful tools for studying the climate system. Their usefulness comes from their ability to differentiate between the intrinsic natural variability of the climate system and its response to exogenous forcing (e.g., Bassett et al., 2020; Deser et al., 2020b; Kay et al., 2015; Leduc et al., 2019a; Maher, Lehner et Marotzke, 2020; Sanderson et al., 2018b; von Trentini et al., 2020; von Trentini, Leduc et Ludwig, 2019; Wood et al., 2021). Additionally, SMILEs are particularly valuable for studying extreme events, such as heatwaves, floods, and droughts, which may have a significant impact on people despite their rarity (e.g., Brunner et al., 2021; Fischer, Beyerle et Knutti, 2013; Maher, Milinski et Ludwig, 2021a).

The large sample size of SMILEs allows for the prediction of future events with long return periods and enables a more precise sampling of the complete probability distribution, including the tails where extreme occurrences occur (e.g., Van der Wiel et al., 2019). Different types of SMILEs are needed for various applications, such as global General Circulation Model (GCM) SMILEs for studying issues affecting the entire climate system and Regional Climate Model (RCM) SMILEs for exploring implications at local scales.

SMILEs have mostly been used to examine the internal variability of the climate system (e.g., Dai et Bloecker, 2019b; Lehner et al., 2020; Rantanen et al., 2022; Zhang et al., 2022b) and extreme events (e.g., Mittermeier, 2022; Poschlod, 2020; Santos et al., 2020; Stevenson et al., 2022).

Examples of SMILE projects include the Community Earth System Model Large Ensemble (CESM-LE, Kay et al., 2015; Sanderson et al., 2018a), the CanESM2 Large Ensemble (CanESM2-LEArora et al., 2011a; von Salzen et al., 2013), and the Community Climate

System Model (CCSM1). The Climate Change and Hydrological Extremes (ClimEx) project is a SMILE project that investigates how extreme hydrometeorological phenomena may impact water management in response to climate change in both Quebec and Bavaria (Leduc et al., 2019a).

1.7 Time of Emergence

The term "Time of Emergence" (TOE) refers to the point at which the climate change signal becomes significantly distinct from the natural climate variability's background noise and can be attributed to a specific cause, such as increased greenhouse gas emissions (Barnes, Anderson et Ebert-Uphoff, 2018; Giorgi et Bi, 2009; Hawkins et Sutton, 2012; IPCC., 2013). TOE is useful for predicting when the consequences of climate change are expected to have a noticeable impact on ecosystems and society and can inform risk assessments, mitigation efforts, and adaptation planning (Ignjacevic, Estrada et Botzen, 2021).

According to the Intergovernmental Panel on Climate Change's (Change; IPCC., 2013) Fifth Assessment Report, there is no single measure for determining TOE. TOE can be calculated in various ways and depends on factors such as the chosen climate variables, the spatial and temporal scales being considered, the baseline period for measuring change, the threshold at which emergence becomes clear, and the reference period (Hawkins et Sutton, 2012; Nguyen-Thuy et al., 2021).

TOE is often considered the initial lead time at which the anthropogenic climate change signal surpasses and consistently remains above a predetermined proportion of the natural variability's amplitude (Giorgi et Bi, 2009; Hawkins et Sutton, 2009a; Li et al., 2017c).

Multiple sequences of internal variability and forced response are produced by large initial condition ensembles (LEs) run with a single climate model. In the time it takes to find forced "fingerprint" patterns, LEs enable researchers to quantify random uncertainty (Murphy et al., 2004; Santer et al., 2019). Each member of the LE contributes a distinct realization of the "noise" of natural internal variability superimposed on the underlying climate "signal". As a result of internal variability in an LE being uncorrelated across realizations, averaging over ensemble members reduces noise and enhances estimates of externally imposed signals. The signal-to-noise (S/N) properties of various areas, seasons, and climate variables can be examined using LEs, and the time of emergence of the signal can be projected (Barrow et Sauchyn, 2019; Frame et al., 2017; Hawkins et Sutton, 2012; Santer et al., 2019; Santer et al., 2011).

One approach to finding the TOE of a climate signal is through the use of statistical testing. These tests can include both parametric and non-parametric methods:
Parametric tests are statistical tests that make assumptions about the underlying distribution of the data. For example, the t-test assumes that the data is normally distributed. These tests can be used to determine if there are significant differences between two groups of data or if a sample comes from a specific population (Maraun, 2013b; Tramblay et Somot, 2018; Xu, Takeuchi et Ishidaira, 2003).

Another approach to finding the TOE of a climate signal is through the use of non-parametric tests. These tests do not make assumptions about the underlying distribution of the data, and can be used when the assumptions of parametric tests are not met. Examples of non-parametric tests include the Mann–Kendall test (Li, Chen et Chen, 2021; Martel et al., 2018) and the Kolmogorov–Smirnov test (Gaetani et al., 2020; Muelchi et al., 2021). These tests can be used to compare multiple time series of observational data, and to identify the point in time when a specific trend or pattern becomes detectable above the background variability.

The Kolmogorov-Smirnov (KS) test is a non-parametric test that can be used to determine if two samples of data come from the same underlying distribution, also known as the null hypothesis. The test compares the empirical cumulative distribution function of the sample data to a theoretical distribution to determine the maximum difference between them, called the KS statistic. A small KS statistic indicates that the samples are likely from the same distribution, while a large KS statistic suggests that the samples are likely from different distributions (Sidney, 1957).

1.8 Research objectives

Literature review indicates that there is a lack of research on the impact of extreme precipitation and streamflow discharge on small catchments, and particularly at sub-daily temporal scales. Previous studies on hydrological change in the United States have mainly focused on the western United States and mountain watersheds, where the loss of snowpack has been a significant factor (Albano, Dettinger et Harpold, 2020; Bales et al., 2006; Barnett et al., 2008; Hammond et Kampf, 2020; Huber, Bugmann et Reasoner, 2006; Pederson et al., 2011; Pierce et al., 2008; Sun et al., 2019). Fewer studies have examined how climate change is affecting hydrologic extremes in the East and Great Lakes region (Hayhoe et al., 2010; Jones et al., 2006; Mortsch et al., 2000; Persaud et al., 2020).

This thesis aims to increase understanding of the effect of climate change and natural variability on hydrometeorological extremes, with a focus on the impact of internal natural variability on flooding trends over small to medium-sized catchments.
More specifically this thesis proposes to use the high temporal and spatial resolution ClimEx SMILE to look at the impact of hydroclimatic extremes of small to medium catchments. In particular, the following specific objectives will be targeted:

1- Evaluate if bias correcting the diurnal cycle of climate variables is needed when conducting impact studies at the sub-daily time scales;
2- Study the impact of the amplification of summer-fall rainfall extremes on streamflow as a function of catchment size;
3- Document the impact of internal variability on the detection of the climate change signal and determination of the time of emergence, for various streamflow metrics.

This thesis comprises six chapters, including the current literature review first chapter. Chapters 2 to 4 each provide one of the three scientific articles that make up this thesis in response to each specific objective stated above. Chapter 5 presents a summary of the major results and is followed by conclusions in Chapter 6.

CHAPTER 2

IMPACT OF CORRECTING SUB-DAILY CLIMATE MODEL BIASES FOR HYDROLOGICAL STUDIES

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Abstract

The study of climate change impact on water resources has accelerated worldwide over the past two decades. An important component of such studies is the bias correction step, which accounts for spatiotemporal biases present in climate model outputs over a reference period, and which allows realistic streamflow simulations using future climate scenarios. Most of the literature on bias correction focuses on daily scale climate model temporal resolution. However, a large amount of regional and global climate simulations is becoming increasingly available at the sub-daily time step, and even extend to the hourly scale, with convection-permitting models exploring sub-hourly time resolution. Recent studies have shown that the diurnal cycle of variables simulated by climate models is also biased, which raises issues respecting the necessity (or not) of correcting such biases prior to generating streamflows at the sub-daily time scale. This paper investigates the impact of bias-correcting the diurnal cycle of climate model outputs on the computation of streamflow over 133 small to large North American catchments. A standard hydrological modeling chain was set up using the temperature and precipitation outputs from a high spatial (0.11º) and temporal (1-hour) regional climate model large ensemble (ClimEx-LE). Two bias-corrected time series were generated using a multivariate quantile mapping method, with and without correction of the diurnal cycles of temperature and precipitation. The impact of this correction was evaluated on three small (<500 km^2), medium and large (>1000 km^2) surface area catchment size classes. Results show relatively small (3 to 5%) but systematic decreases in the relative error of most simulated flow quantiles when bias-correcting the diurnal cycle of precipitation and temperature. There was a clear relationship with catchment size, with improvements being most noticeable on the small catchments. The diurnal cycle correction allowed for hydrological simulations to accurately represent the diurnal cycle of summer streamflow in small catchments. Bias-correcting the diurnal cycle of precipitation and temperature is therefore recommended when conducting impact studies at the sub-daily time scale on small catchments.

Keywords: Hydrological modeling; Bias correction; Diurnal cycle; Impact study; ClimEx large ensemble.

2.1 Introduction

The potential impacts of climate change have become a crucial concern for public safety, the environment and the economy of the twenty-first century (Raza et al., 2019; Vogel et al., 2019; Walsh et al., 2019). There is evidence that the hydrological cycle has already been significantly influenced by the changing climate in many regions, and it has become an important issue for water resource managers and policy makers (Qiu et al., 2019; Yira et al., 2017; Zhao et al., 2019). In particular, it is expected that the frequency of extreme precipitation and convective storms will increase at the local and regional scales, and particularly in mid to high latitudes (Barbero et al., 2017; Martel, Mailhot et Brissette, 2020; Myhre et al., 2019; Pfahl, O'Gorman et Fischer, 2017; Prein et al., 2017b; Sarhadi et Soulis, 2017). Changes in extreme precipitation and patterns of convective storms will in turn impact flood risk (Prein et al., 2017b; Quintero et al., 2018; Westra et al., 2014a). To properly resolve extreme summer-fall convective precipitation, a sub-daily modelling time step is required for most applications (Bao et al., 2017; Beranová, Kyselý et Hanel, 2018b; Sunyer et al., 2017). In hydrology, this is particularly true for small watersheds, which have a sub-daily response time, and are most likely to be affected by the anticipated sub-daily amplification of precipitation extremes (Yuan, Liu et Wan, 2019). In order to better adapt to the consequences of a changing climate, and to mitigate the future flood risk related to precipitation extremes on small watersheds, it is critical to consider a sub-daily time step for the entire hydro-climatic modeling chain (Beranová, Kyselý et Hanel, 2018b; Blenkinsop et al., 2018)).

General circulation models (GCMs) and Earth System Models (ESMs) are invaluable tools for simulating the present and future climates (Alfieri et al., 2015; Panday, Thibeault et Frey, 2015). These models do however require substantial computational power and disk space, which significantly limits both the spatial and temporal resolution at which they can be run, and the frequency at which their outputs can be archived. This is particularly the case for GCMs and ESMs which are run at the global scale. This explains why output data from these models have typically been limited to a relatively coarse spatial resolution of 1^{o} or more (≥100km), and been archived at the daily time scale. These spatial and temporal resolutions are too coarse to allow studying the potential hydrological impacts of climate change on small catchments (Bajracharya et al., 2018; Fatichi et al., 2014; Trzaska et Schnarr, 2014a).

To overcome this issue, regional climate models (RCMs) have been used to dynamically downscale GCM outputs at a higher spatial and temporal resolution over limited area domains. RCMs can better take into account local topography, land sea contrast, soil properties, and land cover, which impact surface forcing and physical processes. The spatial resolution of RCMs is generally in the range of 0.1 to 0.5^{o} (10 to 50km), with typical temporal resolutions of 3 to 6 hours, which are suitable for forcing hydrological models on relatively small catchments. More recently, the use of convection-permitting RCMs has bridged the resolution gap to 0.02^{o} (2 km) or below (Chan et al., 2014; Kendon et al., 2017; Van Lipzig et Prein–nicole, 2015). This increase in spatial resolution requires a corresponding increase in temporal resolution (for numerical stability), and such models are therefore limited to even smaller computational domains.

To properly assess climate model uncertainty, several multi-model (GCM and RCM) ensembles (e.g., CMIP5/6, CORDEX) have been used to address the uncertainty originating from greenhouse gas emission scenarios and structural climate model uncertainty. Internal climate variability is a third source of uncertainty, which can be studied with a multi-member ensemble from a single climate model and single greenhouse emission scenario. Each member of the ensemble originates from micro and macro perturbations to initial conditions (Deser et al., 2020a; Deser et al., 2012b). Using multi-member ensembles has become increasingly popular in the analysis of the impact of internal variability, as well as for exploring the impact of extreme climate events such as extreme precipitation, since these ensembles provide many ergodic climate realizations from which to sample large numbers of extreme events (Martel, Mailhot et Brissette, 2020; Shen et al., 2018; Zhao et al., 2020).

All global and regional climate model outputs are biased to some extent when compared to observations over a common reference horizon. These biases have a complex spatial and temporal structure (Ashfaq et al., 2010; Chen et al., 2013a; Maraun, 2016; Wang et al., 2014). Therefore, a bias correction step is considered as a prerequisite for most climate change impact assessment studies. A wide range of bias correction techniques are available, extending from simple scaling methods to more advanced trend-preserving multivariate distribution mapping approaches. There is a significant body of literature on bias correction methods and several inter-comparison studies have been published (Ajaaj, Mishra et Khan, 2016; Bárdossy et Pegram, 2011; Chen et al., 2013a; Fang et al., 2015; Lafon et al., 2013; Maraun, 2016). However, this is no longer true since climate model outputs are increasingly available at sub-daily time steps. A very limited number of studies has looked at bias correction of sub-daily climate model outputs, but the focus has been on correcting sub-daily annual maximum values (e.g. Li et al., 2017a; Requena et al., 2021). Annual maximum values are important since they are used to determine the return period of extreme events for engineering design. For example, Li et al. (2017) showed that bias correcting the hourly annual maximum rainfall was recommended. It is well recognized that climate model biases are not constant in time, and as a result, different correction factors are typically computed for each month, or using a moving window across a calendar year. It is also known that high-resolution climate models are also biased in the reproduction of the diurnal cycle of many variables (Bannister et al., 2019; Scaff et al., 2019). As climate models slowly continue their steady march towards the sub-daily resolution, interesting research questions must be tackled. Should we bias-correct the diurnal cycles of climate model outputs? If so, how? Do we have reliable reference datasets at the sub-daily time scale? Will this even influence the results of impact studies?

To provide an answer to these questions, this paper examines the impact of bias-correcting the diurnal cycle on the hydrology of several North American catchments. It also examines how the spatial scale influences the dynamic response of watersheds to extreme precipitation. In general, smaller watersheds are more sensitive to intense short-duration storms, whereas streamflows from larger catchments are somewhat smoothed by the flood wave propagation routing process. Therefore, in principle, an accurate representation of the diurnal cycle should be more critical for smaller catchments. To investigate this further, a wide range of catchment sizes has been selected.

This paper is structured into three main sections. The methodology provides an overview of the study area, describes all datasets (observations and climate model) and presents the bias correction method chosen to correct the diurnal cycle. Section 3 presents all results, and section 4 provides a discussion of the main results as well as concluding remarks.

2.2 Materials and Methods

2.2.1 Study area

This study was conducted over the eastern United States in a rectangular region within the computational domain of the high-resolution regional climate model used (see section 2.2 below for additional details). As described below, 133 MOPEX catchments were selected based on the criteria of having observed hydrometric and meteorological data with less than

5% of missing data over a common 24-year reference period. These catchments are dispersed across 4 climate zones of the Köppen climate classification. The impact of the catchment size is examined in this study by classifying catchments into three groups: less than 500 km^2, between 500 and 1000 km^2 and more than 1000 km^2. Catchments smaller than 500 km^2 should have a clear sub-daily hydrological time response as compared to the larger catchments. Figure 2.1 presents the centroid location and relative size of each catchment. Basic catchment characteristics are presented in Table 2.1.

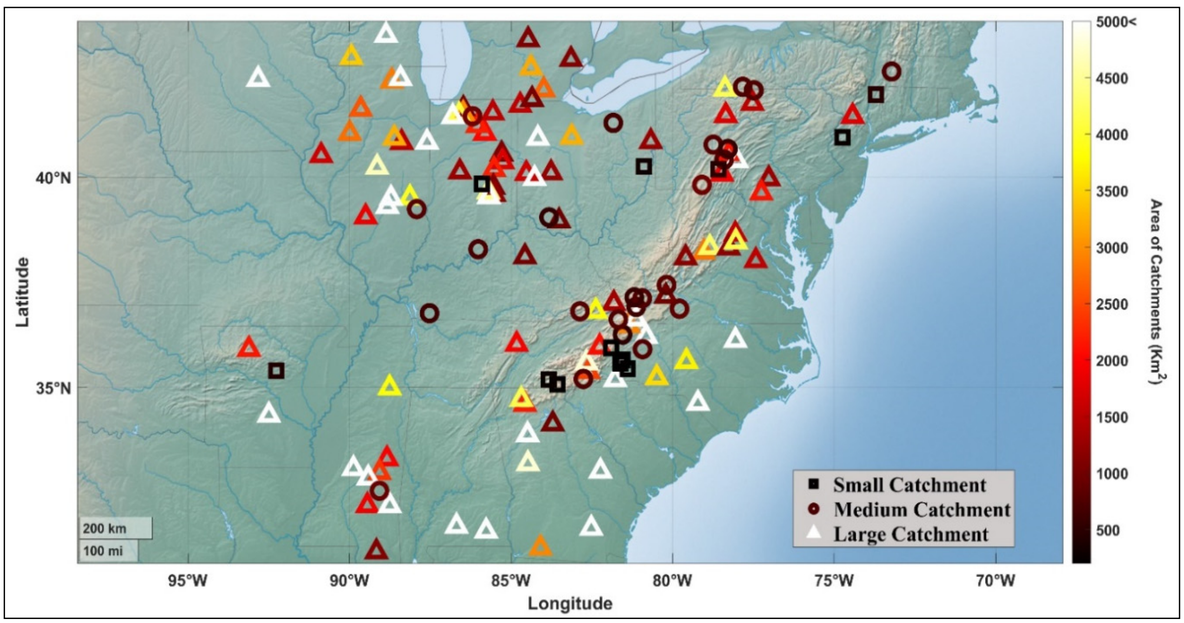

Figure 2.1 Distribution of catchments across North Eastern America. Squares, Circles and triangles symbols correspond to small, medium and large catchments respectively.

Table 2.1 General Characteristic of the three-catchment size groups

	Number of Catchments	Area (km^2)			Annual Temperature (°C)			Annual Precipitation (mm)		
		Min	Median	Max	Min	Median	Max	Min	Median	Max
Small Area	12	66.5	268.8	468.7	*9.4*	*11.9*	*15.3*	*967.2*	*1247.3*	*1891.5*

Medium Area	25	530.9	758.6	994.5	*7.4*	*10.9*	*17.8*	*861.9*	*1072.0*	*2007.8*
Large Area	96	1002.3	3595.1	9885.9	*7.4*	*11.5*	*19.1*	*804.2*	*1049.6*	*1657.3*

2.2.2 Datasets

All the results presented in this paper are available at the hourly time step. All observations cover the 24-year 1980-2003 period, which is defined as the reference dataset.

2.2.2.1 Observed data

Hourly observed precipitation and streamflow data were derived from the Model Parameter Estimation Experiment (MOPEX) (Duan et al., 2006a). MOPEX hourly precipitation is a catchment-averaged value from the closest weather stations. The MOPEX database does not however provide the hourly temperature. Rather than interpolating daily maximum and minimum values to the hourly scale, we took hourly temperature data directly from ERA5 reanalysis (Lindsay et al., 2014). At the catchment scale, Tarek, Brissette et Arsenault (2020a) showed that the ERA5 temperature is just as good as estimates derived from weather stations for hydrological modeling. The mean of all ERA5 grid points within each catchment was computed for every hour.

2.2.2.2 Climate model data

This project uses the ClimEx Large Ensemble (Leduc et al., 2019b). The Climate Change and Hydrological EXtremes project (ClimEx) is a 50-member regional large ensemble computed using the 5th generation of the Canadian Regional Climate Model (CRCM5). CRCM5 was used to dynamically downscale the 50 members of the Canadian Earth System Model (v2) large ensemble (CanESM2-LE) (Arora et al., 2011b) to a 0.11° (12 km) spatial resolution (Leduc et al., 2019b; Martel et al., 2017). The temporal resolution of archived ClimEx data is one hour for precipitation and three hours for most other variables. The ClimEx ensemble provides a sample of 7500 years, with each member covering the 1951-2100 period under the RCP 8.5 scenario. In this study, hourly precipitation and 3-hour temperature data were extracted for all grid points within each catchment over the ClimEx Northeastern-North-American (NNA) domain. The ClimEx temperature was first interpolated to the hourly time step for all grid points by using Piecewise Cubic Hermite Interpolating Polynomials (Barker et McDougall, 2020; Fritsch, 1985). Precipitation and temperature were then averaged at the catchment scale to be consistent with the observed data over the reference period.

2.2.3 Bias correction

The N-dimension multivariate bias correction (MBCn) by Cannon (2018) was selected in this study to correct biases of hourly precipitation and temperature. MBCn was chosen because it is arguably the most advanced quantile-based multivariate bias correction method available (Cannon, Piani et Sippel, 2020; Chen et al., 2018; Meyer et al., 2019; Su et al., 2020). MBCn (Cannon, 2018) is a multivariate generalization of quantile mapping that conveys all aspects of the distribution of observation data to the corresponding distribution from a climate model. MBCn preserves the climate model projection trends for all quantiles, which is a highly desirable property for climate change impact studies (e.g. Maraun, 2016).

All members of the ClimEx large ensemble were pooled together to compute the bias correction factors for both precipitation and temperature. The correction factors were then applied to all the members of the ClimEx ensemble. As discussed by Ayar, Vrac et Mailhot (2021) and Chen et al. (2019), doing so preserves the internal variability of the ensemble. This paper is not directly concerned with the study of internal variability, but using a large ensemble allows the accurate empirical computation of extreme events with very large return periods (Martel, Mailhot et Brissette, 2020). Since climate model biases are not constant across the annual cycle, different correction factors were computed for each month of the year.

In observance of the main objective of the present study, the MBCn bias correction method was applied in two different ways:

1. Standard Bias Correction (SBC): For each calendar month, a single set of quantile correction factors was applied to all hourly data. This approach assumes that all climate model biases are constant across the diurnal cycle. In this variant, for each month, there is one set of quantile correction factors and all hourly values are corrected using this set.

2. Diurnal Bias Correction (DBC): This variant specifically recognizes that climate model biases are not constant throughout the diurnal cycle (e.g., daylight biases may differ from nighttime biases). Bias corrections were therefore computed for each hour, using a 3-hour moving window to pool all hourly values within a given month before using the MBCn algorithm. This was performed to smooth the diurnal cycle of observations, and therefore remove some of the sampling noise in the observed data. In this variant, for each month, there are 24 sets of quantile correction factors (one for each hour).

2.2.4 Hydrological model (GR4H)

A hydrological model is needed to take and transform precipitation and temperature data into streamflow values. In this study, hourly streamflows were simulated by the GR4H (modèle du Génie Rural à 4 paramètres Horaire) hydrological model. GR4H is an hourly rainfall-runoff model derived from its daily time step sibling, GR4J (Perrin, Michel et Andréassian, 2003). GR4H is a lumped conceptual model with two storage reservoirs and four free parameters which define the production and routing functions, and which must be calibrated. GR4H was coupled with the CEMANEIGE degree-day snow model to simulate snowpack accumulation and depletion. CEMANEIGE is a two-parameter snow model developed by Valéry (2010a). The combination of these two models, GR4J (GR4H) and CEMANEIGE, has shown good performance in different studies throughout the world (Raimonet et al., 2018; Riboust et al., 2019; Youssef et al., 2018). GR4h requires precipitation, temperature and potential evapotranspiration (Westra et al., 2014a) as hourly inputs (Van Esse et al., 2013). The Oudin Ep formulation (Oudin et al., 2005) was used here. The combination of this Ep formula with the GR4J hydrological model has been used successfully in many hydrological studies (Arsenault, Brissette et Martel, 2018; Troin et al., 2018).

The calibration of the hydrological model was performed automatically on all catchments using the Shuffled Complex Evolution (SCE-UA) algorithm (Duan, Sorooshian et Gupta, 1994), which has been shown to be highly efficient in a wide variety of problems (e.g. Arsenault et al., 2014a; Huang et al., 2018; Muttil et Jayawardena, 2008). The Nash-Sutcliffe Efficiency (NSE) criterion was used as the calibration objective function. The NSE criterion has been used in many studies, and represents a normalized root mean square error. It compares the hydrological model efficiency to the mean flow as a reference predictor, as shown in the equation (2.1):

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_{Sim}^{t} - Q_{Obs}^{t})^2}{\sum_{t=1}^{T}(Q_{Obs}^{t} - \overline{Q}_{Obs})^2} \tag{2.1}$$

where Q_{Sim}^{t} and Q_{Obs}^{t} are respectively the simulated and observed discharges at time t and $\overline{Q}_{Obs}$ is the mean of the observed discharge.

NSE values range from negative infinity up to 1. A value of 1 indicates a perfect agreement between modeled and observed data, while a 0 value indicates that the hydrological model's performance is no better than what is obtained from using the mean streamflow value as a predicting model. The hydrological model was calibrated over the entire 24-year period following the recommendations of Arsenault, Brissette et Martel (2018). They showed that using the entire observation record for the calibration of a hydrological model results in a more robust parameter set than using a shorter period followed by a validation step. The often-used split sample calibration/validation strategy was therefore not implemented in this study.

2.3 Results

Figure 2.2 presents the NSE criterion values obtained for the calibration procedure described above for the 133 catchments. Overall, the model calibration is good, with a mean NSE value of 0.78 across all catchments. 94.6% of the catchments have an NSE value above 0.7 and 36.9%, a value above 0.8. The smallest NSE value is 0.61. These results show that the hydrological model does a good job at simulating the hourly streamflow on the selected catchments.

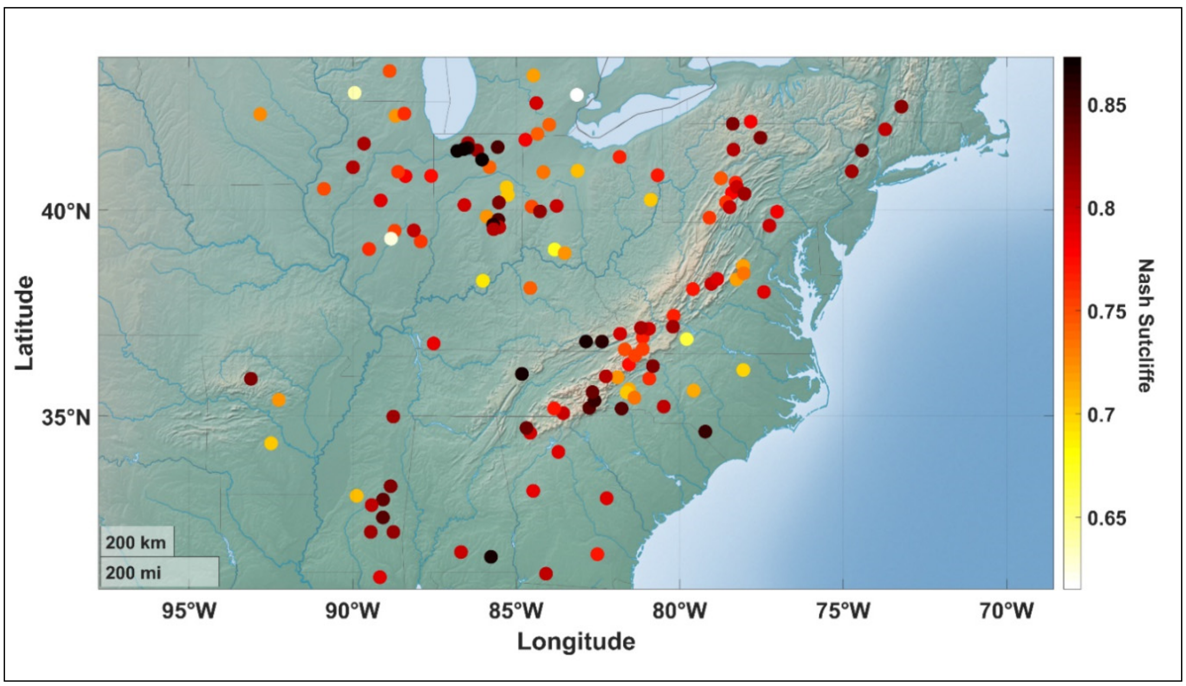

Figure 2.2 NSE calibration results for all catchments.

Figure 2.3 presents the observed and ClimEx simulated temperature diurnal cycles of a selected catchment for all four seasons (left-hand side), as well as the results of both bias correction approaches (right-hand side). The 50 members of the ClimEx ensemble are presented as a shaded envelope, with the ensemble mean as a solid line. Throughout this paper, time refers to the catchment local time. The left-hand side shows that ClimEx simulates a good temperature diurnal cycle, which is fairly close to the observed ones and for all seasons. Over this catchment, ClimEx runs a warm bias, especially for spring, summer and fall. The warm bias tends to be larger during the nighttime. All members of the ClimEx ensemble are very close to one another, with a difference of only about 1 degree between the coldest and warmest members. The diurnal cycle of temperature is hardly affected by internal climate variability.

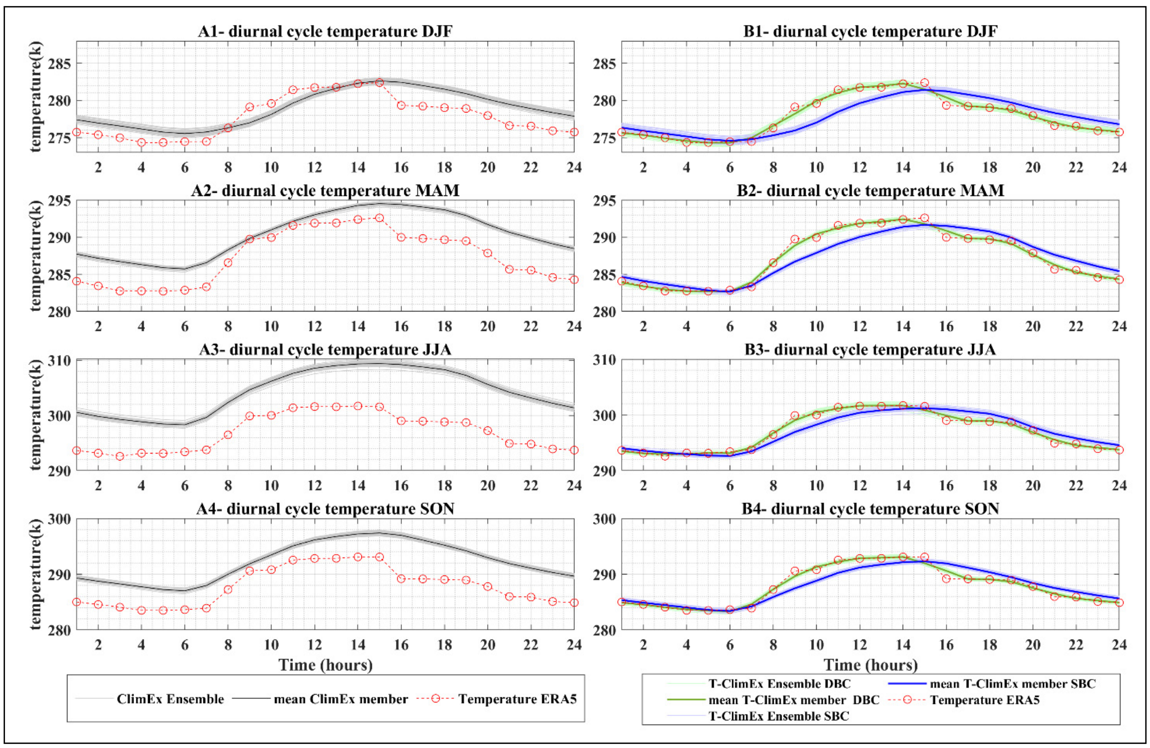

Figure 2.3 Annual diurnal cycle of temperature before bias correction (first column: A1 to A4) and after bias correction (second column: B1 to B4) for catchment 02143040. Each row corresponds to a different season: DJF (December, January, February), MAM (March, April, May), JJA (Jun, July, August), SON (September, October, November). The right-hand side shows both bias correction methods: Standard Bias Correction (SBC) and Diurnal Bias Correction (DBC). The observations (ERA5) are shown in red. Raw (uncorrected) ClimEx data is in grey, SBC is in blue and DBC is in green. The envelope defined by all 50 ClimEx members are shown in the corresponding light colours, whereas the dark coloured lines display the ensemble mean. Time is local with 24h corresponding to midnight.

The right-hand side of Figure (2.3, B1 to B4) presents the performance of Cannon (2018) multivariate bias correction (MBCn) with diurnal cycle bias correction (DBC in green) and standard bias correction (SBC in blue). The pooling of all the ClimEx members to derive a unique set of bias correction factors preserves the signature of internal variability, as can be seen by the width of the blue and green envelopes as compared to those of the gray envelope of uncorrected ClimEx values (A1 to A4). With the standard bias correction (SBC), all hourly values are corrected using common correction factors for each month. The bias correction then reduces to a simple vertical scaling, which reduces the mean daily bias to zero. However, hourly biases remain: these biases are negative from 06h00 to 14h00, and positive from 14h00 to midnight. For the green curves, using a 3-hour moving window results in a diurnal cycle that is smoother than the observed one. This was a methodological choice made in order to filter out variability in the observations, likely resulting from sampling errors. Without the smoothing window, the bias-corrected diurnal cycle would have matched those of observations exactly.

Figure 2.4 presents the observed and ClimEx simulated precipitation diurnal cycles for the same catchment. The layout of Figure 2.4 is the same as for the temperature (Figure 2.3). Compared to the temperature, the simulated internal variability of precipitation is much larger, as shown by the width of the gray envelope on the left-hand side. Internal variability is largest for winter and fall, and smallest during summer. Precipitation differences between members can reach up to 100%, depending on the season and hour, highlighting the key role of internal variability in driving precipitation variability. Over this catchment, ClimEx precipitation is positively biased in winter and spring and negatively biased over the summer. Overall, there are large differences between observed and simulated precipitation, and these differences extend to the diurnal cycle. Summer is the only season where observations and ClimEx have a similar diurnal cycle despite a 3-4 hour lag between the peaks of both cycles. ClimEx presents a strong spring diurnal cycle, which is however, absent in the observations. Winter and fall do not show clear diurnal cycles in both the observations and ClimEx. The large differences between the observations and ClimEx outputs testify to the need for bias correction prior to using climate model outputs in hydrological models (or other impact models).

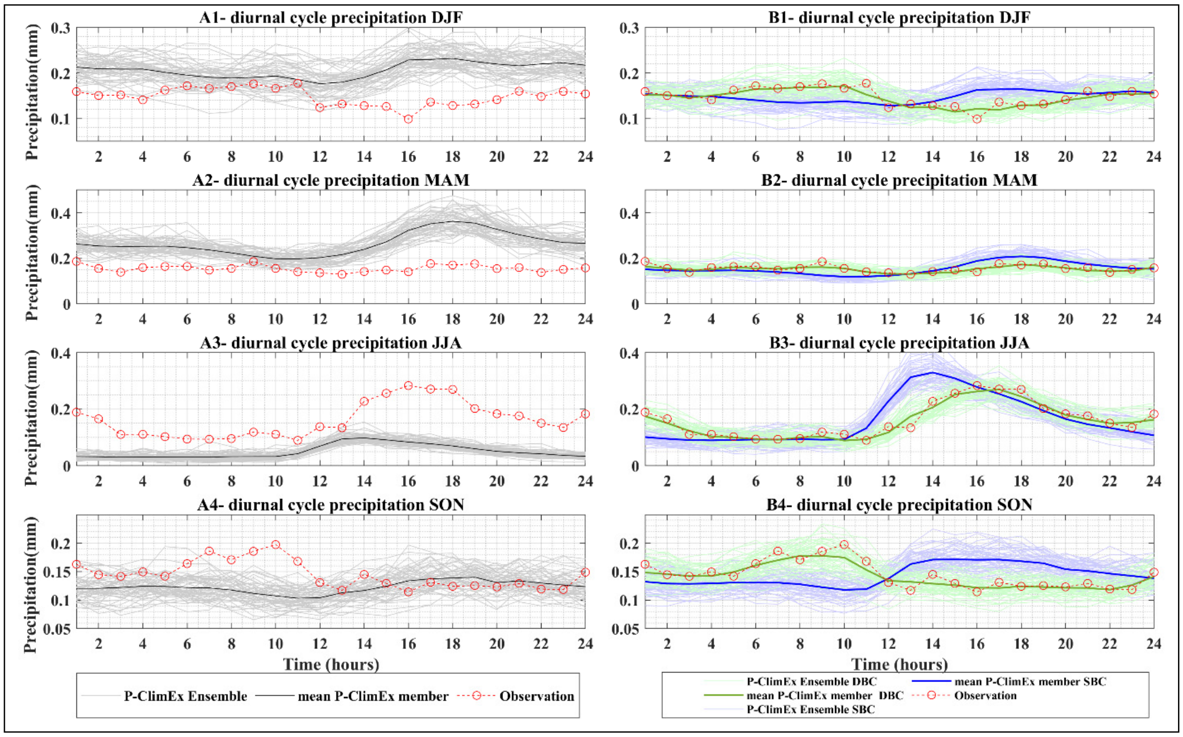

Figure 2.4 Annual diurnal cycle of precipitation before bias correction (first column: A1 to A4) and after bias correction (second column: B1 to B4) for catchment 02143040. Each row corresponds to a different season: DJF (December, January, February), MAM (March, April, May), JJA (Jun, July, August), SON (September, October, November). The right-hand side shows both bias correction methods: Standard Bias Correction (SBC) and Diurnal Bias Correction (DBC). The observations are shown in red. Raw (uncorrected) ClimEx data is in grey, SBC is in blue and DBC is in green. The envelope defined by all 50 ClimEx members are shown in the corresponding light colours, whereas the dark coloured lines display the ensemble mean. Time is local with 24h corresponding to midnight.

Just as in Figure 2.3, the right-hand side of Figure 2.4 presents the performance of the multivariate bias correction (MBC) with diurnal cycle bias correction (DBC in green) and standard bias correction (SBC in blue). Just as before, SBC (blue) simply scales precipitation to correct for the mean daily biases, with no impact on the shape of the modeled cycle. DBC (green), on the other hand, corrects the hourly distributions such that the bias-corrected diurnal cycle of ClimEx matches the observed one. Since precipitation correction is multiplicative, the internal variability envelope appears to be smaller in winter and spring because ClimEx is positively biased for these seasons. The reverse is observed for the summer season, when ClimEx is negatively biased. The relative internal variability (around the ensemble mean) remains the same before and after correction.

Overall, both bias correction methods do what they were designed for efficiently. The transformation of the gray envelopes into the green ones highlights the strength of these distribution mapping approaches. The fact that they can shape severely biased distributions into completely different ones also raises important questions about their use, as will be discussed later.

Now that the bias correction efficiency has been established, we can look at the hydrological modeling to see if the correction of the diurnal cycle has any impact on the hydrological simulations. To this end, raw and bias-corrected hourly precipitation and temperature time series were used to force the GR4H hydrological model to generate streamflow time series. Since the ClimEx ensemble was forced by a GCM (instead of reanalysis), it is not possible to directly compare the hourly simulated streamflow series with ClimEx meteorological data against those simulated using the observed meteorology. For this reason, the first comparison will be based on the mean annual hydrograph. Figure 2.5 shows the mean annual hydrographs for four catchments of different sizes. It shows streamflow observations (redline), as well as streamflow simulations from the hydrological model, using precipitation and temperature from three different sources. They are the uncorrected ClimEx data (grey envelope) and bias corrected ClimEx data with and without accounting for the diurnal cycle biases (DBC, light green envelope with ensemble mean in dark green, and SBC, light blue envelope with the ensemble mean as a dotted dark blue line). Results show that the multivariate bias correction of precipitation and temperature translates into accurate streamflow simulations. The ensemble mean tracks very well with the mean observed hydrographs contained within the ClimEx envelope of internal variability. Observations (red line) display a larger variability since they only contain 23 years of data, whereas the ensemble mean for both DBC and SBC comprise 1150 years (50 members times 23 years), and are therefore much smoother. The internal variability envelopes for DBC and SBC are very close to one another, with the blue envelope almost perfectly overlapping the green one. There are, however, small differences between the ensemble mean curves, indicating that taking the diurnal cycle biases into account impacts streamflow simulations to some extent. The largest differences are observed for the smallest catchment (upper right).

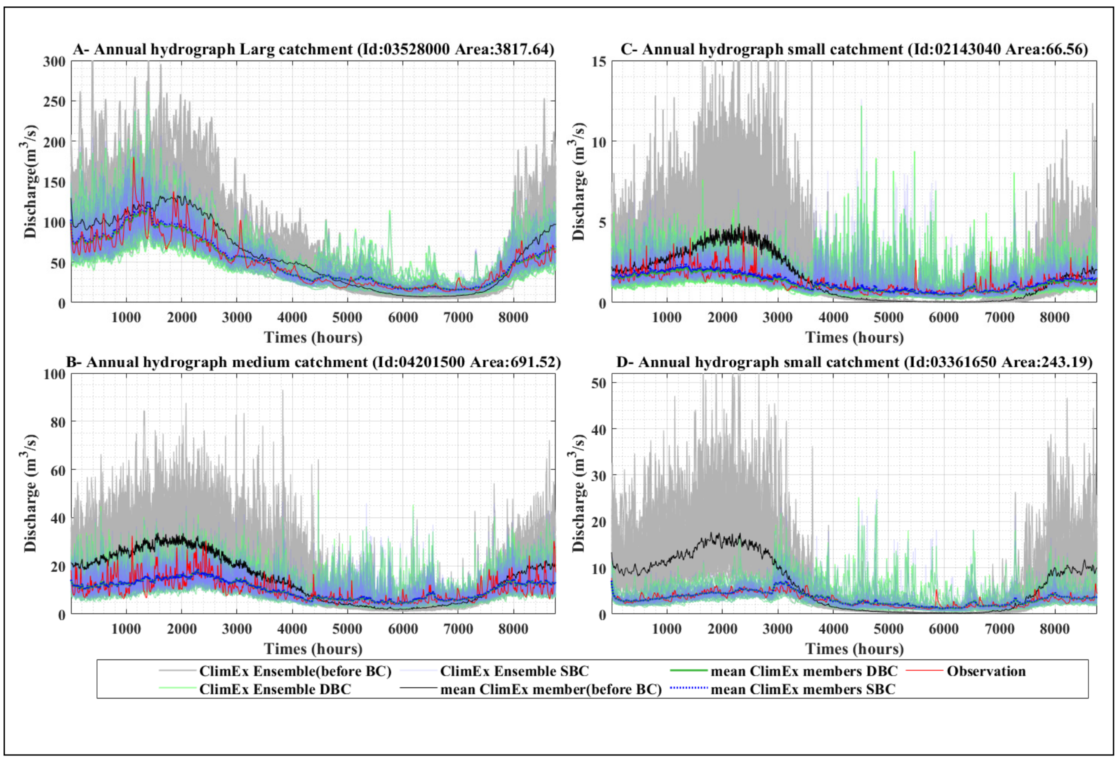

Figure 2.5 Hydrograph annual cycles for four selected catchments. Catchments A and B are classified as large and medium size respectively. Catchments C and D are classified as small. 0 represents January first at 0h00, and 8760 is December 31st at 24h00.

The impact of diurnal cycle bias correction as a function of catchment size is illustrated in Figure 2.6, which shows typical results for a small (66 km^2) and large (3817 km^2) catchments.

Those two catchments have been chosen are they differ mostly with respect to their size. They are located close to one another (Figure 2.6) and share common physiographical properties.

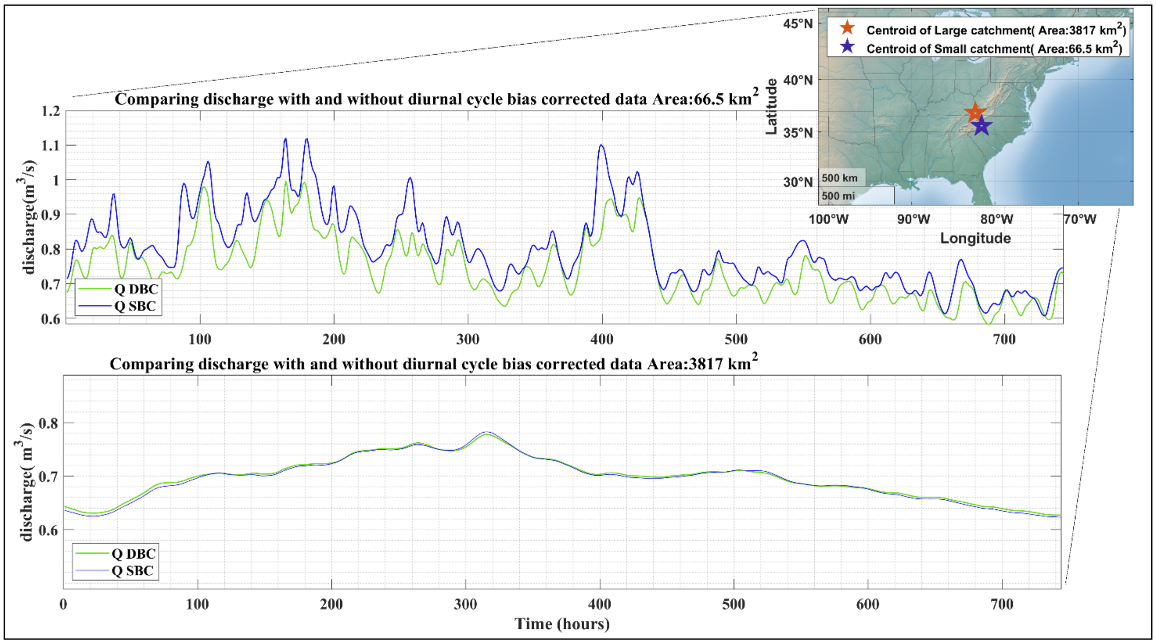

Figure 2.6 Hydrographs of two sampled catchments (small and large size surface area) for the month of July (744 hours = 31 days × 24 hours).

The figure presents a one-month (July) snapshot of streamflow hydrographs for the mean member of the ClimEx ensemble, with standard and diurnal cycle bias correction. The upper graph shows the quicker reactivity of the smaller catchment to meteorological inputs as compared to the larger one. More importantly, Figure 2.6 shows that the diurnal cycle correction has a larger impact on the smaller catchment when compared to the larger one. On larger catchments, the flow routing process acts as a low-pass filter, resulting in somewhat smoothed hydrographs, and blurring the difference between the two bias correction approaches. Figure 2.6, however, only shows that the diurnal cycle bias correction has an impact on streamflows, and not if this impact is beneficial. To figure out if the impact is beneficial, it is necessary to look at streamflow indicators.

Figure 2.7 presents the impact of correcting the diurnal cycle on the relative bias B of mean annual simulated streamflow, as expressed by equation (2.2) and (2.3):

$$B_{DBC} = \frac{\overline{Q_{climexDBC}} - \overline{Q_{obs}}}{\overline{Q_{obs}}} \times 100\% \tag{2.2}$$

$$B_{SBC} = \frac{\overline{Q_{climexSBC}} - \overline{Q_{obs}}}{\overline{Q_{obs}}} \times 100\% \tag{2.3}$$

In the above equations, $\overline{Q_{obs}}$ is the mean annual streamflow resulting from running the hydrological model with observed precipitation and temperature, whereas $\overline{Q_{climexDBC}}$ and $\overline{Q_{climexSBC}}$ respectively represent the mean annual simulated streamflow using bias corrected ClimEx precipitation and temperature, with and without correcting the diurnal cycles of both variables. Figure 2.7 shows boxplots of the relative bias of mean annual streamflow, with and without (DBC and SBC) mean diurnal cycle correction, for the three catchment size categories. Results are not shown for the streamflow simulations without bias-corrections since the errors are up to two orders of magnitudes larger than for the bias-corrected simulations. Each boxplot represents the distribution of mean relative streamflow bias for the 133 catchments. The central box displays the 25th, 50th (median) and 75th quantiles of the distribution, whereas the lower and upper whiskers show the 5th and 95th quantiles. Values below and above the 5th and 95th quantiles are shown as red circles and mean of the distributions are shown by purple crosses. Overall, the relative biases are relatively small across the board, indicating that the bias correction method does a good job at preserving the main characteristics of observed precipitation and temperature, at least in terms of hydrological modeling. Results show that accounting for diurnal cycles biases has an important impact on the representation of the mean annual streamflow. Correcting the diurnal cycle lowers the relative bias and diminishes the spread of the bias estimates. Relative biases are mostly positive with standard bias correction, and tend to be slightly negative with the diurnal bias correction. The impact is particularly clear for the small and medium catchments. For the large catchments, the absolute value of the median bias remains similar (goes from positive to negative), but the spread is lower when correcting the diurnal cycle. This is particularly clear for the central box (25th to 75th quantiles). As shown in Figure 2.3, the climate model diurnal cycle of temperatures is flatter than for observations. Bias correcting the diurnal cycle results in higher mean daily temperature leading to increased evapotranspiration and decreased streamflow values, likely explaining the observed results.

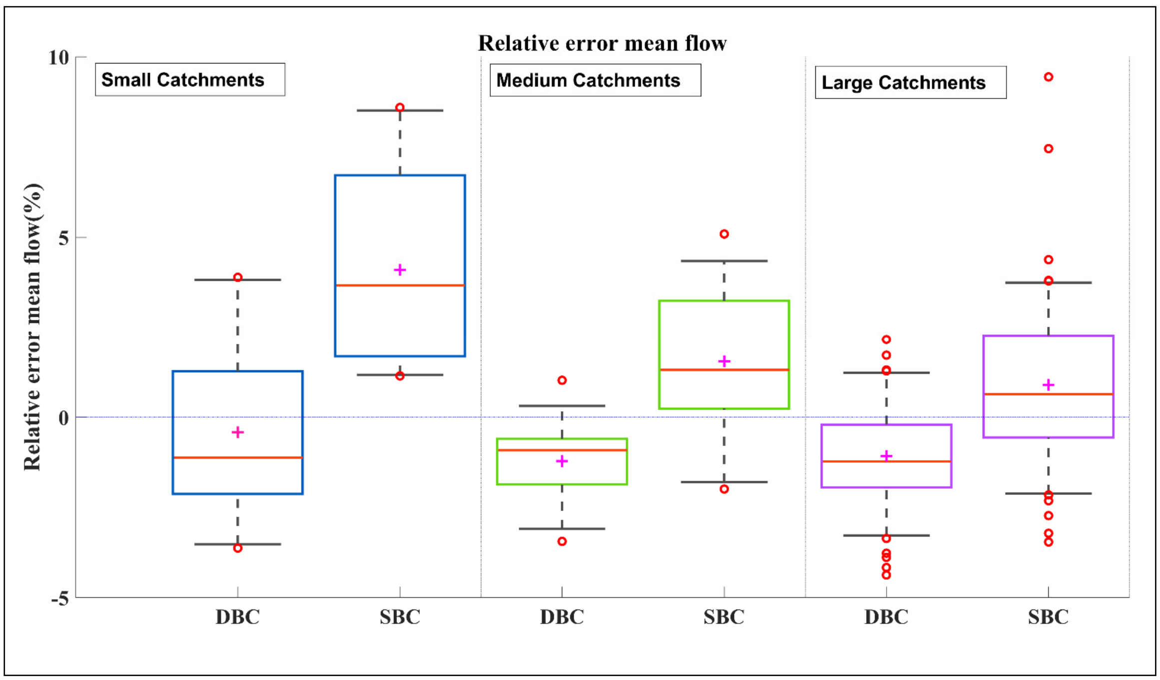

Figure 2.7 Comparing relative error of mean flow with diurnal cycle bias correction (DBC) and standard bias correction (SBC) in three area categories.

To further understand the impact of the diurnal cycle correction, Figure 2.8 shows similar results for low-flow and high-flow metrics. Low flows are represented by the 5th and 10th quantiles of the annual streamflow distribution for each catchment, and high flows, by the 95th and 99th quantiles. All four graphs of Figure 2.8 are in the same format as those in Figure 2.7. The results are therefore expressed as relative biases, and each boxplot represents the distribution of relative biases across all 133 catchments.

Low flows (upper row) are generally not well represented, with relatively large negative biases (mostly in the -10 to -30% range). The negative biases are larger for the smaller catchments. Correcting the diurnal cycle slightly increases the negative biases for the small and medium size catchments, but has a positive impact on spread across all catchments. This is once again particularly clear for the interquartile range. High flows (lower row) are much better simulated, with biases below 10% in most cases, with the exception of Q99 for the small catchments, where the biases are predominantly positive and much larger (+10 to +30%). Correcting the diurnal cycle provides relatively small, but consistent, bias reduction, as well as a reduction of the spread for the medium and large size catchments.

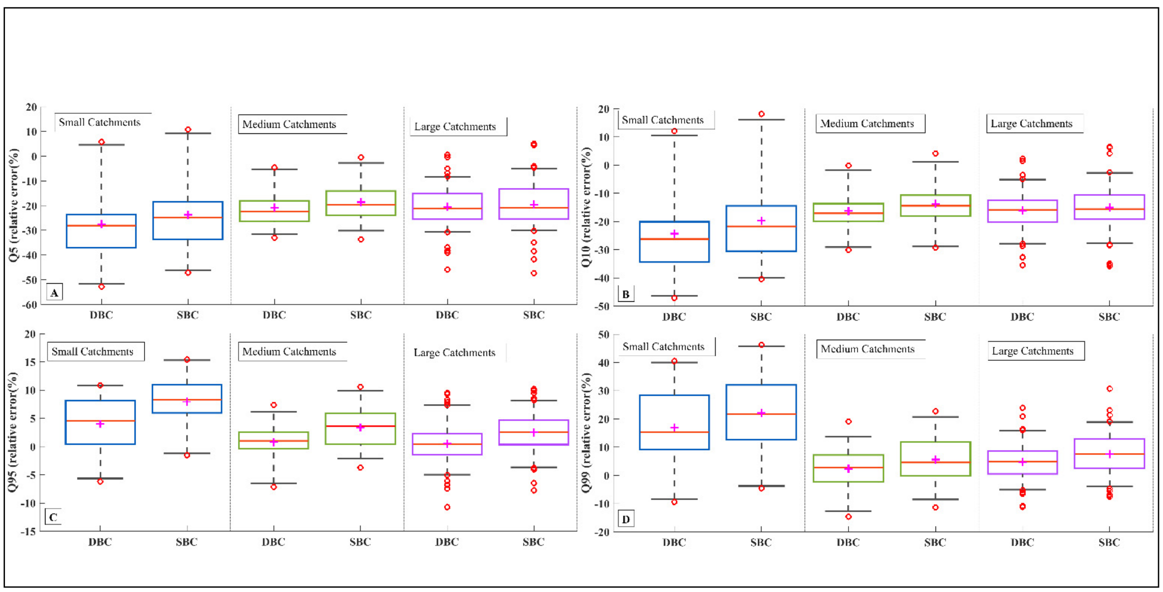

Figure 2.8 Distribution of the relative error ((model-obs)/obs × 100%) corresponding to flow quantiles Q5 (A), Q10 (B), Q95(C) and Q99(D). Boxplots for both bias correction methods (DBC and SBC) are constructed from the distribution of relative errors from all catchments within each size class (small, medium, and large).

Finally, Figure 2.9 presents similar results for the 20-year return period flood. The 95th, 99th and 20-year return period are all high-flow indicators. However, the first two represent relatively frequent high flow thresholds, with several days per year exceeding these values (18 and 3 days per year on average), whereas the 20-year return period threshold is an extreme value threshold that is exceeded once every 20 years on average. The 20-year return period was evaluated with a Log-Pearson III distribution following USGS guidelines (Flynn, Kirby et Hummel, 2006). It was calculated from the simulated flows using observed precipitation and temperature as well as bias-corrected ClimEx outputs. Figure 2.9 shows that bias-corrected data do a good job preserving the signature of meteorological data leading to extreme events. The relative biases are small for the medium and large size catchments, and slightly positive and a bit larger over the small catchments. Correcting the diurnal cycle provides relatively small but systematic bias reduction across-catchment spread improvements. These improvements are larger for the smaller size catchments.

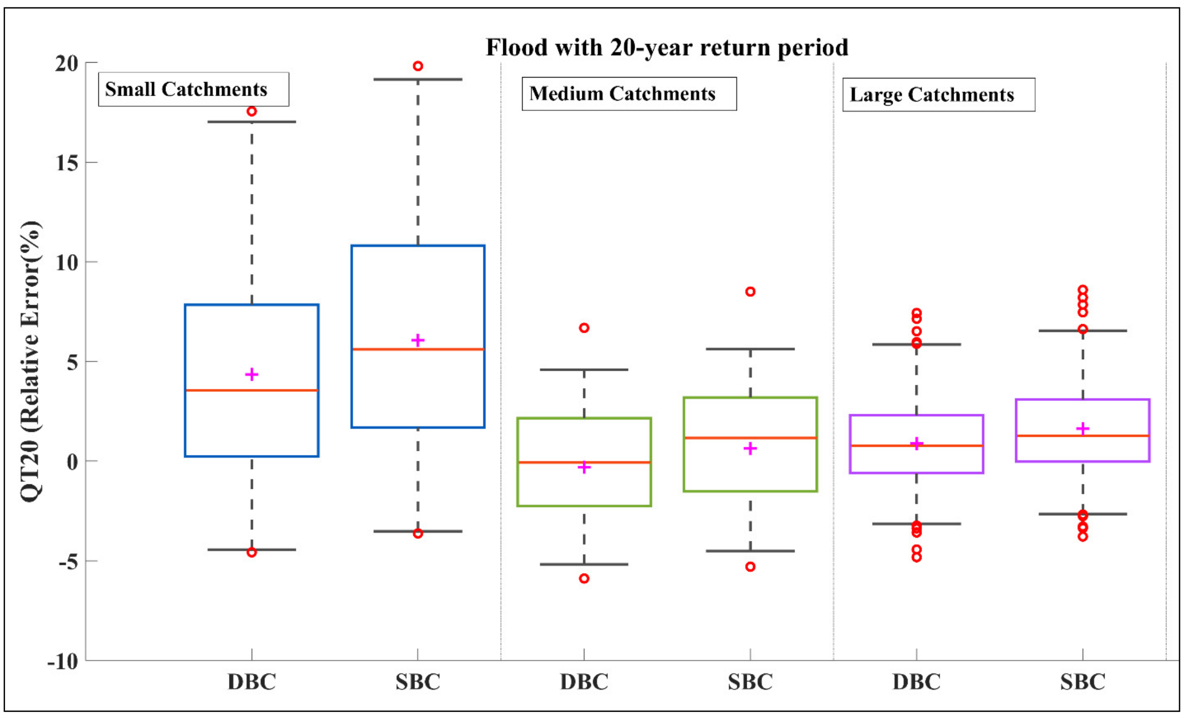

Figure 2.9 Distribution of the relative error ((model-obs)/obs × 100%) for the 20-year flood QT20. Boxplots for both bias correction methods (DBC and SBC) are constructed from the distribution of relative errors from all catchments within each size class (small, medium, and large).

2.4 Discussion

The preceding section has presented a hydrological modeling comparison of the impact of bias-correcting (or not) the diurnal cycle of precipitation and temperature modeled by a high-resolution regional climate model. Figures 2.3 and 2.4 show that bias correction methods can correct deficiencies in the representation of the diurnal cycles of temperature- and precipitation-modeled data. In the case of the temperature, ClimEx simulates a diurnal cycle with an amplitude similar to that of observations, but with a clear bias and timing offset. Both are effectively corrected using the MBCn method. The case of precipitation is more complicated as there are large differences between observations and modeled data. The MBCn method, by construct, was able to perfectly map the climate model biased diurnal cycle onto the observed one. Considering the large differences between both cycles, a valid question is whether or not this bias correction step should even be done. The differences observed between both cycles are rooted in three possible causes: observation errors affecting the observed diurnal cycle, structural errors in the modeling of precipitation in the climate model, and internal climate variability. Measuring precipitation is difficult (Angulo-Martínez et al., 2018; Yang et al., 1999), and particularly so at the sub-daily scale. Measuring issues related to the use of tipping bucket rain gauges have been reviewed by Segovia-Cardozo et al. (2021). Those issues are an underestimation of total amounts, and especially so for high intensity rainfall and light drizzle, losses from evaporation and non-linear response to rainfall intensity. In addition, at the sub-daily scale, the above may cause small shifts in the actual recording of small precipitation. Hourly recorded data is not available at all weather stations, and when it is, records often typically suffer from large amounts of missing data. Performing a reliable estimation of the diurnal cycle is therefore by no means a simple task. In this work, we used catchment-averaged hourly precipitation from the MOPEX database. Catchment selection for inclusion into the Mopex database was based on several quality control requirements, including quality precipitation data and minimum station density. While we can assume that the quality of precipitation data is good (or at least better than average), we have no way to quantitatively assess the quality of the observed diurnal cycle over the reference period. This also limits our ability to evaluate the diurnal cycle from the climate model. Differences are however large enough to suspect potential problems in the physical representation of precipitation in ClimEx. The GCM and RCM climate model structures do not include all mechanisms leading to precipitation in the real world, and this may lead to large errors (Legates, 2014). Even at the 0.11^{o} resolution of ClimEx, convection has to be parameterized, potentially leading to significant errors in the representation of larger precipitation quantiles. Knist, Goergen et Simmer (2020) and Prein et al. (2016) showed that resolving convection in climate models led to a better representation of precipitation intensity and of the diurnal cycle of precipitation, for example. Maraun et al. (2017) make a compelling argument with respect to the selection/disqualification of climate models based on their ability (inability) to represent key physical processes leading to any variable under consideration. Bias-correcting unrealistically simulated variables raises many important issues. Nevertheless, such issues are rather peripheral to the stated goal of this paper, which is to explore the impact of correcting (or not) the diurnal cycle of precipitation. The third factor explaining differences between observed and simulated precipitation cycles is the role of internal variability. Figure 2.4 shows that internal variability plays a very significant role in the representation of the diurnal cycle of precipitation. For the fall period, the difference between the observed and modeled cycles is smaller than the internal variability for most of the cycle. The large internal variability of precipitation has long been recognized in many studies (Dai et Bloecker, 2019a; Deser et al., 2012b), and it shows that 30 years (23 in the case of this study) of observations may simply not be a long enough period to adequately represent the diurnal cycle of precipitation.

After bias correction, climate model precipitation and temperature outputs were used in a hydrological model to generate streamflows. Hydrological modeling results point to a relatively modest but consistent increase in hydrological modeling performance for all metrics (with the exception of low flows) when the diurnal cycle of precipitation and temperature is corrected. The performance increase was clearly larger for the small catchments, but improvements were also seen for the medium and large size classes. The reasons for this improvement are not easy to pinpoint. Correcting the temperature diurnal cycle ensures a more realistic representation of the daily cycle of evapotranspiration, which may explain the better representation of the mean annual streamflow discharge. We can gain some insights by looking at the diurnal cycle of streamflow for summer (JJA) for one small and one large catchment, as shown in Figure 2.10. Small catchments are known to have such a cycle, where increased evapotranspiration in the afternoon (resulting from the strong temperature diurnal cycle) leads to a corresponding reduction of streamflow. It can be seen that the streamflow cycle is very well modeled for the small catchment when the diurnal cycle of both variables is corrected. For the large-size catchment, the diurnal streamflow cycle is flat for both observed and simulated streamflow. This shows that the catchment response time (flow routing transfer time or time of concentration) is too large for the day-time increased evaporation to show at the basin outlet. The small differences induced by the diurnal cycle of precipitation and temperature data are smoothed out during flow routing to the basin outlet. The internal variability of precipitation is transferred to streamflow, as represented by the large envelope from the 50 members of the ClimEx ensemble.

The absence of performance improvements for the low flow criterion can be partly explained by methodological choices. Modeling low flows is a more difficult task than modeling high flows, especially for conceptual models whose simplified structure is ill-suited to accurately represent the contribution of groundwater, which is complex, heterogeneous and sometimes dominant in the absence of precipitation. It is also well-known that the NSE criterion that was chosen for the hydrological model calibration is more sensitive to high-flows (Krause, Boyle et Bäse, 2005; Muleta, 2012). Since modeled low flows displayed large biases with and without bias correction of the diurnal cycle, we do not believe that discussing badly modeled streamflow metrics is very relevant. A discussion on low flows would be better served by using a hydrological model targeted at droughts, either with a different model structure or using a different objective function during calibration.

There are many limitations to this study. A single climate model was used and our results should be replicated with other climate models. Potential differences may be related to bias correction and hydrological modeling. No bias correction method can correct all statistics and particularly so when it comes to joint distribution properties (P and T in this case). In addition, hydrological models are good spatial integrators, but they are sensitive non-linear integrators. As such, small changes between two climate models (e.g., spatial resolution, interannual variability) could ultimately results in different streamflow simulations. While dramatically different results using other climate models are not expected, a different sensitivity to catchment size could possibly be observed. On the other hand, there are still not many climate model runs available with a high enough temporal and spatial resolution to apply to the study of small catchments, where the amplification of extreme precipitation is more likely to become critical as the climate becomes warmer.

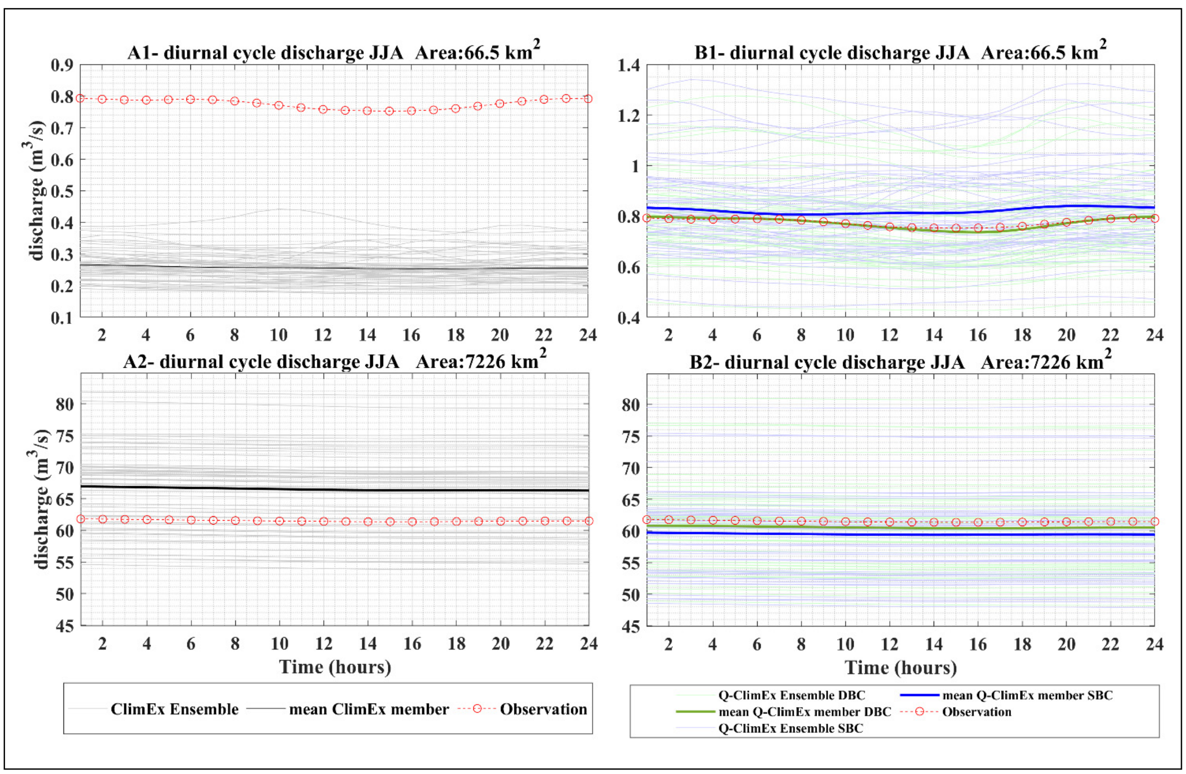

Figure 2.10 Annual diurnal cycle of discharge in JJA (Jun, July, August) before bias correction (first column: A1 and A2) and after bias correction (second column: B1 and B2) for two selected catchments. First row is for catchment 02143040 (small size classification) and second row is for catchment 02156500 (large size classification). The

observations are shown in red. Streamflow simulations using uncorrected ClimEx members are shown in light grey, and the ensemble mean is in black. Simulations using bias corrected data are in light blue (SBC) and light green (DBC) with the corresponding dark colours showing the ensemble mean. Time is local with 24h corresponding to midnight.

There are even fewer large ensembles being run at those fine resolutions. As shown in this paper, using a large ensemble shines a bright light on the role of internal climate variability in defining an accurate diurnal cycle for precipitation. The importance of internal variability and how it brings irreducible uncertainty to the bias correction process has been discussed in details by (Chen, Brissette et Lucas-Picher, 2015; Chen et al., 2018; Chen et al., 2016; Maraun, 2012; Teutschbein et Seibert, 2013). A single bias correction method was used in this study. It is well-known that the choice of a bias correction method has implications, which are often very significant, on streamflow metrics, and that a large amount of uncertainty can arise from this choice (Chen et al., 2013b; Iizumi et al., 2017). For small catchments, we believe that using a multi-variate method is highly desirable as preserving correlations between precipitation and temperature is key for an adequate representation of the diurnal cycle of key variables such as streamflows (as shown in Figure 2.10, for example). Small catchments modeled at the sub-daily scale would be very good targets to allow testing the advantage of multi-variate bias correction methods against univariate ones. Considering the subtle non-linear interactions between precipitation and temperature when modeling streamflows, it is possible that the improvements shown here in the representation of streamflows on small catchments may not have been realized using a univariate correction. This is something which could be tested in future work.

Hourly temperature from the ERA5 reanalysis was used instead of observations from stations. However, at the catchment scale, recent work at the daily temporal scale (Tarek, Brissette et Arsenault, 2020a; 2020b) showed that the ERA5 temperature was as good as, or better than, temperature gridded datasets derived purely from weather station observations. In addition, Lompar et al. (2019) showed that using the ERA5 hourly temperature to replace missing data in observed time series led to very low RMSE values. This good performance of hourly temperature data is not entirely surprising considering that the surface temperature is assimilated by ERA5 and that the surface temperature can relatively easily be inferred from geopotential heights, which are typically well reproduced by reanalysis.

One important remaining limitation of this work lies in the bias-correction not having been evaluated in a split-sample methodology. The efficiency of any bias correction scheme on an independent period depends on the stationarity of the biases. It has been shown in many studies that climate model biases are not constant in time (e.g.Maraun, 2012; Wan et al., 2021) and that non-stationarity can be amplified when using a hydrological model to simulate streamflows (Hui et al., 2020). The results presented here show that bias-correcting the diurnal cycle results in streamflow simulation improvements when tested on a common time-window with that of the bias correction process. Performing the same test on a different time window may impact the bias correction of the diurnal cycle of precipitation and temperature. In particular, the diurnal cycle of precipitation is not-stationary due to internal variability (as shown in Figure 2.4), and it is possible that the advantages of the sub-daily bias correction method may be somewhat reduced when tested over an independent validation period, as found by Chen et al., (2018) in a comparison study of multivariate vs univariate bias correction methods. On the other hand, the diurnal cycle of temperature, which controls evapotranspiration (an important part of the diurnal streamflow cycle) is much less affected by internal variability (Figure 2.3).

In light of the above results, and despite the limitations of this study, some recommendations can be made to climate change impact modelers concerned with the impact of extreme precipitation on small catchments. For catchments smaller than 500 km^2, a sub-daily hydrological modeling step is generally required for a good simulation of the flood peak and timing. For such catchments, the bias correction should include a step to account for differences between the observed and modeled diurnal cycles of temperature and, to a lesser extent, precipitation. Climate models do generate (as shown here) a realistic temperature diurnal cycle, and correcting for differences in timing and magnitude will ensure that the daily cycle of potential evapotranspiration matches that of observations. As discussed above, bias-correcting the diurnal cycle of precipitation is a bit more controversial. Taking into account the large internal variability of precipitation, as well as the potential issues surrounding the reliability of modeled precipitation, and especially extreme precipitation under a parameterized deep convection, arguments could be advanced from either side. Considering that these problematic issues also exist at the daily scale, and that bias correction of precipitation at this time scale is almost universally performed in impact studies, we feel that bias-correcting the diurnal cycle of precipitation is likely the best recommendation. A comparison between correcting only the temperature diurnal cycle versus correcting both the precipitation and temperature could help in figuring out the variable from which most of the improvement is derived.

The issue of climate model resolution also needs to be raised. Climate model resolution has been steadily improving and there is hope that with a higher resolution, the need for bias correction will be lessened (Lucas-Picher et al., 2021a). There are however computational physical limits as to how rapidly model resolution can decrease. Model resolution also competes with added model complexity, leading to a convergence between GCMs and ESMs (Bierkens, 2015) at the global modelling scale, rather than a sharp decrease in resolution. Regional climate models have seen the largest increase in spatial resolution, albeit at the expense of a progressively smaller computational domain. Climate model improvements have been shown to reduce biases. These improvements come from the increased resolution (e.g. Lucas-Picher, Laprise et Winger, 2017a) resulting in a better representation of local topography and land surface, and from better physics (e.g. Kendon et al., 2017). However, climate models remain an imperfect representation of the real climate system, and the sensitivity of impact models (e.g., hydrological model) to input data (e.g., precipitation, temperature) will still require some level of post-processing to insure realistic outputs from impact models. The ClimEx ensemble used in this study comes from a high-resolution regional climate model and quite clearly requires bias correction, showing that spatial resolution is not the only piece of the puzzle. Using uncorrected ClimEx data results in unrealistic streamflow simulations (e.g., Figure 2.5). However, with better and higher-resolution models, there is hope that post-processing methods will only end up correcting minor model deficiencies, and not correcting bad physics over a given area (e.g. Maraun et al., 2017) such as an incorrectly modeled precipitation annual cycle for example. Increasing spatial resolution has however opened the door to convection-permitting models, which require a resolution of around 0.03° (3-4 km) or better to resolve convection without the need for parametrization. Convection-permitting models are becoming more common and have shown to improve the representation of precipitation and extreme precipitation (Lucas-Picher et al., 2021a). With the better physics of these models, it is likely that bias-correcting the daily cycle of precipitation will still be needed, but will be done for the right reasons, rather than to correct for sometimes implausible large biases. For larger catchments (> 500 km^2), results have shown that improvements linked to the diurnal cycle correction become progressively smaller. For sub-daily hydrological modeling, it is however recommended to correct the diurnal cycle of temperature to ensure adequate representation of the potential evapotranspiration diurnal cycle. Correcting the daily cycle of precipitation is unlikely to make a big difference on streamflow metrics, considering the smoothing impact of flow routing. However, no ill effect of the diurnal cycle correction was observed for the medium to large catchments in this study. For those catchments, even though it was not investigated, it is likely that the relatively small improvements noted originated from the correction of the temperature daily cycle and not from precipitation.

2.5 Conclusion

This paper investigated the impact of bias-correcting the diurnal cycle of a climate model on the computation of streamflow over 133 small to large catchments, using a high spatial (0.11°) and temporal (1-hour) regional climate simulation (ClimEx-LE) over Eastern North America. The ClimEx regional climate model simulated a very realistic temperature diurnal cycle, but with timing and amplitude biases. There were however large differences between the simulated and observed diurnal cycles of precipitation. These differences result from a combination of observation errors, internal variability of precipitation and an inadequate representation of physical processes leading to precipitation by the climate model. These biases were successfully corrected using a multivariate quantile mapping method. The impact of bias-correcting (or not) the diurnal cycle of precipitation and temperature was evaluated on small (<500 km^2), medium and large (>1000 km^2) catchments. Results indicate that correcting the diurnal cycle results in better streamflow simulation, especially for smaller catchments, which have a definite sub-daily response time. For the small catchments, the relative error between observed and simulated flow quantiles was reduced. For example, the median reduction was 5% for the 95th and 99th quantiles, and 4% for the median value of the 20-year flood across all small catchments. For larger catchments, bias-correcting the diurnal cycle only results in minor streamflow improvements. Despite the large differences in the diurnal cycles of observed and simulated precipitation, and the limitations of climate models in generating precipitation with parameterized convection, we nonetheless recommend bias-correcting the diurnal cycle of both temperature and precipitation when conducting climate change impact studies on small catchments at the sub-daily time step.

2.6 Appendix

Appendix Table 2.1 USGS ID of the selected MOPEX catchments.

01197500	03175500	02138500	01567000	02126000	02472000	03324300	03524000
01518000	03238500	02143000	01574000	02135000	02478500	03326500	03528000
01520000	03303000	02143040	01628500	02156500	02479300	03328500	03540500
01541000	03346000	02143500	01631000	02202500	02482000	03331500	04100500
01556000	03438000	03111500	01643000	02217500	02486000	03339500	04113000
01558000	03443000	03361650	01664000	02228000	03011020	03345500	04115000
02018000	03473000	03504000	01667500	02329000	03109500	03349000	04164000
02058400	03531500	03550000	01668000	02339500	03164000	03361500	04176500
02118000	04201500	07261000	01674500	02347500	03168000	03362500	04178000
02475500	04221000	01371500	02016000	02365500	03237500	03364000	04185000
03079000	05517000	01543500	02055000	02375500	03266000	03365500	04191500
03161000	01372500	01548500	02083500	02383500	03269500	03451500	04198000
03167000	01445500	01559000	02102000	02387500	03274000	03455000	05430500
03173000	01560000	01562000	02116500	02448000	03289500	03465500	05435500
05592500	05593000	05594000	07029500	07056000	07290000	07363500	05526000
05440000	05447500	05454500	05515500	05517500	05518000	05520500	05552500
05554500	05555300	05569500	05582000	05584500			

2.7 Code and data availability

The MOPEX climate and streamflow database can be downloaded from the following link: (https://hydrology.nws.noaa.gov/pub/gcip/mopex/US_Data/) (Duan et al., 2006)
ERA5 data are available on the Copernicus Climate Change Service (C3S) Climate Data Store: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form (Hersbach and Dee, 2016).
ClimEx data can be downloaded from:
https://www.climex-project.org/en/data-access
The GR4J model (Perrin et al., 2003) and CemaNeige snow module (Valéry et al., 2014) are available on the Matlab File Exchange:
https://www.mathworks.com/matlabcentral/fileexchange/61720-gr4j-rainfall-runoff-model-deterministic-and-stochastic-methods-with-matlab.
The SCE-UA global optimization algorithm can be downloaded from:
https://www.mathworks.com/matlabcentral/fileexchange/7671-shuffled-complex-evolution-sce-ua-method

2.8 Acknowledgements

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The CRCM5 was developed by the ESCER Centre at Université du Québec à Montréal (UQAM; www.escer.uqam.ca) in collaboration with ECCC. Computations with the CRCM5 for the ClimEx project were made on the SuperMUC supercomputer at the Leibniz Supercomputing Centre (LRZ) of the Bavarian Academy of Sciences and Humanities. The operation of this supercomputer is funded via the Gauss Centre for Supercomputing (GCS) by the German Federal Ministry of Education and Research and the Bavarian State Ministry of Education, Science and the Arts.

CHAPTER 3

TEMPORAL AND SPATIAL AMPLIFICATION OF EXTREME RAINFALL AND EXTREME FLOODS IN A WARMER CLIMATE

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Abstract

This work explores the relationship between catchment size, rainfall duration and future streamflow increases on 133 North American catchments with sizes ranging from 66.5 to 9886 km^2. It uses the outputs from a high spatial (0.11°) and temporal (1-hour) resolution Single Model Initial condition Large Ensemble (SMILE) and a hydrological model to compute extreme rainfall and streamflow for durations ranging from 1 to 72 hours and for return periods of between 2 and 300 years. Increases in extreme precipitation are observed across all durations and return periods. The projected increases are strongly related to duration, frequency and catchment size, with the shortest durations, longest return periods and smaller catchments witnessing the largest relative rainfall increases. These increases can be quite significant, with the 100-year rainfall becoming up to 20 times more frequent over the smaller catchments. A similar duration-frequency-size pattern of increases is also observed for future extreme streamflow, but with even larger relative increases. These results imply that future increases in extreme rainfall will disproportionately impact smaller catchments, and particularly so for impervious urban catchments which are typically small, and whose stormwater drainage infrastructures are designed for long-return period flows, both being conditions for which the amplification of future flow will be maximized.

Keywords: Hydrology, Climate change, Extreme rainfall, Extreme floods

3.1 Introduction

Extreme streamflow estimation is essential for the design of hydraulic infrastructures and flood warning systems, as well as for proper risk assessment in flood zones. Several studies based on the historical record or on climate projections have shown how climate change can impact the hydrological cycle (Chen, Xu et Guo, 2012; Croitoru et Minea, 2015; Donat et al., 2013; Markonis et al., 2019). Rainfall and extreme rainfall changes are especially critical to the management of water resources (Arnbjerg-Nielsen, 2006; Milly et al., 2008; Samuels, Rimmer et Alpert, 2009; Wang, Hagen et Alizad, 2013). These changes can substantially affect streamflow regimes in terms of mean flow, seasonality, as well as intensity and frequency of extreme runoff (Bormann, 2010; Gobiet et al., 2014; Guerreiro et al., 2018; Moustakis et al., 2021; Strasser et al., 2018). Changes to projected future rainfall display complex spatial patterns (Rajulapati et al., 2020) that are globally dependent on latitude. At higher latitudes, a transition from snowfall towards rainfall is expected in the winter over many regions (e.g., Minville, Brissette et Leconte, 2008; Riboust et Brissette, 2015), although many other factors have an influence such as local topography and local climate zone. There is also a strong scientific consensus that deep convection will become more frequent and intense. In a warmer climate, leading to more extreme precipitation, and particularly so for short-term duration and longer return periods (Cannon et Innocenti, 2019; Cuo, Pagano et Wang, 2011; Fildier, Parishani et Collins, 2017; Martel et al., 2021; O'Brien et al., 2016; Pendergrass, 2020; Pendergrass, Reed et Medeiros, 2016; Semie et Bony, 2020). This shift towards more extreme and shorter duration rainfall will have a significant impact on summer-fall floods in smaller catchments (Bertola et al., 2020; Martel et al., 2021; Prein et al., 2017a).

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (Change, 2007) stated that the frequency of extreme precipitation is expected to grow over mid-latitude regions by the end of the century. Increasing temperature impacts moist convection by increasing evapotranspiration and convective available potential energy (CAPE), thereby strengthening convective processes. This is consistent with the Clausius Clapeyron (CC) equation, which states that atmospheric water vapor pressure increases at a rate of 7% per 1°C of warming. However, the relationship between warming and precipitation, and particularly with extreme precipitation, is complex and depends on many factors such as type, return period and duration of rainfall.

Berg, Moseley et Haerter (2013) divided observational rainfall into two groups: convective and large-scale stratiform rainfall. They postulated that with increasing temperature, the probability of occurrence of convective extreme rainfall rises, leading to more intense precipitation, with shorter duration (Berg, Moseley et Haerter, 2013; Westra et al., 2014a). The rate of increasing extreme precipitation is not uniform for stratiform and convective precipitation. Anticipated increases in extreme stratiform precipitation align with the Clausius-Clapeyron rate, while extreme convective precipitation could potentially surpass this rate, achieving Super-Clausius-Clapeyron levels. As a result, extreme convective precipitation may play a more significant role in shaping future precipitation patterns compared to its influence in today's climate (Guerreiro et al., 2018). Prein et al. (2017a) examined the impact of climate change on a mesoscale convective system using a convection-permitting regional climate model. They found that sub-daily convective extreme rainfall is expected to increase over most of North America, and particularly so in the Northeast US and Canada. Similar conclusions have been reached in a number of observation-based studies (e.g., Diffenbaugh, Scherer et Trapp, 2013; Feng et al., 2016; Gensini et Mote, 2015). There is increasing scientific agreement that extreme rainfall scaling is related to both duration and frequency (Cannon et Innocenti, 2019; Martel et al., 2021), with short-duration, low- frequency sub-daily rainfall most likely to follow Super-CC scaling. This finding is supported by the observational record and regional climate model projections (Lenderink et Van Meijgaard, 2008b; 2010; Panthou et al., 2014; Westra et al., 2014a). The amplification of short-duration, long-return period rainfall is expected to be one of the most important impacts of climate change (Forestieri et al., 2018; Ganguli et Coulibaly, 2019; Martel et al., 2021; 2020).

To properly evaluate the impact of changes in rainfall magnitude on future floods, rainfall duration and catchment size need to be jointly considered, since rainfall durations commensurate with catchment reactivity (time of concentration) are most likely to maximize streamflow extremes. Smaller catchments are therefore most likely to face an increased flooding risk from convective storm cells, whereas catchments whose size is larger than that of storm cells are potentially less affected due to flood wave attenuation across the catchment (Prein et al., 2017a). The reduction of spatially-averaged rainfall intensity over progressively larger areas (e.g., catchments) has been the subject of many studies, and most notably through the use of Areal Reduction Factors (ARFs) (e.g., Ball et al., 2016; Wright, Smith et Baeck, 2014). ARFs are defined as the ratio of rainfall depth across a given area (for a given duration and return period) compared to point rainfall, as typically measured by weather stations. ARFs start from 1 (local scale/very small catchments) and approaches 0 as the considered surface areas increase and becomes progressively larger than storm cells. ARF values have been found to decline faster for short-duration events due their highly convective nature and small spatial extent (Mineo et al., 2018; Ramos, Creutin et Leblois, 2005). Catchment size is therefore a critical aspect to consider in flooding related to extreme rainfall (Fowler, Wasko et Prein, 2021; Westra et al., 2014a). Failing to consider shorter-duration rainfall amplification may lead to potentially significant underestimations of future flood probability in smaller catchments (Cheng et AghaKouchak, 2014).

Currently, a significantly large body of literature is available on the impacts of climate change on water resources. Most of the work was however conducted at the daily time scale, since, until recently, most climate model projections outputs were available at this time step. Therefore, few studies have explored the impacts on water resources at the sub-daily time step. Since the largest increases in extreme rainfall are expected to be for sub-daily durations, we can thus predict a disproportionate impact on small catchments, whose hydrological response is rapid and commensurable with that of convective precipitation systems. These findings point to major climate change impacts on small rural and urbanized watersheds, including in cities and urban areas that are already very vulnerable to rainfall extremes. For most of these catchments, a daily simulation time step may be too coarse. Accordingly, the main objective of this work is to look at the impact of the amplification of extreme precipitation on runoff as a function of rainfall duration and catchment size. This main objective is split into three specific objectives, namely: 1) quantify future changes in extreme rainfall at the sub-daily time scale; 2) simulate the impact of changes in extreme rainfall on streamflow; and 3) explore the relationship between catchment size, rainfall duration and future streamflow increases.

3.2 Methodology

The methodological framework of this study is presented in Figure 3.1. A database of 133 catchments with surface areas ranging between 66.5 and 9886 km^2 is set up within the North American computational domain of the ClimEx experiment (Leduc et al., 2019a), which is described later herein. An hourly database of precipitation, temperature and streamflow data is used in each catchment to calibrate a hydrological model over a common 1980-2003 reference period. Following a bias correction step, the hourly precipitation and temperature outputs from ClimEx are used to generate climate scenarios over the 1980-2003 reference and 2075-2099 future periods. The scenarios both contain 1200 years (50 members times 24 years/member) representing climate conditions over the 24-year reference and future periods. Extreme rainfall and streamflow values are then analyzed as a function of the return period, rainfall duration and catchment size. Each methodological step is detailed below.

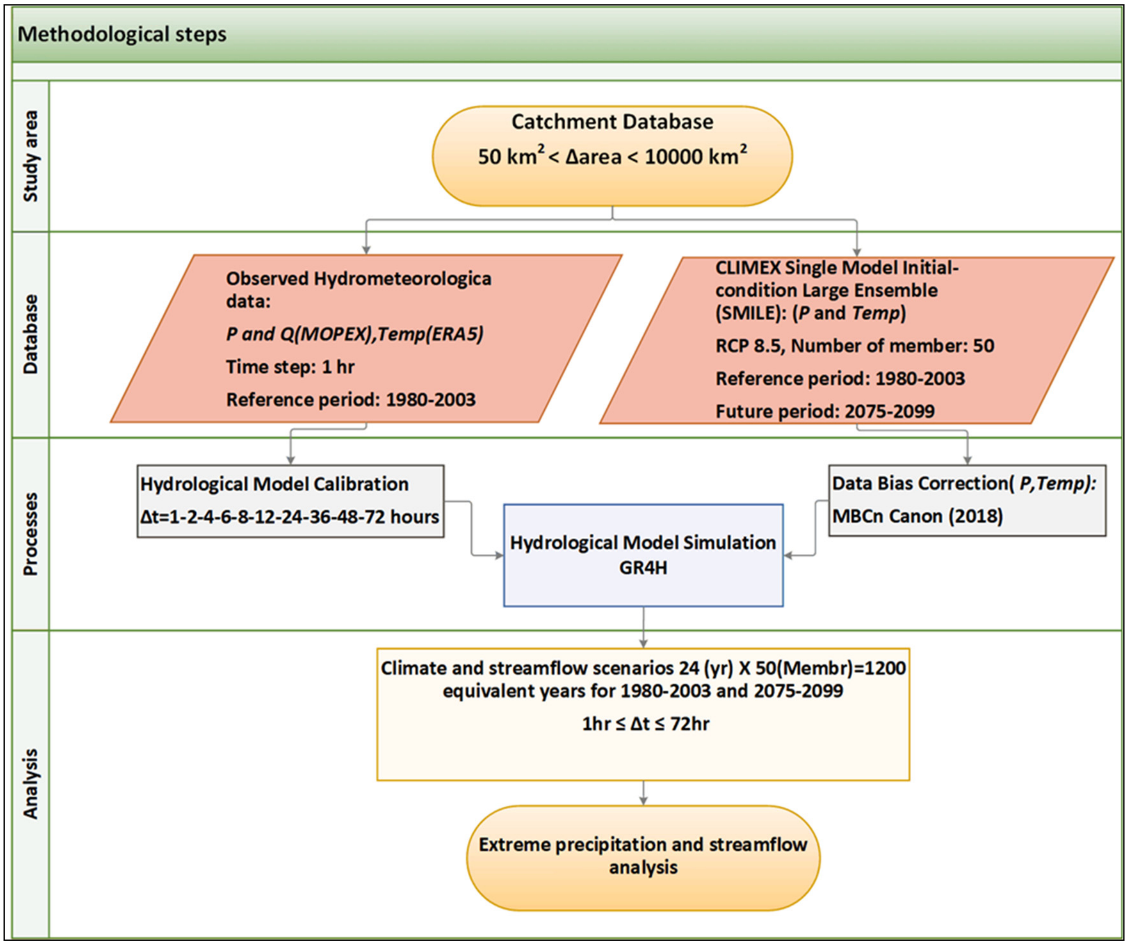

Figure 3.1 Methodological framework of this study

3.2.1 Catchment database

133 catchments dispersed across Northeastern USA were selected from the Model Parameter Estimation Experiment (MOPEX) database (Duan et al., 2006b). The MOPEX database was chosen since it contains a quality-controlled database of hourly precipitation averaged at the catchment scale. MOPEX precipitation is derived from the combination of daily and hourly weather station datasets from the National Climate Data Center and the Natural Resources Conservation Service. Daily precipitation data were disaggregated from the nearest hourly gauge, and a minimum number of gauges per unit area was required for catchments to be included in the database. All chosen catchments are located within the ClimEx Northeastern

North America computational domain. A maximum of 5% of missing data for precipitation, temperature and streamflow data was used as a threshold for inclusion in the database. Figure 3.2 presents the location of these catchments. The catchments cover four distinct climate zones of the Köppen climate classification. The catchment areas vary between 66.5 and 9886 km^2. In order to investigate the impact of the catchment size, all 133 catchments are separated into three different size groups: smaller than 500 km^2, between 500 and 1000 km^2 and larger than 1000 km^2. The three groups respectively contain 12, 25 and 96 catchments. The median values for total annual precipitation and mean annual temperature were respectively 1247, 1072 and 1049 mm, and 11.9,10.9, and 11.5 °C, across all three size classes. Using three groups containing an equal number of catchments was also considered, but by doing so, the mean catchment size of each group was deemed too large to appropriately separate catchments with a clear sub-daily response (< 500 km2) from those with a daily response (>1000 km2). The 500 km2 and 1000 km2 values are somewhat arbitrary, considering that catchment response time depends on many factors in addition to size (e.g., average slope, land use), but they were found to be adequate for the study area in the absence of large mountain ranges. Many catchments are located in the Appalachian range, but none occupy areas with long continuous slopes that would significantly impact response time.

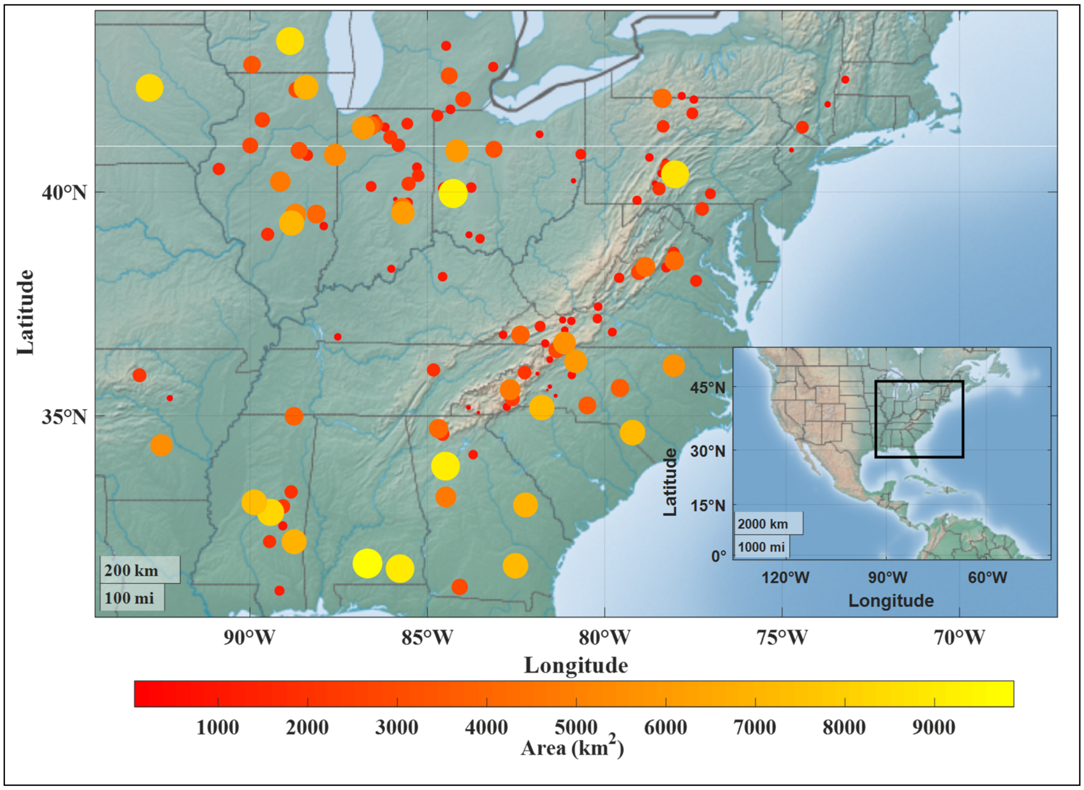

Figure 3.2 Location of the centroid coordinates of all selected catchments. The color and size of the circles are functions of the catchment surface area.

3.2.2 Observed hydrometeorological data

In this study, hourly precipitation, temperature and streamflow datasets over a common 1980-2003 period are used to define the reference period. This 24-year reference period is shorter than the typically recommended 30-year duration typically used to define the reference climate. This choice was dictated by hourly precipitation data availability. It is worth noting that several climate change impact studies have moved towards shorter durations (typically 20 years) for various reasons (e.g., Martel, Mailhot et Brissette, 2020). Hourly precipitation and discharge data for all catchments are taken from the Model Parameter Estimation Experiment (MOPEX) database (Duan et al., 2006b). In the MOPEX dataset, precipitation is averaged at the catchment scale. Since hourly temperature data is not available in the MOPEX database, hourly temperature from the ECMWF Reanalysis v5 (ERA5) dataset was used as a substitute. Tarek, Brissette et Arsenault (2020a) showed that ERA5 temperature is just as accurate as the weather station temperature for hydrological modelling. This is not entirely surprising since ERA5 incorporates measured surface temperature in its assimilation scheme. The spatial and temporal resolution of ERA5 are respectively 30 km and 1 hour. Hourly temperature was averaged at the catchment scale using all grid points inside the catchment boundaries. For the smaller catchments, if no grid point was found within their boundaries, the closest ERA5 grid point to the catchment centroid coordinates was used. The reference period dataset is used for the hydrological model calibration as well as for bias-correcting ClimEx hourly precipitation and temperature outputs.

3.2.3 Hydrological model and calibration

The rainfall-runoff model selected for this study is GR4H. It was first implemented by Mathevet (2005) specifically to be run at the hourly time step, and is based on GR4J, a widely used daily lumped continuous rainfall-runoff model introduced by Perrin, Michel et Andréassian (2003). GR4J has been used in multiple studies (Harlan, Wangsadipura et Munajat, 2010; Kunnath-Poovakka et Eldho, 2019b; Traore et al., 2014), including in many climate change impact studies (Brigode, Oudin et Perrin, 2013; Li et al., 2013; Tian, Xu et Zhang, 2013). GR4H has been optimized to the hourly time step (Bennett et al., 2014), but its structure is very similar to that of GR4J. GR4H is therefore also a lumped conceptual continuous rainfall runoff model. Its structure includes two storage reservoirs (production and storage) and two unit hydrographs which are used for flow routing. It has four parameters that need to be adjusted for optimal model performance: the maximum capacity of the production and routing reservoirs (X1 and X3), a groundwater exchange coefficient for the production store (X2) and the time base of the unit hydrograph (X4) for the flow routing reservoir. Snowpack accumulation and depletion are simulated by coupling GR4H with the two-parameter CEMANEIGE degree-day snow model (Valéry, 2010b). The CEMANEIGE-GR4H model requires potential evapotranspiration and precipitation at the hourly time step as inputs. The PET formulation of Oudin (Oudin et al., 2005) was chosen for this work. It is a radiation-based formula which uses hourly (or daily) temperature as its sole input. This formulation was specifically developed to work with the GR4J model, and has been shown to provide better simulation results as compared to other possible alternatives (Oudin et al., 2005).

The CEMANEIGE-GR4H hydrological model was calibrated over each of the 133 study catchments using the Shuffled Complex Evolution (SCE-UA) algorithm (Duan, Sorooshian et Gupta, 1994). This widely used algorithm was chosen based on the work of Arsenault et al. (2014a), who showed that it was among the best performers for hydrological models having fewer than 10 model parameters. Calibration was performed using the entire 24-year period, following the recommendations of Arsenault, Brissette et Martel (2018), who showed that using the more traditional split-sample calibration/validation approach was more likely to lead to a sub-optimal parameter set. The Nash-Sutcliffe efficiency criterion (NSE; NSE Nash, 1970) was used as the calibration objective function for all catchments using the hourly observed and simulated streamflow. The NSE criterion is a normalized root mean square error equation and is given as equation (3.1):

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_{sim}^{t} - Q_{obs}^{t})^2}{\sum_{t=1}^{T}(Q_{obs}^{t} - \overline{Q_{obs}})^2} \tag{3.1}$$

where Q_{sim}^{t} and Q_{obs}^{t} respectively represent simulated and observed streamflow at time t; $\overline{Q_{obs}}$ is the mean of the observed discharge and NSE is bounded by the [-Inf, 1] interval. A perfect match between simulated and observed discharge returns a value of 1, whereas a value of 0 implies a model predictive power equivalent to that of using the mean annual streamflow as a predicting model.

3.2.4 Climate model data

This work examines the impact of climate change on extreme precipitation in small catchments with a need for an hourly modelling time step. Accordingly, the ClimEx Single-Model Initial-Condition Large Ensemble (SMILE) was chosen (Leduc et al., 2019a). ClimEx is a high spatial (12 km) and temporal (1 hour for precipitation and 3 hours for temperature) resolution regional climate model. It was generated by dynamically downscaling the CanESM2 SMILE

(CanESM2-LE) over two computational domains covering Europe and Northeastern North America. CanESM2 is the second version of the Canadian Centre for Climate Modelling and Analysis (CCCma) earth system model, with a spatial resolution of 2.8° (Arora et al., 2011b). CanESM2-LE is a 50-member large ensemble derived from random atmospheric perturbation applied on historical data (Sigmond et Fyfe, 2016). As described in Leduc et al. (2019), the CanESM2-LE was generated using a two-step perturbation process. Starting with a 1000-year equilibrium simulation (CMIP5 pre-industrial Control run), five sets of random atmospheric perturbations were applied in 1850, and the five runs evolved independently for 100 years, resulting in five different ocean states in 1950. From 1950 onwards, 10 sets of random atmospheric perturbations were added to each of the original five simulations, resulting in a total of 50 simulations. CanESM2-LE and ClimEx both provide 50 members over the 1950 to 2100 period under historical forcing, and following the RCP 8.5 scenario from 2005. Large ensembles were developed to better understand the impact of internal variability (Deser et al., 2012c; Frankcombe et al., 2015; McKinnon et Deser, 2018; Thompson et al., 2015), but they can also be used to robustly sample very rare events since they provide multiple realizations of the climate under identical forcing (Maher, Milinski et Ludwig, 2021b). Thus, for the 24-year reference period (1980-2003), ClimEx provides 1200 equivalent years (50×24). Extreme precipitation with long return periods (e.g., 100 years) can therefore be empirically determined without necessarily having to extrapolate existing data using a fitted Generalized Extreme Value distribution, as is generally done with samples of limited size. This advantage of large ensembles has been exploited in many recent studies on extremes (e.g. Ehmele et al., 2020; Martel, Mailhot et Brissette, 2020; Zhao et al., 2020). For each catchment in the present study, ClimEx hourly precipitation and 3-hour temperature data was extracted for all grid points within a catchment boundary and averaged over both the reference (1980-2003) and future (2075-2099) periods. The 3-hour averaged temperature was subsequently interpolated to the hourly time step using a Piecewise Cubic Hermite Interpolating Polynomial (Barker et McDougall, 2020; Epstein, 1976). Only one catchment (the smallest at 67 km^2) did not contain a CLIMEX grid point within its boundary. The CLIMEX grid point closest to the catchment centroid was therefore used in this case.

3.2.5 Bias correction

Many studies have discussed the necessity of bias-correcting climate data to provide accurate streamflow representation when using a hydrological model (Crochemore, Ramos et Pappenberger, 2016; Hagemann et al., 2011; Tan et al., 2020; Teutschbein et Seibert, 2012; Tiwari, Mukhopadhyay et Mishra, 2022). In this study, the hourly ClimEx temperature and precipitation data were bias-corrected by using the N-dimension multivariate bias correction (MBCn) method of Cannon (2018). MBC-n is a multivariate generalization of quantile mapping that considers the dependency among different variables (Cannon, 2018). By applying MBC-n, all statistical characteristics of an observed continuous multivariate distribution are transferred to the corresponding multivariate distributions of simulated variables. MBC-n is arguably the most advanced quantile mapping algorithm available. Unlike many other multivariate methods, it is not limited to correcting a given measure of joint dependence (e.g., Pearson or Spearman rank correlation) (Cannon, 2018). MBCn also possesses the highly desirable attribute of preserving the climate change signal from the parent climate model across all quantiles, which is a significant limitation in most other quantile mapping methods (Maraun et al., 2017).

In this study, the bias correction factors were computed after pooling all 50 members of the ClimEx dataset (temperature and precipitation) together to preserve the underlying internal variability (Chen et al., 2019). The correction factors were computed on a monthly basis to account for the seasonality, and on an hourly basis to correct for biases in the model reproduction of the diurnal cycles (Faghih, Brissette et Sabeti, 2021). More details can be found in the above references.

3.2.6 Streamflow scenarios and analysis of extremes

The bias-corrected temperature and precipitation data were used as inputs to the calibrated hydrological model. For both the reference and future periods, the hydrological model was run at the hourly step for the 50 members of the ClimEx ensemble, for a total of 1200 equivalent years for each period. For each of those years, the maximum accumulated rainfall over durations of 1, 2, 6, 12, 24, and 72 hours was selected using a 1-hour moving window. Since this paper focuses on rainfall-generated floods, accumulated rainfall was only computed over months during which the snow cover was deemed negligible. As this study covers a variety of catchments and climate zones, the selected period was catchment-specific and restricted to the months in which the mean average temperature was above 0 °C. Other higher temperature thresholds were tested with no significant impact on the results. Annual maximum computed streamflow discharge and rainfall were taken over the same selected period. For example, for the 6-hour duration, precipitation was accumulated over all possible 6-hour continuous intervals and the maximum value for each year was selected. The process was similar for streamflow, although the average streamflow (and not the accumulated value) was computed for all possible 6-hour continuous intervals. This procedure resulted in 1200 values (24 years times 50 members) for the maximum yearly accumulated rainfall and maximum yearly discharge (for all 6 durations).

Finally, rainfall and streamflow values corresponding to return periods of 2, 10, 20, 50, 100 and 300 years were computed for each catchment using the unbiased Cunnane ranking formula.

3.3 Results

Figure 3.3 presents the calibration results over the 24-year reference period. The first year is used for hydrological model spin up and is not otherwise used in any of the methodological steps. The median NSE value is equal to 0.78 and the range for the 133 catchments goes from 0.61 to 0.87. There is little difference across the three class sizes, with medians of 0.73, 0.76 and 0.79, respectively, for the small, medium and large size classes. These values show that the GR4H-CEMANEIGE hydrological model performs very well over the reference period and that it is able to adequately represent the main hydrological processes over the study area.

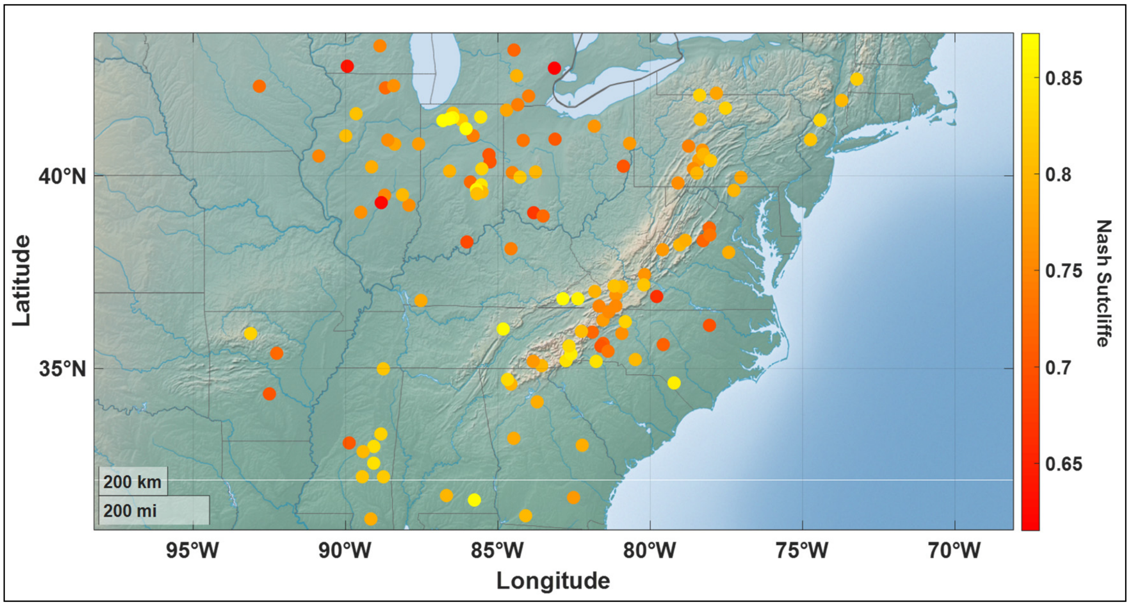

Figure 3.3 NSE calibration value for all study catchments

Figure 3.4 displays the projected change in extreme rainfall between the reference and future periods. Changes are all presented in terms of relative percentage increases. A value of 25% represents a 25% increase for a given rainfall duration and return period. Figure 3.4 is divided into 6 subplots corresponding to the 6 rainfall durations under study (1, 2, 6, 12, 24 and 72 hours). For each of these subplots, 6 series of three boxplots are presented. The 6 series correspond to the 6 return periods (2, 10, 20, 50, 100 and 300 years) considered, and the three boxplots correspond to the three catchment size classes (small - S, medium - M, and large L). Each boxplot represents the distribution of rainfall increases amongst all catchments within each size class (12, 25 and 96 catchments, respectively). The boxplots show the median (red line), 25th and 75th quantiles of the distribution (blue box), whereas the upper and lower whiskers present the min/max range of values. The red crosses are considered statistical outliers. To better outline the results, Table 3.1 presents the median values of Figure 3.4.

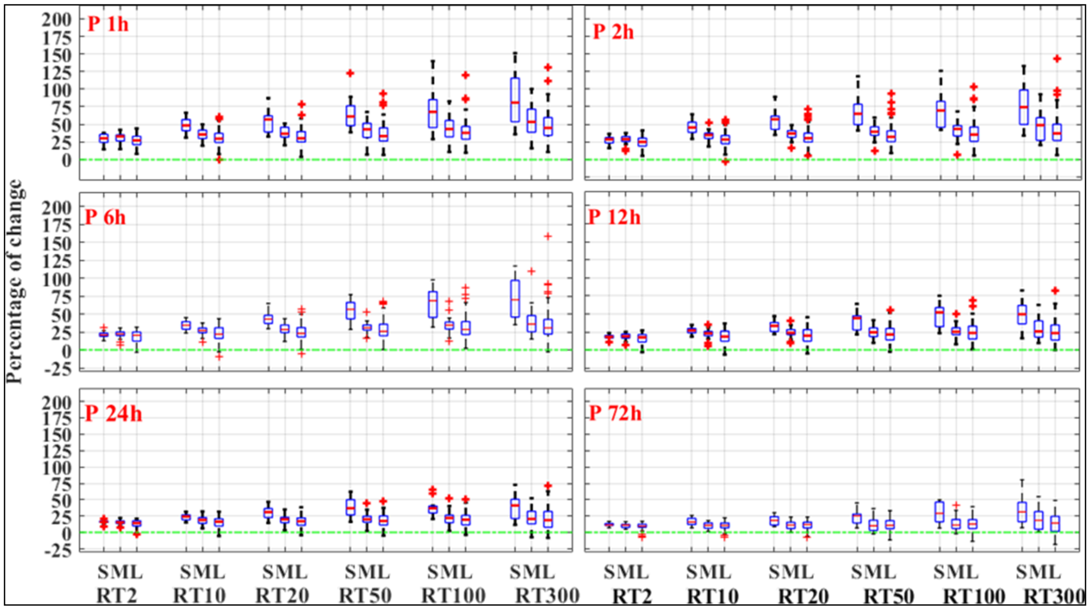

Figure 3.4 Extreme rainfall increase (%) between the reference (1980-2003) and future (2075-2099) periods as a function of rainfall duration (6 main subplots) and return period (X-axis). The series of three boxplots respectively represent the small (S), medium (M) and large (L) catchment size classes.

Table 2.1 Median values of the extreme rainfall increase (%) presented in Figure 3.4

P 1h																	
RT2			**RT10**			**RT20**			**RT50**			**RT100**			**RT300**		
S	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**
30.3	32.8	27.7	48.5	34.9	29.6	57.2	36.9	29.6	61	42.8	33.2	67.6	43.2	37.8	80.7	53.3	44.7
P 2h																	
RT2			**RT10**			**RT20**			**RT50**			**RT100**			**RT300**		
S	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**
29.4	29.6	25	45.3	34.7	28.6	57	36.8	30.3	65	39.3	32.1	69.5	43.3	35.3	74.3	48.7	37
P 6h																	
RT2			**RT10**			**RT20**			**RT50**			**RT100**			**RT300**		
S	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**
20.9	23.1	20.9	34.7	28.3	23	43.1	29.3	23.2	59	31.3	27.1	68.9	34.8	28.8	70.2	38.8	31
P 12h																	
RT2			**RT10**			**RT20**			**RT50**			**RT100**			**RT300**		
S	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**
18.5	19.5	17.2	26.4	22.8	19.2	35	23.8	20.6	44	24.6	21.5	52.2	25.3	24.1	49.6	28.5	23.6
P 24h																	
RT2			**RT10**			**RT20**			**RT50**			**RT100**			**RT300**		
S	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**
16.5	16.1	14.6	24.8	19.4	17.1	31.7	20.7	17.6	38	20.7	18.2	38.1	22.6	19.7	41.3	20.8	19.4
P 72h																	
RT2			**RT10**			**RT20**			**RT50**			**RT100**			**RT300**		
S	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**	**S**	**M**	**L**
11.9	10.8	11.1	18.6	12.3	12.5	19.6	12	13.6	27	12.4	12.3	30.1	14.2	13.5	37.5	20.3	17

Figure 3.4 and Table 3.1 display four important features:

First, generalized increases in extreme precipitation are observed across all durations and return periods, with a few rare exceptions (mostly outlier catchments in the longer rainfall durations).

Second, with the exception of the 2-year return period, the projected increases in extreme rainfall are strongly related to catchment size, with the smaller catchments seeing a much larger change compared to the medium and large ones. For example, the 100-year 1-hour rainfall sees a projected median increase twice as large as that of the large size class.

Third, the projected increases in extreme rainfall are clearly related to rainfall duration, with the shorter duration witnessing the largest increases.

Fourth, the projected increases in extreme rainfall are clearly related to the return period of the rainfall duration, with the longer return period witnessing the largest increases.

To sum up, Figure 3.4 shows that projected increases in extreme rainfall become greater for smaller rainfall durations, longer return periods, and smaller areas. This behavior observed in the ClimEx rainfall data is consistent with what has been observed in recent works with other climate models, as previously discussed in the literature review.

Figure 3.5 presents the same results in a different format. The three subplots in the figure present the results for the three catchment size classes. For each of these subplots, the median relative increase in precipitation (boxplot red line in Figure 3.4) is color-plotted as a function of rainfall duration and return period. Figure 3.5 clearly shows the amplification of rainfall in a warmer climate as a function of decreasing duration and increasing return period for all three size classes. The impact of the catchment size is made quite clear by comparing all three subplots.

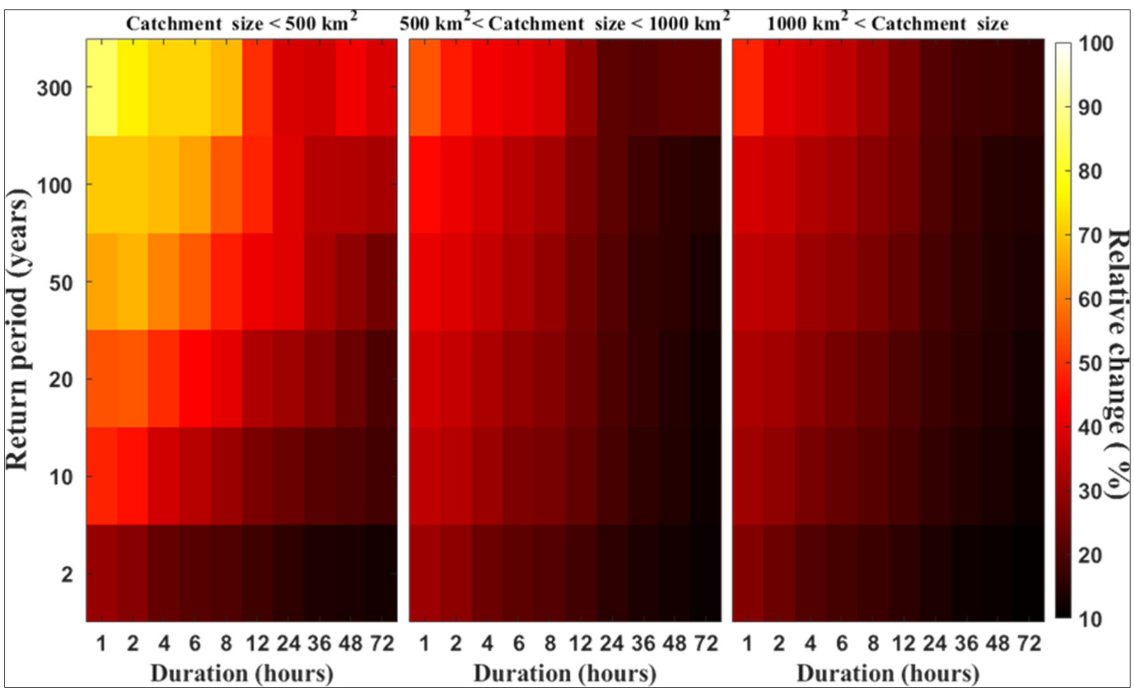

Figure 3.5 Extreme rainfall median increases (%) between the reference (1980-2003) and future (2075-2099) periods as a function of rainfall duration (X-axis) and return period (Y-axis). The three subplots respectively represent the small (S), medium (M) and large (L) catchment size classes.

Figure 3.6 presents the future return period of the 100-year reference period rainfall. A value below 100 indicates an increasing frequency in the future. For example, a future return period of 20 years indicates that the 100-year rainfall of the reference period will occur every 20 years (on average) for the future period, a five-fold increase in frequency. A value above 100 indicates that the same 100-year rainfall will become less frequent in the future.

Results strongly emphasize the strong increases in the frequency of the reference period 100-year rainfall, particularly for durations shorter than 12 hours. For such durations, the median 100-year rainfall becomes at least 6 times more frequent over the future period for all catchment size classes. Increases are larger and boxplots are tighter for the small catchments, but the latter may be related to the different number of catchments in each of the three size classes. The frequency increases become progressively smaller for the longer rainfall durations and the difference between size classes becomes larger. The spread of the small catchment boxplots is considerably tighter, but, once again, this may be due to the smaller number of catchments. There is a relatively small number of catchments for which there is no increase in the future frequency of the 100-year rainfall (future return period longer than 100 years). These are all large and, to a lesser extent, medium size catchments. This occurs only for rainfall durations equal or longer than 24 hours (with a single exception for the 12-hour duration). This behavior is not random, and is only seen in catchments located at the northern end of the study location.

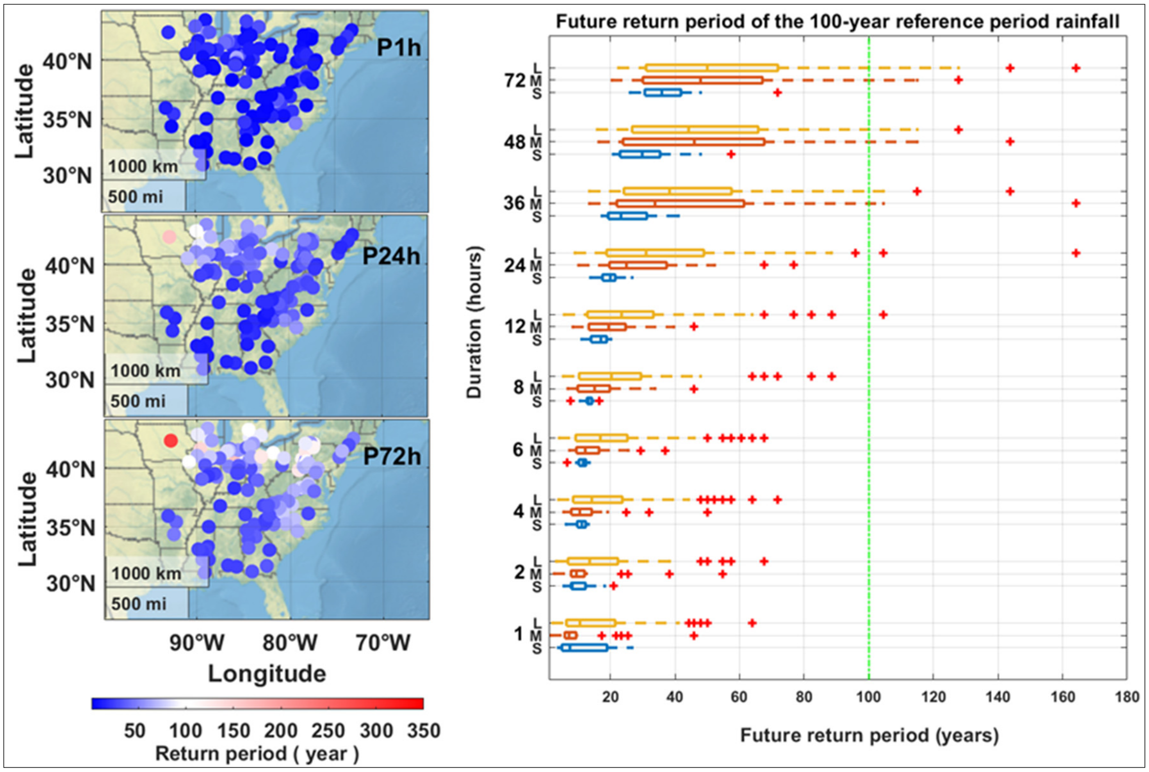

Figure 3.6 Right-hand side: Future return period (X-axis) of the 100-year reference period rainfall, as a function of catchment size class and rainfall duration (Y-axis). Left-hand side: Geographical distribution of future return period for 1, 24 and 72 hours.

The results presented above are consistent with the recent body of literature on sub-daily precipitation in a changed climate. However, how these changes will impact streamflow is not clear, considering the potential impact of increased evapotranspiration due to warmer temperature. The next figures (3.7, 3.9, 3.10) follow the layout of Figures 3.4, 3.5 and 3.6, but for streamflow. To allow for a direct comparison, the corresponding figures are all plotted using the same scales.

Figure 3.7 displays the projected changes in extreme streamflow between the reference and future periods. Changes are all presented in terms of relative percentage increases, just as was the case for Figure 3.4. Figure 3.7 follows the same patterns observed for precipitation in

Figure 3.4, and the four main observed patterns also apply here. These patterns show larger relative increases for shorter durations, lower frequencies (longer return periods) and smaller catchments. However, the relative increases appear to be larger for extreme streamflow as compared to extreme rainfall. To better explore this apparent increase, Figure 3.8 plots the ratio of the relative streamflow increase over that of precipitation. A value larger than 1 indicates that the relative streamflow increase is larger than that of precipitation, while a value smaller than 1 indicates the opposite.

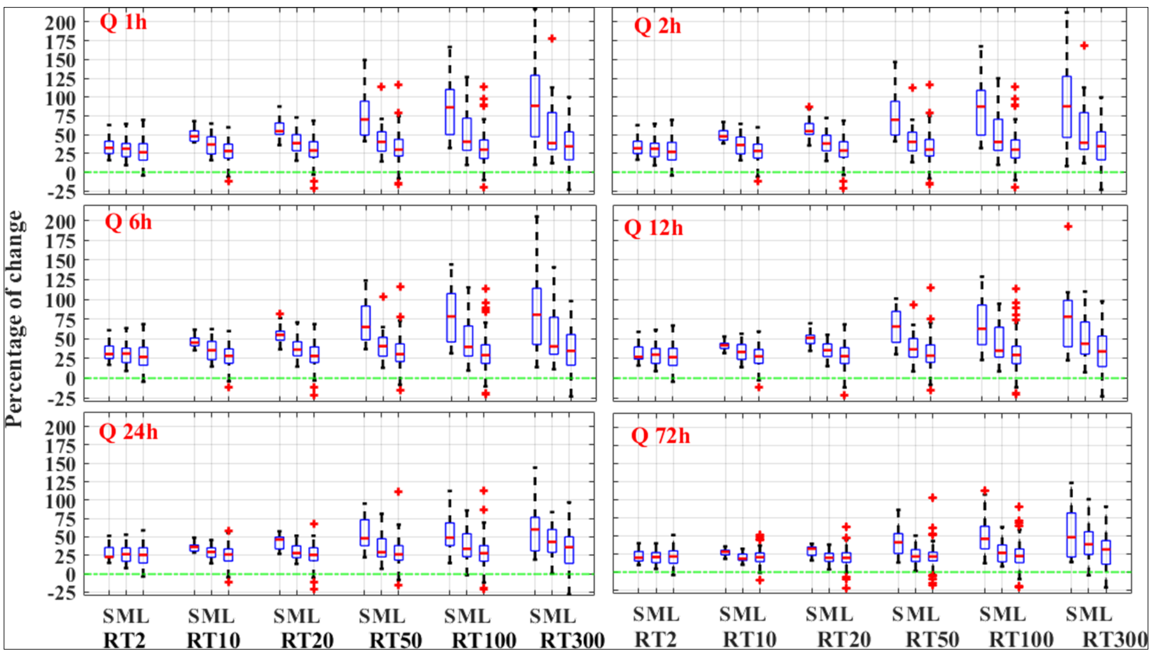

Figure 3.7 Extreme streamflow increases (%) between the reference (1980-2003) and future (2075-2099) periods as a function of rainfall duration (6 main subplots) and streamflow return period (X-axis). The series of three boxplots respectively represent the small (S), medium (M) and large (L) catchment size classes.

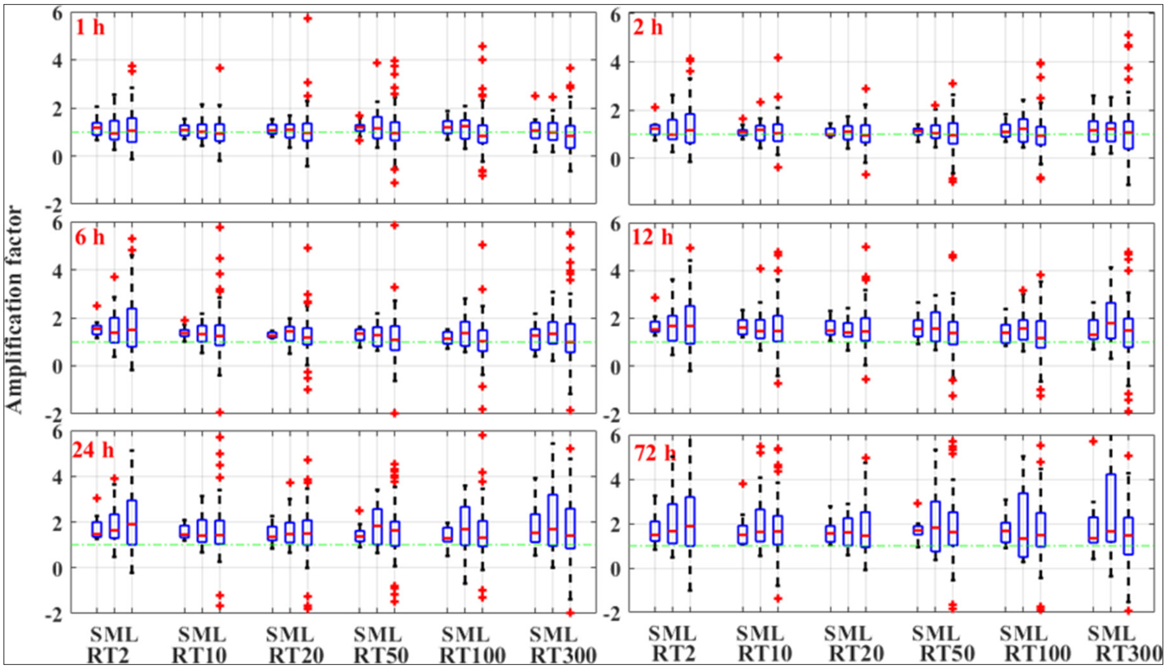

Figure 3.8 Ratio of the relative increase of streamflow (Figure 3.7) over that of precipitation (Figure 3.4)

Three main observations can be made from Figure 3.8:

First, all boxplots are more or less lined up on horizontal lines, therefore showing little dependence on the return period.

Second, the median ratios are systematically larger than 1, indicating that relative increases in streamflow tend to be larger than those of extreme rainfall.

Third, the ratios get larger for longer duration rainfall. While the median values are only slightly above 1 for the 1- and 2-hour durations, they rise progressively all the way to 72 hours when the 25th quantile is above 1, in all cases. There is, however, a lot of variability, with a significant number of catchments having a ratio below 1.

Figure 3.9 presents the same results as Figure 3.7, but in a different format. Just as was the case for Figure 3.5 (sister figure for rainfall) the three subplots of Figure 3.9 present the results for the three catchment size classes. In each subplot, the median relative streamflow increase (boxplot red line in Figure 3.7) is color-plotted as a function of rainfall duration and return period. The lighter the color, the larger the median relative increase. Figure 3.9 clearly shows the amplification of streamflow in a warmer climate as a function of decreasing duration and increasing return period for all three size classes. The changes are also strongly dependent on catchment size, with the smaller size class showing the largest increases. When compared to Figure 3.5 (rainfall), the colors are noticeably lighter, indicating the comparatively larger relative increases of streamflow.

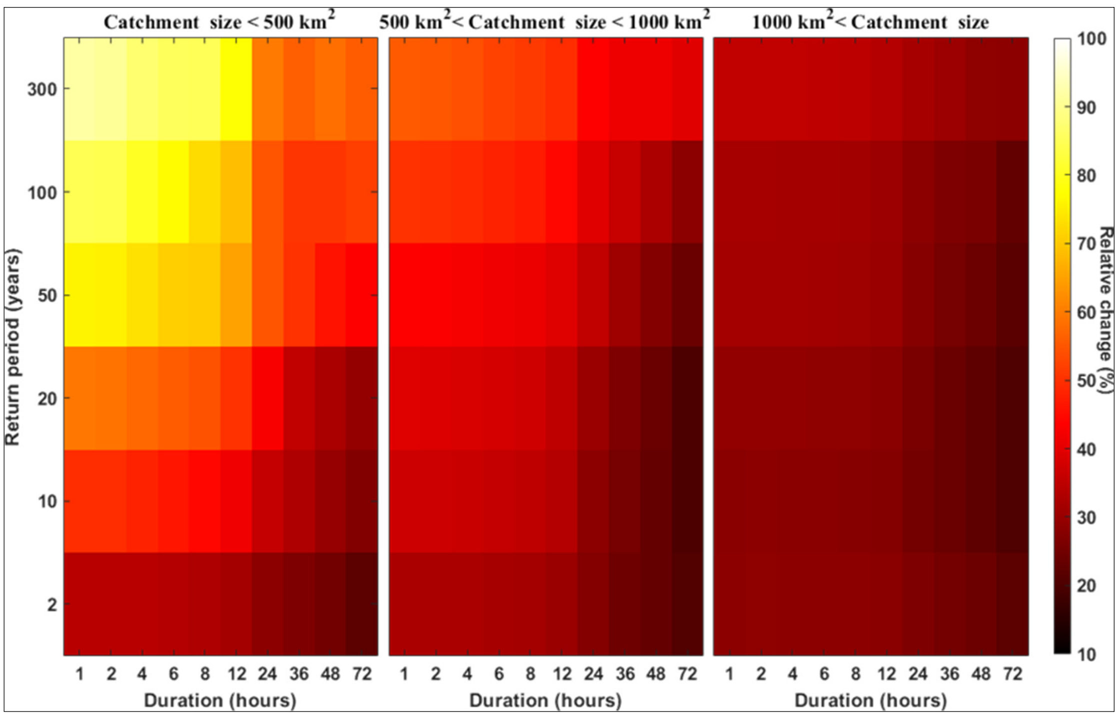

Figure 3.9 Extreme streamflow median increases (%) between the reference (1980-2003) and future (2075-2099) periods as a function of rainfall duration (X-axis) and return period (Y-axis). The three subplots respectively represent the small (S), medium (M) and large (L) catchment size classes.

Figure 3.10 presents the future return period of the 100-year reference period streamflow. Just as was the case for Figure 3.6 (sister figure for rainfall), a value below 100 indicates an increasing frequency in the future. The results are similar to those for rainfall (Figure 3.6), and particularly so for the 72-hour duration. However, for the 1-hour (and 24-hour to a lesser extent) durations, the colors are darker, indicating a smaller increase in frequency (return period) as compared to rainfall. Therefore, despite the larger increase in relative streamflow (compared to rainfall), it nonetheless translates into a smaller decrease in future return period. These increases are however significant, with future median return periods ranging between 20 and 45 years (2.2 to 5 times increase in frequency). Just as was the case for precipitation, the largest changes are observed in the Great Lakes region.

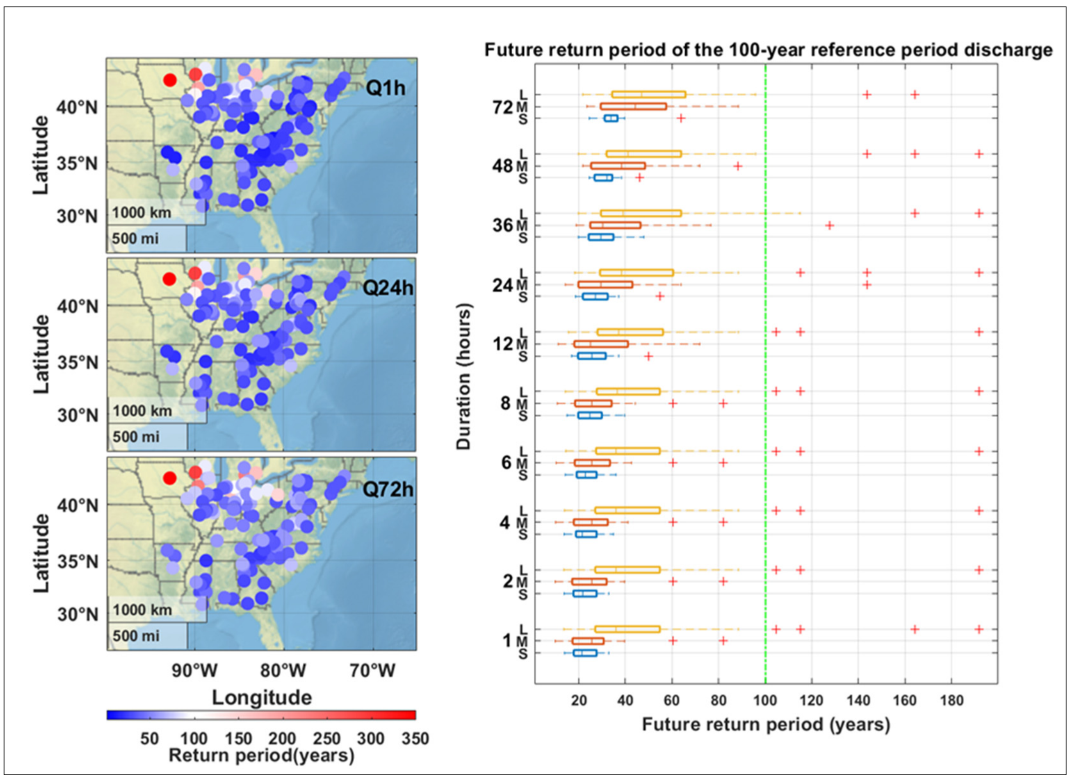

Figure 3.10 Right-hand side: Future return period (X-axis) of the 100-year reference period streamflow, as a function of catchment size class and rainfall duration (Y-axis). Left-hand side: Geographical distribution of future return period for 1, 24 and 72 hours.

3.4 Discussion

This work investigated the amplification of extreme rainfall and extreme streamflows in a warmer climate, and how catchment size impacts the this amplification. It made use of the high temporal and spatial resolutions of the ClimEx SMILE coupled with a hydrological model to simulate future extreme flows. Results demonstrate quite convincingly the amplification of future rainfall as a function of both duration and return period, with low frequency and shorter duration extreme rainfall seeing the largest relative increases in a warmer climate. The increases are especially notable over the smaller catchments for all rainfall durations, but especially so for the shorter durations. These results are consistent with recent climate modelling studies (Cannon et Innocenti, 2019; Hosseinzadehtalaei, Tabari et Willems, 2020; Westra et al., 2014a) and observations over the historical data record (Lenderink et Van Meijgaard, 2008b; 2010; Panthou et al., 2014). In addition to duration and return period, these results suggest that future extreme rainfall increases are also constrained with respect to storm size, with smaller storm cells becoming more intense as compared to larger ones.

A similar pattern of future change is observed with modelled streamflows, but with the notable difference that the relative amplification of extreme flows tends to be larger. This result is in line with the finding of Dougherty and Rasmussen (2020) who observed larger increases in future runoff than rainfall in flood-producing storms. However, we find that the amplification factor of Figure 3.8 (ratio of the relative increase of streamflow over that of precipitation) depend mostly on extreme rainfall duration, with durations longer than 8 hours showing systematically larger values (compared to shorter durations) and above 1 for almost all catchments. The amplification factors do not appear to be closely related to catchment size. The complex relationship between rainfall characteristics and runoff has been explored in a few studies (e.g., Reaney, Bracken et Kirkby, 2007; Wainwright et Parsons, 2002), which showed that the temporal variability of precipitation interacts with the catchment scale to reduce the apparent runoff coefficients as catchments get larger. We do not clearly observe this in our study. This could be due to the fact that a series of maximum annual rainfall and streamflows were sampled independently, meaning that for any given year, the maximum annual streamflow may be independent from its precipitation counterpart. Antecedent soil moisture conditions are important for the generation of extreme streamflows, and would typically explain this. While amplification factors tend to be larger than 1 for relative changes, our results show that changes expressed in terms of changes in return period tend to be larger for rainfall than for streamflow, and particularly so for durations below 12 hours. Results show that the current 100-year rainfall may become 3 to 20 times more frequent in the future (depending on catchment), versus 2 to 6 times more frequent for streamflows. This is likely a consequence of streamflow distributions having a heavier tail (Basso, Schirmer et Botter, 2015; Bernardara et al., 2008) than for rainfall.

Overall, the results presented in this work demonstrate the importance of catchment size on future flooding changes, with smaller size catchments being significantly more impacted by projected increases in extreme rainfall in a warmer climate. The projected changes in extreme floods indicate that storm drainage infrastructures are particularly at risk, especially those in urban areas, which typically serve small catchments, and those in small and steep rural catchments, which are already susceptible to flash floods (Zhang et al., 2019; 2021).

There are several limitations associated with this study, the most important being the use of a single climate model under a single greenhouse gas emission scenario (RCP 8.5). Several studies have clearly outlined the uncertainty related to the choice of climate models (Chen et al., 2011b; Giuntoli et al., 2015; Giuntoli et al., 2018) with respect to future impacts of climate change. There is a large consensus on benefits of using of multi-model GCM ensembles when performing impact studies to adequately frame the uncertainty associated with GCM climate sensitivity. The methodological choice of using the ClimEx SMILE was based on its high temporal and spatial resolutions. This allowed long streamflow and precipitation return periods (up to 300 years) to be robustly sampled over a wide range of catchment sizes, without the need for any additional downscaling step. In fact, ClimEx data had to be upscaled at the catchment scale prior to the hydrological modelling. Upscaling is considered robust, while statistical downscaling of climate model data is considered hazardous, and especially so for the commonly used model output statistics methods (Maraun et al., 2017). It would not be possible to perform this work in the framework of a multi-model ensemble as no such ensemble exists with the appropriate spatial and temporal resolutions allowing to study rainfall and streamflow amplification on catchments with a clear sub-daily response. Another advantage of using a large-ensemble is that it controls for model uncertainty and captures the uncertainty related to internal climate variability The RCP 8.5 scenario is no longer generally considered as a realistic scenario (e.g., Hausfather et Peters, 2020) since current fossil fuel consumption no longer tracks well with the scenario. However, this high-emission scenario is still useful even though a +5º world by the end of this century appears less and less likely. Climate simulations rarely run past 2100, and therefore, a +5º future world may still be reached, albeit at a slower pace, than according to RCP8.5. A high-emission scenario results in larger impacts to be modelled, which allows for a clearer vision through the fog of climate internal variability, which is particularly important for precipitation (Chen et al., 2021b; Deser et al., 2020b). It would definitely be worthwhile to redo this experiment with other climate models and emission scenarios when outputs are more commonly available at the proper spatial and temporal resolutions.

A single hydrological model was used in this study. The choice of a hydrological model is now known to have a potentially large impact on uncertainty (Giuntoli et al., 2018; Krysanova et al., 2018), although this has been shown mostly for low flow metrics. This is likely because most rainfall-runoff hydrological models are ill-suited to modelling low flows. During droughts, streams are mostly fed from the water table, and groundwater models are best-suited to this task. The hydrological model used in this study is a simple lumped conceptual model. Although this class of models has been shown to perform as well as more complex physically-based models for streamflow simulation at a catchment outlet (e.g. Reed et al., 2004), its empirical nature may make it less suited for climate change impact studies, when the climate may have drifted from that of the reference period over which the hydrological model was calibrated. Of particular interest is the potential evapotranspiration formula, which is modelled as a function of temperature. The temperature sensitivity of ETP formulations has raised concerns with respect to their suitability in climate change impact studies (e.g., Dallaire et al., 2021; Wang et al., 2017a). However, the recent works of Lemaitre-Basset et al. (2021) and Seiller et Anctil (2016) point to ETP formulations not being a major source of uncertainty. In light of this, and since this study is concerned with high flows, for which rainfall-runoff models are considered robust, it is unlikely that using another hydrological model would lead to different conclusions.

The ClimEx SMILE has a high spatial resolution of 11 km. This high resolution remains however too coarse to physically resolve deep convections resulting from sub-grid processes. Convection is therefore parameterized in ClimEx data. It is now generally accepted that convection-permitting models are more better able to simulate extreme rainfall (Lucas-Picher et al., 2021a). However, the resolution needed to run this class of model makes it expensive to run and most current studies are centered on relatively small computational domains and short time horizons. Convection-permitting models will eventually allow the study of future sub-hourly rainfall data to better frame the impacts on streamflow on small catchments. Many infrastructures require rainfall information at the sub-hourly time scale and these models will permit a better understanding of rainfall and streamflow amplification at even finer scales than done here. Ultimately, streamflow amplification will need to be studied up to the acre/hectare scale, which is typical for urbanized sub-catchments. This is roughly two orders of magnitude finer than the smallest catchments included in this study.

Finally, our results strongly reflect the climate of our study area (northeastern United States), which is essentially composed of two climate zones (from Köppen's classification): the humid continental zone (Dfb) and the humid subtropical zone (Cfa). Therefore, any extension of the results of our study to other climatic zones must be done with caution. This is particularly the case for arid and semi-arid zones where mean annual precipitation is expected to decrease in a warmer climate. However, recent observation-based work (e.g., Sun et al., 2021; Kirchmeier-Young and Zhang, 2020) shows that extreme precipitation could increase in large parts of the world, and even in some regions where mean annual precipitation is decreasing. This suggests that the findings of our work may be applicable to many other climate zones around the world.

Overall, our results point to increases in extreme rainfall and extreme streamflow across all durations, return periods and catchment sizes. However, the larger increases are systematically skewed towards shorter durations, longer return periods and smaller catchment sizes. It is clear that smaller rural and urban catchments will be significantly more impacted by the expected changes in future extreme rainfall as compared to larger catchments. It is therefore imperative to rapidly reviewed design rainfall and streamflow values (e.g., 100 year flood) (e.g., Martel et al., 2021) since such values are ubiquitous in engineering design, and drainage infrastructures have typical lifespans exceeding 50 years. This is especially critical for impervious urbanized catchments, which are particularly vulnerable to rainfall increases.

3.5 Conclusion

This study assessed how future extreme rainfall and floods are impacted by catchment size, over a sample of 133 North American catchments ranging from 66.5 to 9886 km2. The ClimEx Single Model Initial Condition Large Ensemble experiment was utilized to examine the intensification of extreme rainfall and floods in a warmer climate. This experiment offers 50 sets of climate variables at a 0.11o spatial resolution and time steps as frequent as hourly. We analyzed extreme rainfall and floods with durations ranging from 1 to 72 hours and return periods spanning from 2 to 300 years across all catchments.

The main conclusions of this study are as follows:

1) An increase in extreme rainfall between the reference and future periods is observed in all catchments, for all durations and return periods. The increase gets progressively larger for the shorter duration and longer return periods for all catchments, which confirms the results of recent studies based on regional climate models and on observations.

2) The increase in extreme rainfall is largest on the smaller catchments, indicating that future changes in extreme rainfall are also strongly dependent on the spatial scale of future storms. As well, they are largest for the smaller catchments.

3) The pattern of increases in future extreme streamflow is very similar to that of future extreme rainfall. The largest increases for future extreme floods are observed on the smaller catchments, over shorter durations and longest return periods. The relative increases are larger

for streamflow than for rainfall. Extreme rainfall duration appears to be the most important factor in the amplification of future extreme events. Overall, the results presented in this study indicate that the projected future changes in extreme rainfall will disproportionately affect smaller catchments, especially urban areas, where flood management design criteria are based on short-duration long-return period rainfall.

3.6 Data availability

All data and models used in this study can be found using the links in Table 3.2. The list of MOPEX catchments selected for this study is presented in Appendix (Table A1).

Table 3.3 Data and model availability

Datasets/Model	**Source**	**Reference**
MOPEX	https://hydrology.nws.noaa.gov/pub/gcip/mopex/US_Data	(Duan et al., 2006b)
ERA5	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form	(Hersbach et al., 2018)
ClimEX	https://www.climex-project.org/en/data-access	(Leduc et al., 2019a)
MBCn	https://rdrr.io/cran/MBC/man/MBCn.html)	(Cannon, 2018)
GR4H	https://rdrr.io/cran/airGR/man/RunModel_GR4H.html	(Perrin, Michel et Andréassian, 2003)

3.7 Appendix

Appendix Table 3.1 USGS ID of the selected MOPEX catchments.

Catchment ID								
01197500	03175500	02138500	01567000	02126000	02472000	03324300	03524000	05440000
01518000	03238500	02143000	01574000	02135000	02478500	03326500	03528000	05447500
01520000	03303000	02143040	01628500	02156500	02479300	03328500	03540500	05454500
01541000	03346000	02143500	01631000	02202500	02482000	03331500	04100500	05515500
01556000	03438000	03111500	01643000	02217500	02486000	03339500	04113000	05517500
01558000	03443000	03361650	01664000	02228000	03011020	03345500	04115000	05518000
02018000	03473000	03504000	01667500	02329000	03109500	03349000	04164000	05520500
02058400	03531500	03550000	01668000	02339500	03164000	03361500	04176500	05526000
02118000	04201500	07261000	01674500	02347500	03168000	03362500	04178000	05552500
02475500	04221000	01371500	02016000	02365500	03237500	03364000	04185000	05554500
03079000	05517000	01543500	02055000	02375500	03266000	03365500	04191500	05555300
03161000	01372500	01548500	02083500	02383500	03269500	03451500	04198000	05569500
03167000	01445500	01559000	02102000	02387500	03274000	03455000	05430500	05582000
03173000	01560000	01562000	02116500	02448000	03289500	03465500	05435500	05584500
05592500	05593000	05594000	07029500	07056000	07290000	07363500		

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(http://collaboration.cmc.ec.gc.ca/cmc/cccma/CanSISE/output/CCCma/CanESM2/).
The CESM1 ensemble was downloaded from the Large Ensemble Community Project (Schwarzwald et Lenssen) website (http://www.cesm.ucar.edu/projects/community-projects/LENS/).
The CRCM5 was developed by the ESCER Centre at Université du Québec à Montréal (UQAM; www.escer.uqam.ca) in collaboration with ECCC. Computations with the CRCM5 for the ClimEx project were made on the SuperMUC supercomputer at the Leibniz Supercomputing Centre (LRZ) of the Bavarian Academy of Sciences and Humanities. The operation of this supercomputer is funded via the Gauss Centre for Supercomputing (GCS) by the German Federal Ministry of Education and Research and the Bavarian State Ministry of Education, Science and the Arts.

CHAPTER 4

QUANTIFYING THE ROLE OF INTERNAL CLIMATE VARIABILITY ON FUTURE STREAMFLOW PROJECTIONS

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Abstract

Uncertainty about the future impacts of climate change represents a significant barrier to implementing adaptation measures. This work explores the impact of internal climate variability on streamflow projections for 133 catchments across the eastern and northeastern United States. Using data from a single model initial-condition large ensemble (SMILE) at high spatial and temporal resolution, this work assesses the magnitude of anthropogenic climate change and internal climate variability on projected future streamflow. The impact of catchment size is studied by grouping catchments into three different size classes (<500 km^2, between 500 and 1000 km^2, and >1000 km^2). Results show that in a warmer climate, low to middle quantiles of future streamflow will systematically decrease, while the upper quantiles will increase. Increases are largest for more extreme streamflow indices. Using three different approaches, the role of internal variability is studied to estimate the time of emergence (TOE). In this case, results show that the climate change signal of extreme floods and droughts emerges later than that of median flow quantiles, even though the changes for floods as droughts is more significant. There is a clear relationship between catchment size and TOE, with small catchments seeing an earlier TOE for floods, and a later one for droughts. These results provide insight into adaptation times for small to large watersheds.

Keywords:
Hydrology, Anthropogenic climate change signal, Internal variability, Extreme events, TOE, Small catchments

4.1 Introduction

Understanding internal climate variability is crucial in climate change impact studies as it helps quantify uncertainties in projections, assess regional vulnerabilities, and evaluate the influence of extreme events. It also plays a role in understanding the impacts at different temporal scales, improving climate models, and detecting and attributing climate change signals to specific causes. By considering internal climate variability, researchers can develop more effective mitigation and adaptation strategies. These strategies can then provide an implementation timeline that considers the joint impact of anthropogenic and natural influences on our evolving climate.

Climate change results from both internal and external forcing (Stocker et al., 2014). Internal climate variability (ICV) is the nonlinear fluctuation of the earth's climate, which results from the chaotic behaviour of the coupled atmosphere-ocean system (Feldstein, 2000; Schneider and Kinter, 1994). ICV manifests itself at many different timescales, generating regional climate anomalies which can last from a few months to as much as several decades (Delworth et al., 1993; Kwon and Deser, 2007; Nguyen et al., 2018; Pachauri and Meyer, 2014).

The external forcing of the climate system can either be natural (e.g. volcanic eruptions, solar flare variability) or anthropogenic in nature (Giorgi and Bi, 2009). Anthropogenic climate change (ACC) is the term used to describe the response of the climate system to an increase in greenhouse gas emissions, stratospheric ozone concentrations and tropospheric aerosols (Höök and Tang, 2013; Magnan et al., 2021). External forcing processes typically impact the climate at a scale shorter than 5 years (e.g., volcanic eruptions) or at a much longer time scale (e.g., tens of thousands of years for the Milankovitch cycles) (Helama et al., 2010; Pachauri and Meyer, 2014). Most impact studies are concerned with the evolution of the climate over the next few decades or century, and therefore, natural external forcing is typically neglected (Chen and Brissette, 2019).

As a result, the two primary factors influencing climate change at the multi-decadal timescale (typical of impact studies) are the internal climate variability (ICV) and anthropogenic climate change (ACC) (Deser et al., 2012b; Kay et al., 2015). Both factors need to be properly taken into account to adequately estimate future changes and uncertainty (Kay et al., 2015; Thompson et al., 2015).

Climate anomalies resulting from ICV are important because they have the potential to obscure or strengthen the signal of anthropogenic climate change, particularly in the short term, and especially at the local and regional scales (Barrow and Sauchyn, 2019; Deser et al., 2012a; Fischer and Knutti, 2014). In this context, ICV is often referred to as climate noise since it hinders the ability to measure and detect the ACC signal (Maraun, 2013). According to several studies, the ACC signal for precipitation may be hidden by ICV until the next century, in some regions of the world (Hawkins and Sutton, 2012; King et al., 2015; Maraun, 2013; Sanderson et al., 2018). For example, the 2000-2012 apparent warming ‘hiatus’ was a manifestation of ICV (Fyfe et al., 2016). The role of ICV has been the subject of many recent studies, which have explored its magnitude at various spatial and temporal scales (e.g. Hawkins et al., 2014; Martel et al., 2018).

The magnitude of internal climate variability (ICV) is crucial to the anthropogenic climate change (ACC) signal, with a strong ICV/ACC ratio possibly obscuring the detection of ACC (Fatichi et al., 2014). The 'time of emergence' (TOE) concept is frequently used to distinguish when the ACC signal surfaces from ICV noise, proving useful for impact assessments and adaptation planning (Gaetani et al., 2020; King et al., 2015; Stocker et al., 2014). TOE has been estimated for various climate variables using multiple techniques, each yielding potentially different results (Gaetani et al., 2020; Zhuan et al., 2018). A common characterization of TOE uses a signal-to-noise (S/N) ratio, defining it as the time when ACC (signal) surpasses ICV (noise) (Hawkins and Sutton, 2012). However, determining ACC and ICV signals, especially ICV, presents a challenge.

The signal-to-noise ratio, which helps in distinguishing between the anthropogenic climate change (ACC) signal and internal climate variability (ICV) noise, can be estimated using various methods. Typically, the ACC signal is gauged through a linear or occasionally non-linear trend. Alternatives, such as calculating the difference in mean values over two time periods, have been proposed to assess variable trends without assumptions on underlying patterns (e.g. Barnes and Barnes, 2015; Frame et al., 2019; Hawkins et al., 2020; Lehner et al., 2017; Nguyen et al., 2018; Zhuan et al., 2018).

Estimating ICV is, comparatively to ACC, more complex. The limited duration of historical time series limits our ability to evaluate ICV and renders the estimation of multidecadal ICV components nearly impossible in most cases (Maher et al., 2020). An alternative method is to use an ensemble of simulations derived from multiple climate models. This approach is based on the assumption that multi-model mean responses produce a more robust ACC, and that the variability between all climate model runs can been used to estimate ICV(Nguyen et al., 2018). However, the multi-model approach makes it difficult to separate model-specific ICV from inter-model structural variability (Deser et al., 2012a).

To better understand ICV, a superior alternative is to run several simulations with a single climate model, with each simulation subject to slight variations in initial conditions. This approach allows for a reliable evaluation of the forced response and internal variability of that specific climate model (Deser et al., 2012a; Wills et al., 2020).

Single Model Initial-condition Large Ensembles (SMILEs), which run identical models with slight variations in atmospheric initialization, help assess how minor perturbations influence climate system trajectories over short and long terms (Bengtsson and Hodges, 2019; Deser et al., 2016). They have been used to quantify internal variability's impact on climate change detection (Deser et al., 2012a; Maher et al., 2020; Martel et al., 2018). Findings indicate that internal variability often obscures anthropogenic climate change detection until late in the century, especially in extreme precipitation and local/regional temperature trends (Fischer and Knutti, 2014; Maraun, 2013; Martel et al., 2018).

Internal Climate Variability (ICV) is typically calculated from the spread of future projections in ensembles, often using pre-industrial control simulations as the basis (Chadwick et al., 2019; Martel et al., 2018). ICV is often measured by the standard deviation of a variable's mean value across ensemble members. The Time of Emergence (TOE) is defined as the moment when the ACC/ICV (signal-to-noise) ratio surpasses and sustains beyond a specific threshold (Chadwick et al., 2019; Lee et al., 2016).

Statistical methods have also been used to determine the TOE. Deser et al. (2012b) used the standard error of the mean difference between two time-horizons across all members of the CESM2 ensemble to estimate the 95% confidence interval needed to determine a TOE. Other studies have used the Kolmogorov-Smirnov (KS) test to determine the TOE (Gaetani et al., 2020; Im et al., 2021; King et al., 2015; Leng et al., 2016; Mahlstein et al., 2012; Pohl et al., 2020; Zhuan et al., 2018). The Time of Emergence (TOE) is recognized when distributions of a variable between two time-frames show a statistically significant difference that persists in subsequent years (Chadwick et al., 2019). The KS-test, which does not assume any data distributions, is particularly robust for identifying TOE, especially for climate extremes (King et al., 2015). It has been applied in various contexts such as identifying changes in river flow regimes and precipitation metrics (Gaetani et al., 2020; Zhou et al., 2018). Another approach by Martel et al. (2018) utilizes a non-parametric estimate (Sen’s slope) to define the TOE as the first year where a statistically significant trend appears in the majority of the ClimEx SMILE members.

There is a significant body of literature on how ICV can impact the detection of ACC (e.g. Deser et al., 2012a; Fasullo and Nerem, 2016; Maher et al., 2020). However, most existing works focus on the TOE of precipitation and temperature (Chadwick et al., 2019; Chen et al., 2021; Martel et al., 2018; Otto-Bliesner et al., 2016; Ricke and Caldeira, 2014; Zhuan et al., 2018). Finding how ICV affects the streamflow is complicated by the fact that it has a strong non-linear response to changes in temperature and precipitation. The impact may also depend on the climate as Deb et al. (2019) showed that ICV may be less important in arid and semi-arid catchments. In addition, since the ICV of precipitation is strongly related to the spatial scale (Chen and Brissette, 2019; Chen et al., 2021), it is likely that this will be transferred to streamflow and that small and large catchments may therefore react differently to ICV.

Estimating future streamflow and associated uncertainty is of utmost importance, as the design of numerous infrastructures and land use management are strongly influenced by river regimes and floodplains.

This study's primary objective is therefore to assess the influence of internal climate variability on the detectability of the climate change signal in streamflow across 133 US catchments. Specifically, it aims to:

- Quantify the climate change impact on streamflow extremes such as floods and droughts.
- Examine the role of internal climate variability in detecting near-future and long-term changes by identifying the time of emergence for different streamflow indices.
- Investigate how catchment size affects the detectability of the anthropogenic climate change signal on streamflow.

In line with these objectives, we propose a robust, large-sample methodology to analyze internal climate variability's impact on streamflow and the emergence of the anthropogenic climate change signal.

4.2 Material and methods

4.2.1 Study area

To cover a diversity of hydroclimatic conditions, 133 catchments were chosen from the Model Parameter Estimation Experiment (MOPEX) database (Duan et al., 2006). These catchments are spread over the Northeastern quadrant of the United States. The catchment area ranges from 66.5 to 9886 km^2. In order to better understand the effect of catchment size, catchments were clustered into three size classes: less than 500 km^2 (small), between 500 and 1000 km^2 (medium) and larger than 1000 km^2 (large). The catchment locations and size distribution are shown in Figure 4.1.

The catchments fall under 4 zones of the Köppen climate classification (Kottek et al., 2006): humid subtropical climate, hot-summer humid continental climate, warm-summer humid continental climate and subarctic climate. The study area was chosen at the intersection of the MOPEX and the computational domains of the ClimEx regional climate dataset used in this study, as will be described later. All selected MOPEX catchments within the study area had less than 5% of missing data. All MOPEX catchments are free of any upstream regulation (Schaake et al., 2006).

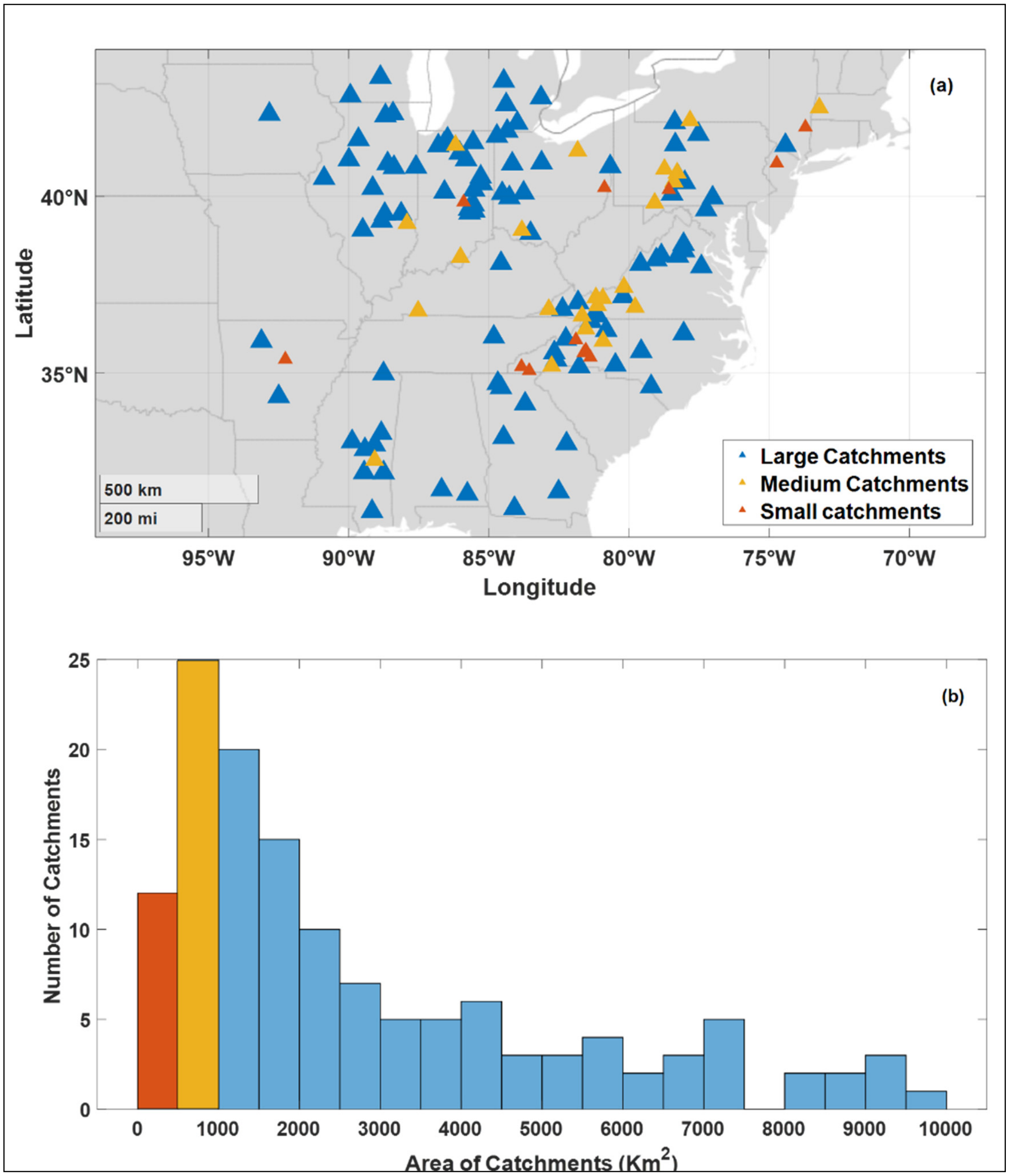


Figure 4.1 Location of the centroid of the 133 selected MOPEX Catchments (a) and distribution of catchment sizes (b).

4.2.2 Datasets

All the datasets used in this study were at the hourly time step. The reference dataset for observed streamflow and climate information covers the 1981-2003 period, for a total length of 23 years. This period was chosen as it was the longest one which intersects all the observation datasets.

4.2.2.1 Observed data

Datasets for precipitation, temperature, streamflow discharge and climate data were used in this study. Hourly accumulated precipitation and hourly streamflows were taken from the MOPEX database (Duan et al., 2006). Because hourly temperatures were not available in the MOPEX database, hourly temperature estimates were taken from the ECMWF Reanalysis v5 (ERA5). Tarek et al. (2020) showed that the ERA5 temperature is just as accurate as that measured at weather stations, at least for the purposes of hydrological modelling. ERA5 temperature has 30-km spatial and hourly temporal resolutions. The mean catchment-averaged temperature is obtained by averaging all ERA5 grid points within each catchment. In the few cases where no grid point was present within a catchment boundary, the closest three grid points were averaged. Catchment-averaged precipitation and temperature is used for the hydrological model calibration (against observed streamflow data) and for the bias correction of climate model data. Over the reference period, precipitation records from the MOPEX catchments are mostly complete with some rare missing data that were set to zeros for hydrological modeling and NaNs (Not a Number) for the rest of the analysis. Records were also nearly complete for streamflow. Missing values were treated as NaNs and disregarded in the computation of the objective function. Temperature records were complete.

4.2.2.2 Climate model data

This work addresses the role of internal climate variability in the detection of the anthropogenic climate change signal of various streamflow indices, and how it relates to catchment size. To this end, data from the ClimEx Single-Model Initial-Condition Large Ensemble (SMILE) (Leduc et al., 2019) was used to project hourly temperature and precipitation. ClimEx is a large dataset which was produced by dynamically downscaling the 50 members of the Canadian Earth System Model large ensemble (CanESM2-LE) with the 5th generation of the Canadian Regional Climate Model (CRCM5, Martynov et al., 2013; Šeparović et al., 2013). The 50-member ClimEx dataset covers the 1950-2100 period using historical forcing until 2005, and using the RCP8.5 trajectory afterward. ClimEx data spanning the period from 1981 to 2098 was extracted for use in this study. The last two years were omitted due to some inconsistencies found in the data over these two years. ClimEx has a high spatial (0.11°) and temporal (hourly for precipitation, 3-hourly for temperature) resolution, making it ideally suited for studying climate change impacts on small catchments. The 50-member ensemble allows the robust computation of very large extremes. For each 31-year period, 1550 years of data (31 years x 50 members) representing the same climate can therefore be accessed to sample very rare events (following the ergodicity principle). ClimEx was generated over two large regional computational domains covering Europe and the North-East of North America. ClimEx temperature is the only variable used in this study that wasn't readily available at the hourly time-step. The 3-hourly temperature ClimEx data were interpolated to the hourly time step using a Piecewise Cubic Hermite Interpolating Polynomial (Barker and McDougall, 2020; Fritsch and Carlson, 1980).This interpolating method preserves monotonic behaviour and shape of original data and guarantees smoothness by having continuous first-order derivatives, It is also not very sensitive to noise, making it very appealing for weather data.. Catchment-averaged hourly data was obtained by averaging all data points within each catchment boundary. Considering the high spatial resolution of ClimEx, multiple data points were averaged, even for the smallest catchments.

4.2.3 Bias correction

All climate models are biased when compared to an observed dataset over the same spatial domain. These biases have many origins, including scale mismatch and the imperfect representation of various physical processes within each climate model. Without a bias correction step, the outputs of impact models (e.g., hydrological models) would also be biased, sometimes to the point at generating simulations that would be considered unrealistic (Crochemore et al., 2016; Teutschbein and Seibert, 2012). A downscaling step is also often considered necessary to deal with the scale difference between climate model and impact model outputs. In this work, because of the high spatial resolution of ClimEx, all climate datasets (observed and simulated climate model) had to be upscaled to the catchment scale, thus negating the need for any statistical downscaling. For the bias correction step, ClimEx precipitation and temperature data were jointly bias-corrected at the hourly scale using the N-dimension multivariate bias correction (MBCn) of Cannon (2018). MBC-n is a multivariate extension of quantile mapping which preserves the statistical properties of the model variables, including joint properties. It also preserves the climate change signal projected by the climate model after post-processing, which is not the case for many bias correction methods. MBCn is arguably the most advanced quantile mapping bias correction available. Following the recommendations of Faghih et al. (2022), the precipitation and temperature diurnal cycle was also corrected, which was shown to improve hydrological simulations on small catchments. This step recognizes that climate model biases differ when comparing daytime and nighttime data, in addition to the long-recognized fact that biases changes along the annual cycle. Finally, the computation of bias correction factors followed the procedure recommended by Chen et al. (2019) and Vaittinada Ayar et al. (2021) when dealing with a climate model large ensemble. All 50 members were pooled together to compute the bias correction factors in order to preserve the internal variability signal contained in the uncorrected climate model data. Correcting each member separately, as has been done in some studies, brings all members into the reference dataset, thus eliminating the internal variability present across all members of the ensemble. This would in turn propagate to more distant time horizons and result in incorrect estimations of the time of emergence of a climate variable.

4.2.4 Hydrological model and calibration

For this study, the GR4H hydrological model (Mathevet, 2005) was chosen to model hourly discharge. GR4H is the hourly version of the daily GR4J model (Perrin et al., 2003), a well-known lumped conceptual rainfall-runoff model which has been extensively used in hydrological modelling and climate change impact studies (Kunnath-Poovakka et Eldho, 2019a; Tian, Xu et Zhang, 2013; Troin et al., 2018). The GR4J model structure consists of two storage reservoirs (production and routing) and two unit hydrographs. To achieve best model performance, the four parameters of Table 4.1 must be calibrated.

Table 4.1 Parameters of GR4H for calibration

x_1	Capacity of the production soil (SMA) store (Magnan et al.)
x_2	Water exchange coefficient (Magnan et al.)
x_3	Capacity of the routing store (Magnan et al.)
x_4	Time parameter (days) for unit hydrographs

GR4H was coupled to the CemaNeige degree-day snow model (Valéry, Andréassian et Perrin, 2014) to simulate snow accumulation and melting processes. CemaNeige was specifically developed to be matched with GR4J and adds two parameters to be calibrated. The inputs to the combined CemaNeige-GR4H model are hourly temperature, precipitation, and potential evapotranspiration. To compute the evapotranspiration, the Oudin formulation was employed (Oudin et al., 2005). The hydrological model was automatically calibrated on all catchments using the Shuffled Complex Evolution (SCE-UA) algorithm (Duan, Sorooshian et Gupta, 1994). This algorithm has been widely used for the calibration of hydrological models, and was shown by Arsenault et al. (2014b) to be particularly well suited for models having less than 10 parameters to adjust. Following the work of Arsenault, Brissette et Martel (2018) and

Shen, Tolson et Mai (2022), the hydrological model was calibrated using the entire length of available data (with a one-year warmup period) without any validation step. Their work showed quite convincingly that splitting the sample into calibration and validation periods was more likely to result in a sub-optimal parameter set. The objective function used for the calibration was the Nash-Sutcliffe efficiency (Christensen et al., 2007) criterion (NSE; NSE Nash, 1970). This criterion is arguably the most common objective function used for the calibration of hydrological models. It is computed as equation (4.1):

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_{sim}^{t} - Q_{obs}^{t})^2}{\sum_{t=1}^{T}(Q_{obs}^{t} - \overline{Q_{obs}})^2} \tag{4.1}$$

where Q_{sim}^{t} and Q_{obs}^{t} denote simulated and observed streamflow at time t and $\overline{Q_{obs}}$ represents the mean of the observed discharge. The NSE metric ranges from -∞ to 1. A value of 1 indicates a perfect fit between the simulated and observed discharge, whereas a value of 0 indicates that the model has a performance equal to that of using the mean discharge as a predictor.

The calibration results for all catchments are shown in Figure 4.2. NSE values range from 0.61 to 0.87, with a median value of 0.78. The median NSE values for the three catchment size classes are respectively equal to 0.73, 0.76, and 0.79 for the small, medium, and large size classes. The GR4H-Cemaneige hydrological model performs very well on all three catchment size classes. The relatively lower NSE values for the smaller catchments are probably related to the quicker reaction time of the catchments, resulting in rapidly changing hydrographs that are more difficult to model. Flow routing across larger catchments typically results in smoother, easier to model hydrographs.

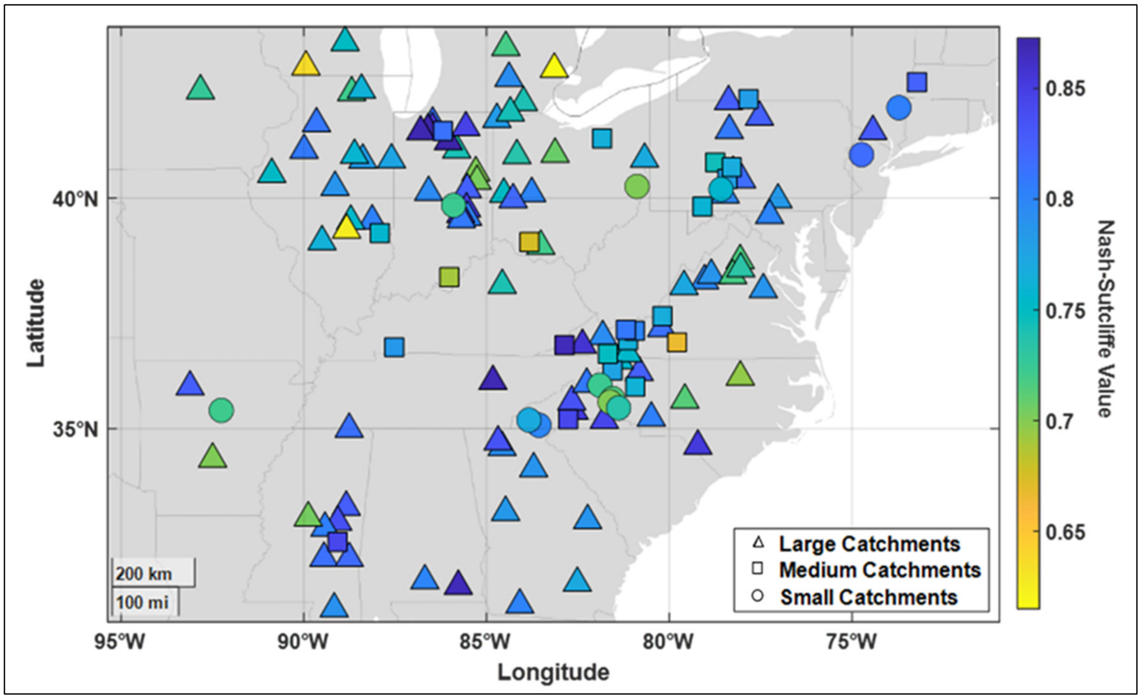


Figure 4.2 Nash-Sutcliffe model efficiency calibration values

4.2.5 Streamflow indices

To study the impact of internal variability and time of emergence, a total of 26 indices were selected, as shown in Table 4.2. These indices represent various quantiles of the streamflow distribution, as well as a series of extreme values for both low and high flows. These streamflow indices were computed over the 1981-2011 period as well as for 9 subsequent future 31-year windows centered in 2005 (1990-2020), 2015, 2025, 2025, 2035, 2045, 2055, 2065,2075 and 2083 (2078-2098). All 50 members were pooled over each 31-year period such that a total of 1550 years, representative of each 31-year period, were available.

Table 4.2 Streamflow indices examined in this study, "RT" to represent "Return period".

Number	ACRONYM	Description
Group 1 quantiles 1 to 10	Q 0.1 Q 1 Q 10 Q 30 Q 50 Q 70 Q 90 Q99 Q99.5 Q99.9	31-year streamflow quantiles
Group 2 high flows 11 to 18	RT 2 RT 5 RT 10 RT 20 RT 25 RT 75 RT 100 RT 300	Streamflow values corresponding to the 2, 5, 10, 20, 25, 75-year floods return period as evaluated using a Log-Pearson III distribution following USGS recommendations
Group 3 low flows 19 to 26	RT 2 RT5 RT 10 RT 20 RT 25 RT 75	Streamflow values corresponding to the 2,5, 10, 20, 25, 75-year droughts return period as evaluated using a Log-Pearson III distribution following USGS recommendations

	RT 100 RT 300	

4.3 Estimation of time of emergence

The main objective of this study was to evaluate how internal variability affects the ability to detect changes in streamflow indices. For this, details on how the anthropogenic climate change (ACC) and internal climate variability (ICV) were computed are needed.

4.3.1 Determination of anthropogenic climate change (ACC)

To detect the ACC signal for the selected hydrological variables, simulated hydrological data (using the 50-member ClimEx ensemble) was used. The determination of ACC was estimated using the statistical method described by Deser et al. (2012b). The following four steps were used to estimate the ACC:

1) For each member of the ClimEx ensemble, all streamflow indices were first computed over the 1981-2011 reference period;
2) The values of the same indices were also computed for all consecutive 31-year periods, starting in 1989 (1989-2019) and ending in 2068 (2068-2098). The hydrological indices were therefore computed for 80 31-year periods (1 reference period and 79 future periods) for each member of the ClimEx ensemble. Using overlapping 31-year periods, differing by 1 year, enables a more precise determination of the Time of Emergence (TOE) compared to the use of 9 discrete future windows, as was done for assessing changes in streamflow indices.
3) For each of the 50 ClimEx members, the epoch difference between the mean of all 80 31-year future periods and the mean of the reference period (1981-2011) was calculated;

4) Finally, the multimember ensemble mean of epoch differences was defined as the ACC.

4.3.2 Determination of internal climate variability (ICV)

In this study, the internal climate variability is evaluated as follows: first, all hydrological indices are computed for each of the 50 members over the 31-year historical period (1981-2011). The ICV is then defined as the standard deviation of these 50 values.

4.3.3 Signal-to-Noise ratio (SNR)

The role of internal climate variability (ICV) in relation to the ACC is investigated using the signal-to-noise ratio (SNR) suggested by Hawkins et Sutton (2009b) as equation (4.2):

$$SNR = \frac{ACC}{ICV} \times 100\ \% \tag{4.2}$$

In general, the value of SNR shows the importance and role of internal climate variability in the emergence of the anthropogenic climate change signal. An increase in the value of SNR is corelates directly with a decrease in the magnitude of internal climate variability and vice versa.

4.3.4 Time of emergence (TOE)

The TOE was used as a criterion to measure the importance of ICV with respect to ACC (Zhuan et al., 2018). In general, TOE may be characterized as the moment when the magnitude of ACC exceeds the ICV (Hawkins et Sutton, 2009b) or the moment when a substantial statistical difference exists between the reference period and the future period (Gaetani et al., 2020; King et al., 2015; Mahlstein, Hegerl et Solomon, 2012; 2011). In this study, TOE is estimated through three different techniques to allow a better understanding of its uncertainty, which depends on the estimation method selected. The three methods used in this paper, namely, Signal-to-noise ratio (SNR), Standard error of mean (Leng et al., 2016) and the KS-test, are described in more detail next.

4.3.4.1 TOE estimation using signal-to-noise ratio (SNR)

Several SNR thresholds have been suggested in the literature to define the time of emergence. In this work, as suggested by (Barrow and Sauchyn, 2019; Sui et al., 2014), an SNR greater than 1 was chosen for the determination of the TOE. The TOE is defined as the first time period during which the SNR is greater than 1 and stays above this threshold in all subsequent periods. The middle year of the first time period is defined as the TOE. Figure 4.3 graphically illustrates the SNR method for changes in the mean annual maximum streamflow. The green line represents the absolute epoch difference of mean annual maximum streamflow for one catchment. The epoch difference refers to the absolute or relative change in a streamflow index between a future 31-year period (graphically depicted at the center of this period) and the 31-year reference period (averaged across all members of the ensemble). If the epoch difference is expressed in absolute format, it has the same units as the considered streamflow index (mm/hour in this case). Each gray line represents one member of the ensemble and the blue lines depict the $\pm$ 1σ interval based on the reference period. The TOE occurs when the green line crosses the blue line (in this case it crosses the upper threshold line since the streamflow index value is increasing in the future.

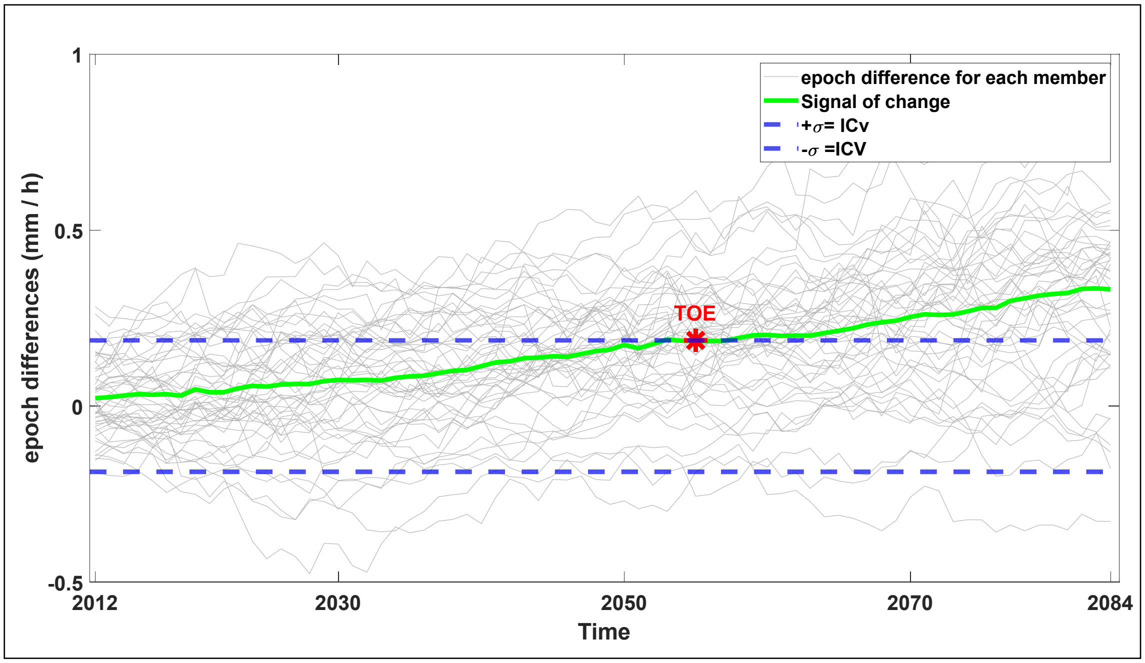


Figure 4.3 Determination of the time of emergence (TOE) using the signal-to-noise ratio (SNR) method with a ± 1σ threshold.

4.3.4.2 TOE estimation by standard error of mean

Deser et al. (2012c) defined the time of emergence as the time when the ACC signal becomes statistically significant at the 95% level, when compared to the standard error of the mean computed across all members. The SEM is equal to $\frac{\sigma}{\sqrt{n}}$, where σ is the standard deviation of the epoch difference for all members, and n is the number of members (50 in this study). The standard error of the mean can be used for statistical testing. For a two-sided test at the 95% level, the time of emergence is obtained when the ACC first becomes larger than:

$$ACC \geq \frac{2\sigma}{\sqrt{n-1}} \tag{4.3}$$

and stays larger for all subsequent time periods.

4.3.4.3 Kolmogorov-Smirnov test (KS-test)

The Kolmogorov-Smirnov test (Chakravarti, Laha et Roy, 1967) is a non-parametric test that is widely used to compare two distributions. This test has frequently been used in climate and hydrological impact studies (Gaetani et al., 2020; Im et al., 2021; Muelchi et al., 2021).
The TOE is determined as the middle year of the first future period when the distribution of a given variable is statistically different from that of the same variable over the reference period, and remains statistically different for all subsequent time periods.

4.4 Results

Figure 4.4 presents the projected anthropogenic climate change (ACC) signal on 8 different quantiles of the streamflow distribution (Q0.1, Q1, Q10, Q50, Q70, Q90, Q99 and Q99.9) taken from Table 4.2 (Group 1). The figure is a heatmap of the ensemble-mean epoch difference (between nine 31-yr future periods and the 1981-2011 historical period) for the three catchment size classes (columns 1 to 3). Changes are presented in their relative form (%) to account for the wide range of streamflow magnitudes across catchments. Catchments are ordered by latitude along the Y-axis.

The same general pattern of change is observed for all three size classes. Streamflow decreases are projected for most of the quantiles whereas increases are projected for the very largest ones. It is at the 90th quantile that the transition between decreases and increases appear to occur. The largest decreases (up to 40%) are seen in the medium and large catchments, whereas the largest increases (up to 40%) are projected for the smaller size class. The projected streamflow increases for the large quantiles get consistently larger for the more distant horizons, as is typically the case in impact studies. This is also the case for decreasing streamflow for the medium and large catchments. The picture is more complex for the small size class, where decreasing flows are projected until 2050, followed by a trend reversal for the lower quantiles. The impact of latitude manifests itself only for the larger catchments, with southern catchments seeing larger increase for the large quantiles, and even some modest increases for the low quantiles.

To better understand the impact of anthropogenic climate change on the three catchment size classes, and to more clearly outline the variability existing within each size class, Figure 4.5 presents the box plots of relative change for the nine epoch differences. The box plots present the distribution of changes within each catchment size class. The central rectangle shows the 25th and 75th quantiles of the distribution, with the median as the central line. The lower and upper whiskers show the smallest and largest values. Red crosses, when present, show statistical outliers. To better outline differences, the three size classes are plotted with different colours: red blue and green respectively for the small (s), medium (M), and large (L) catchments.

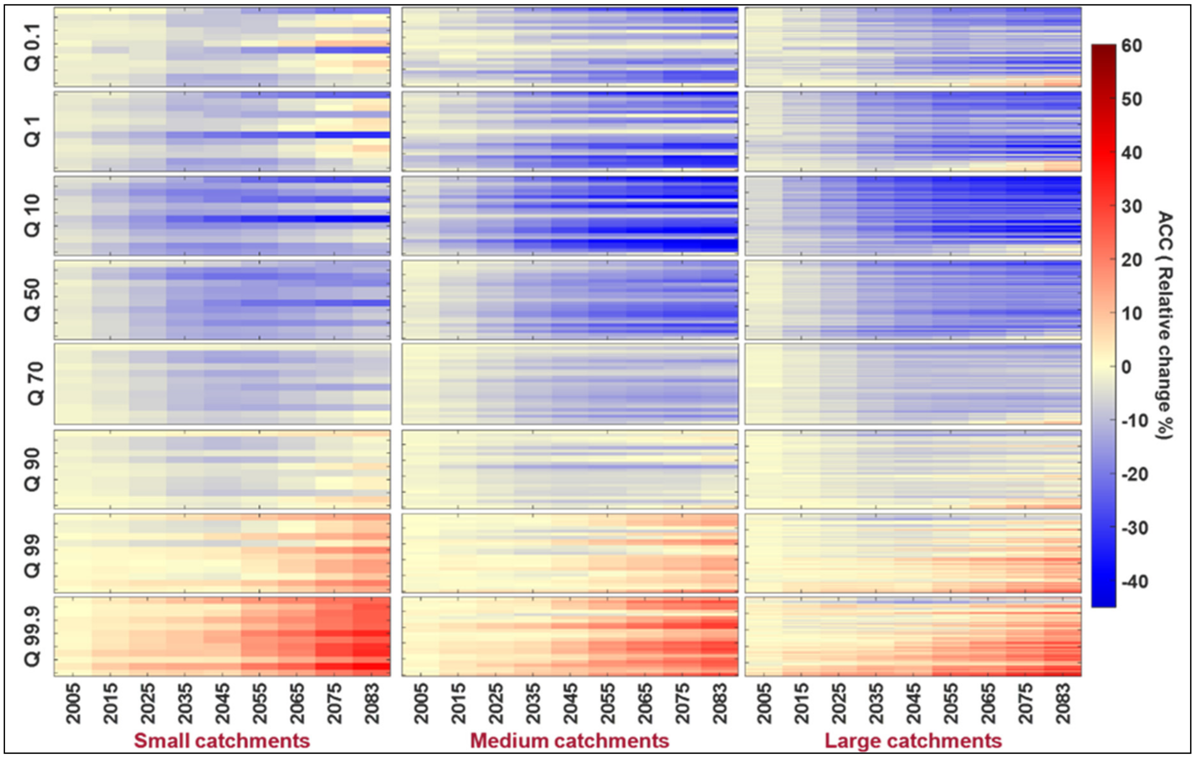


Figure 4.4 Projected anthropogenic climate change impact for streamflow quantiles of Table 2 (Group 1 indices) Q0.1, Q1, Q10, Q50, Q70, Q90, Q99 and Q99.9. The change is presented as the ensemble mean difference between 9 future periods (centered around the years shown on the X-axis) and the 1981-2011 reference period. The three columns correspond to three catchment size classes: small (left), medium (middle), and large (right). The catchments are sorted by their latitude in the Y-axis.

Figure 4.5 shows that changes in the three largest quantiles of Table 4.2 (Q99, Q99.5 and Q99.9) are steadily increasing as the future time horizon become more distant, and that projected changes are clearly related to catchment size, with the smallest catchments seeing the largest changes. The changes are more complex in the other quantiles. For the low to median quantiles (Q0.1 to Q50), Figure 4.5 shows quite clearly how the small catchments behave differently when compared to catchments from the other two size classes. The medium and large size classes see a steady decrease across all future time periods, whereas the smaller catchments see a decrease followed by a trend reversal around 2050. The spread of the distributions is relatively large, outlining a relatively large range of increases/decreases across each of the size class, although the direction of the change is generally the same for all catchments. Overall, the projected future climate change impacts are clearly related to catchment size, with the smaller size class responding differently than the larger ones.

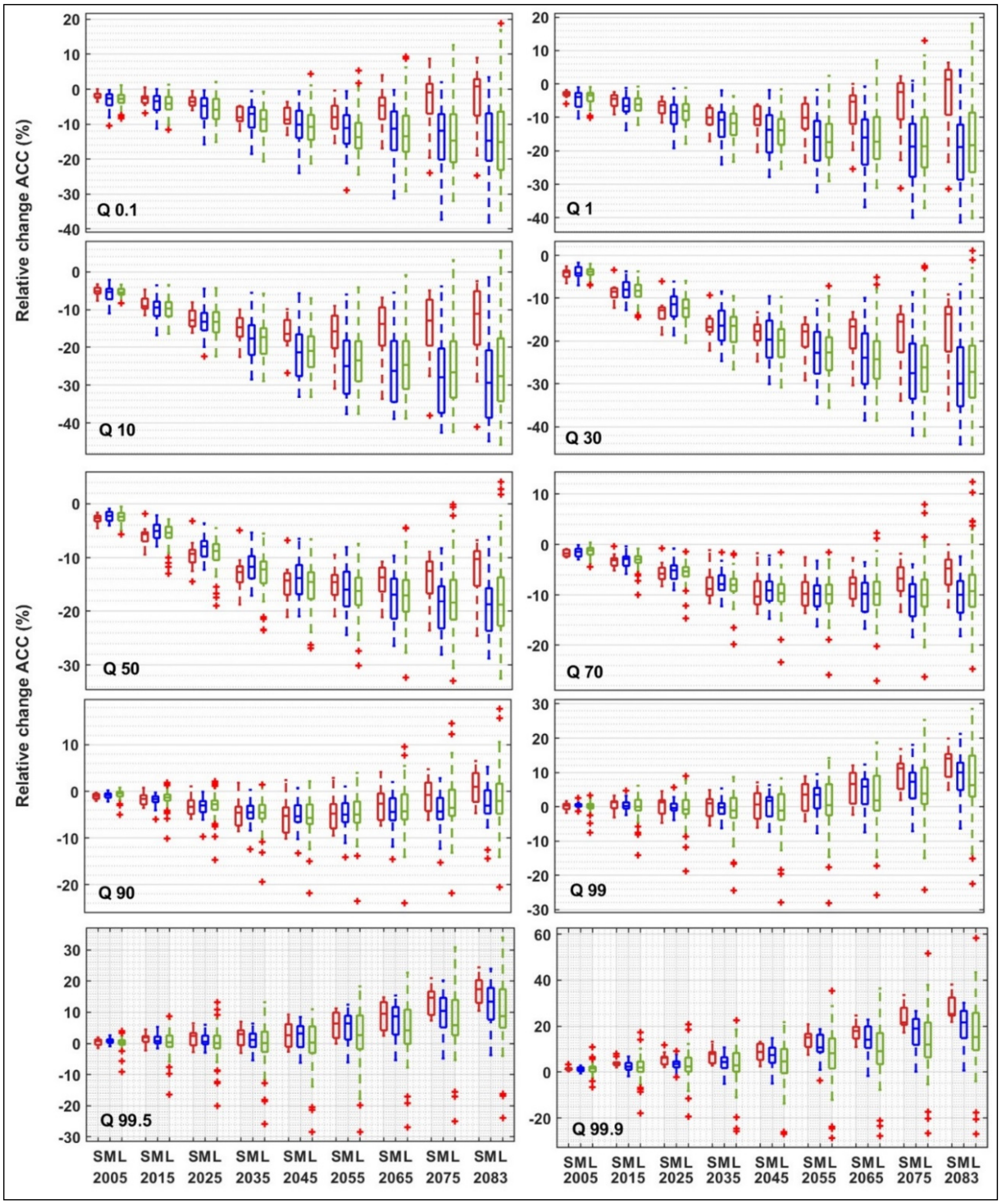


Figure 4.5 Projected anthropogenic climate change impact for the streamflow quantiles of Table 2 (Group 1 indices) Q0.1, Q1, Q10, Q30, Q50, Q70, Q90, Q99, Q99.5 and Q99.9). The

change is presented as the ensemble mean difference between 9 future periods (centered around the years shown on the X-axis) and the 1981-20110 reference period. The smaller catchments are in red, the medium in blue, and the largest in green.

In light of the different behaviours between low and high flows, Figures 4.6 and 4.7 explore both tails of the streamflow distribution by looking at floods and droughts, with a return period of 2, 20, 100 and 300 years. Figures 4.6 and 4.7 follow the same format as that of the preceding two figures.

Three main features can be noted from these figures.
First, there is a general increase in flood and drought intensity until the end of the century, irrespective of the catchment size and return period (within each of the 24 panels, the colours get darker from left to right).

Second, the catchment size has a large impact on the expected flooding increases, with smaller catchments experiencing a much larger rise than medium and large catchments. For droughts, the situation is reversed, with the small catchments experiencing a smaller decline than for the other two groups.

Third, the expected increases in flooding are clearly correlated with the flood return period, with the longer return period experiencing the greatest increases. For droughts, the streamflow decreases are very similar for all 4 return periods.

Figure 4.8 shows a map of the signal-to-noise ratios (SNRs) for streamflow quantiles (Table 4.2, group 1 streamflow indices). The left- and right-hand sides respectively show the SNR for the near (2030-2060) and far (2068-2098) future periods. An SNR value between -1 and 1 (white colour) indicates that the internal climate variability plays a significant role in hiding the anthropogenic climate change, and this will be reflected in a later time of emergence.

What Figure 4.8 illustrates most clearly is that the SNRs increase as we go from the near to the future period for all quantiles, with the exception of quantile 90, which has a weak climate change signal as it is situated in the transition between increasing and decreasing flows, as discussed earlier. It also shows that there is considerable spatial variability within the study domain. The SNRs are smaller around the Great Lakes and stronger along the Appalachian and along the Atlantic, with the exception of quantile 10 and 50, where the SNRs are relatively uniform across the study domain.

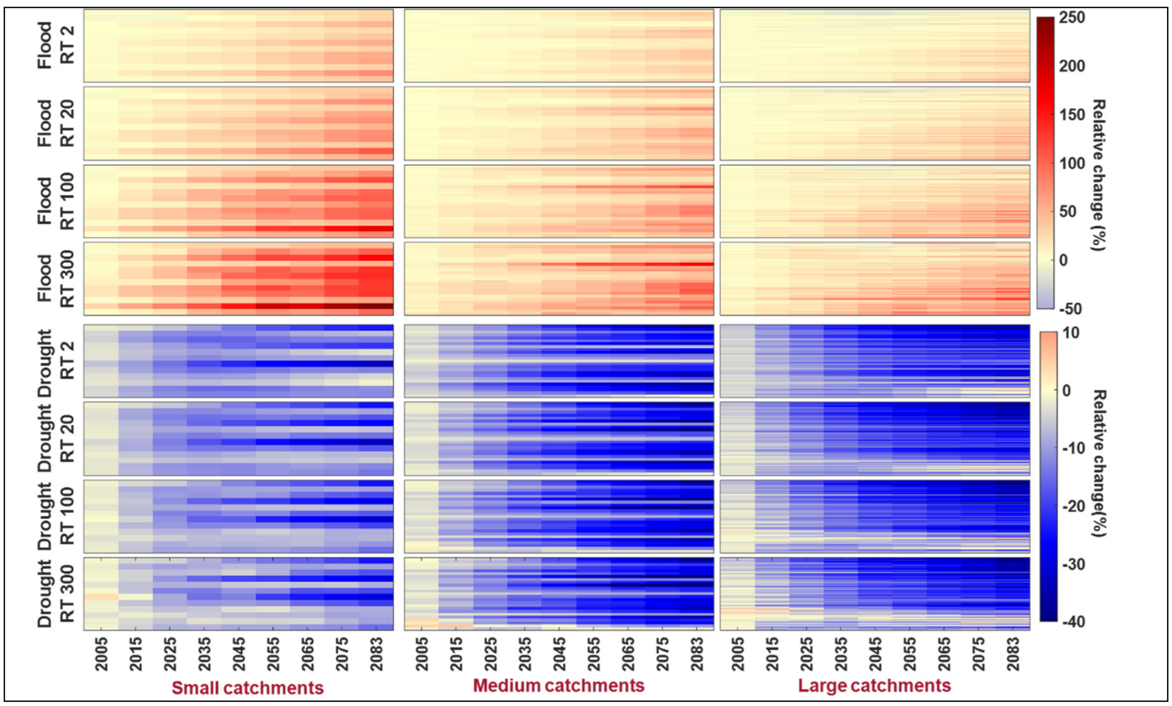


Figure 4.6 Projected anthropogenic climate change impact for extreme high and low flows with return periods of 2, 20, 100 and 300 years, "RT" to represent "Return period". The change is presented as the ensemble mean difference between 9 future periods (centered around the years shown on the X-axis) and the 1981-2011 reference period. The three columns correspond to three catchment size classes: small (left), medium (middle), and large (right). The catchments are sorted by their latitude in the Y-axis.

Figure 4.9 follows the layout of Figure 4.8, but looks at floods and droughts with a return period of 2 and 100 years. The 20- and 300-year return periods were omitted from Figure 4.8 since they present patterns that are very similar. The spatial patterns are somewhat similar to those seen in Figure 4.8. However, the SNR of extreme droughts is weaker in the southern portion of the domain and stronger overall for extreme floods.

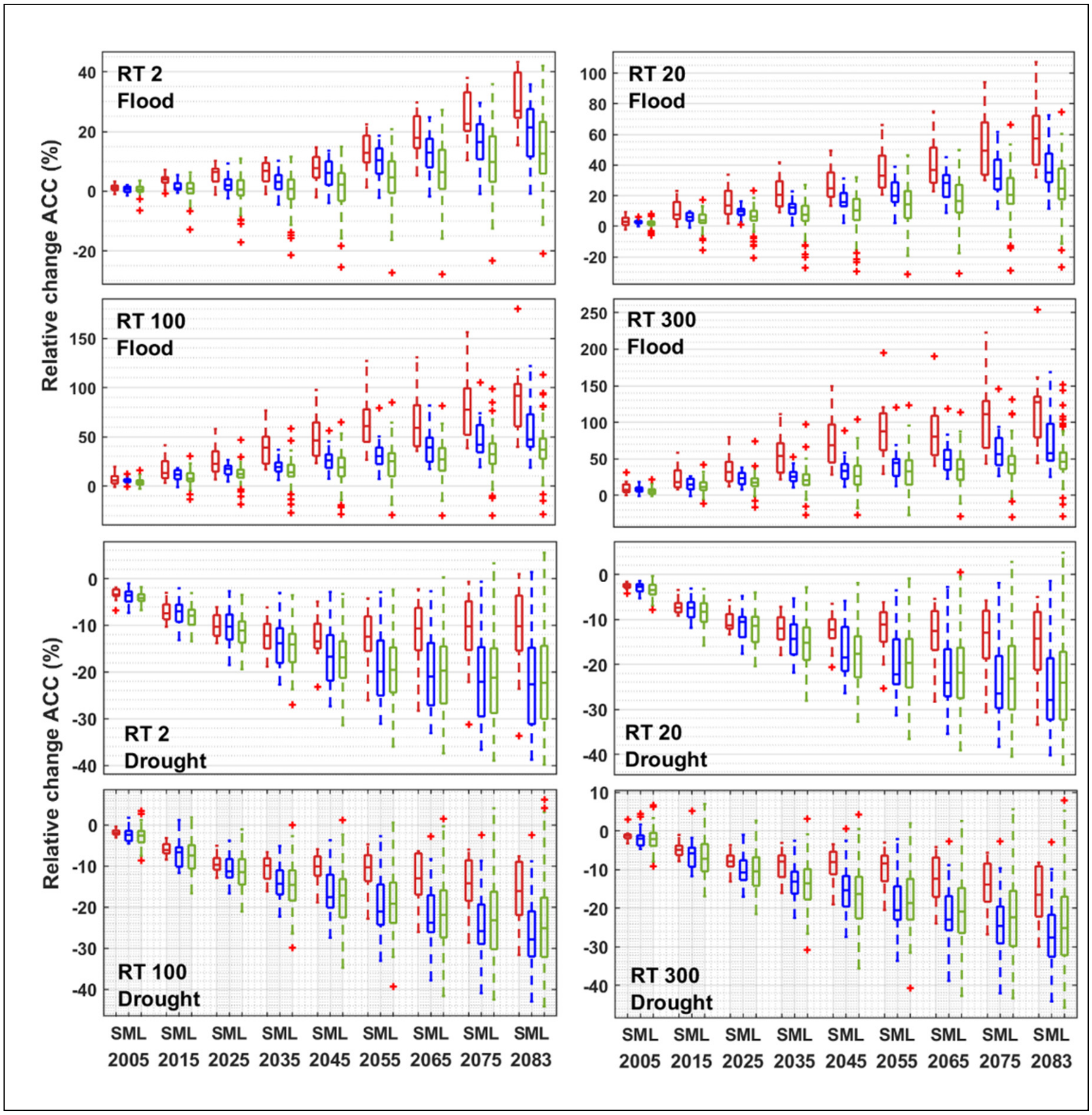
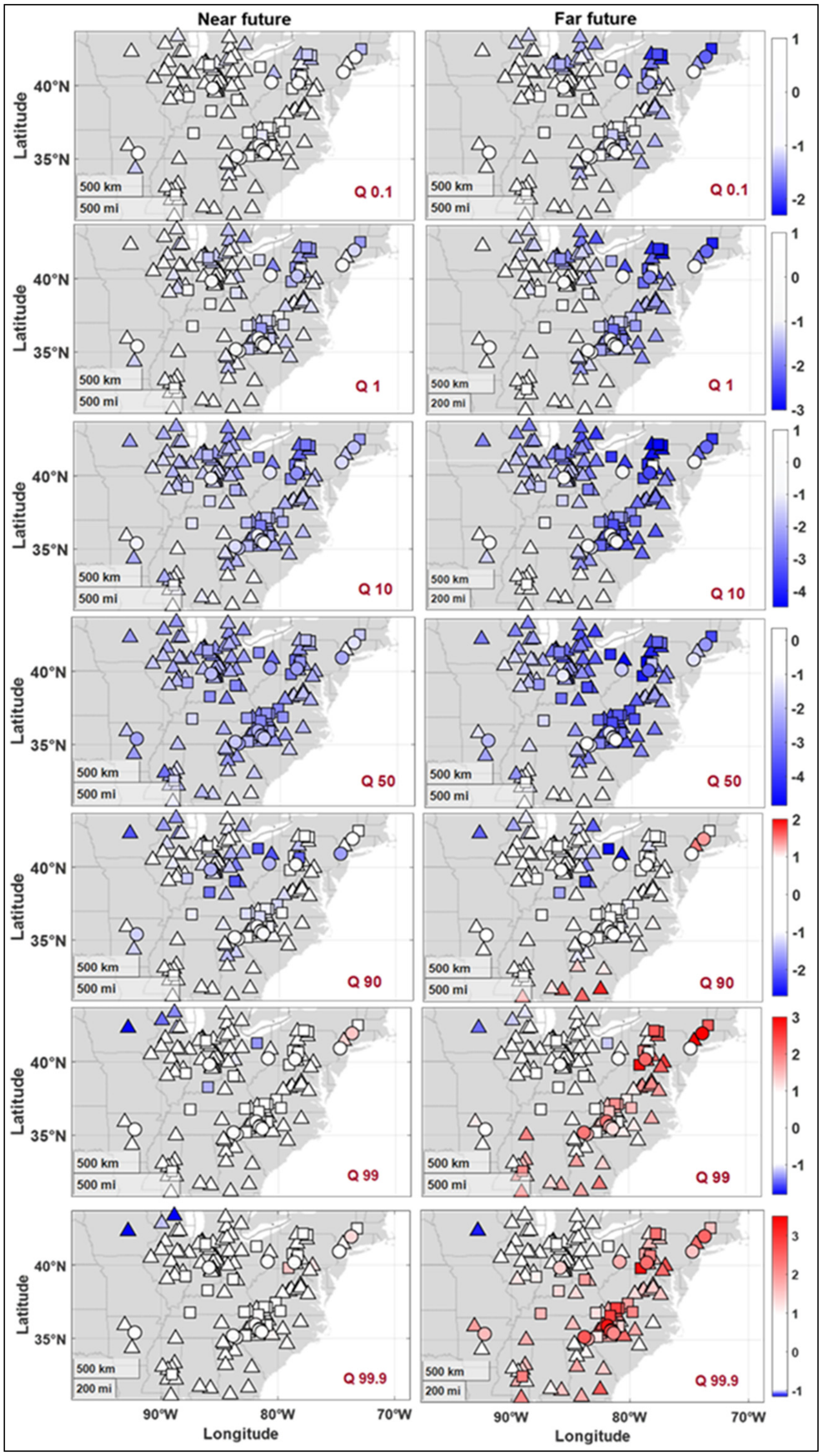


Figure 4.7 Projected anthropogenic climate change impact for extreme high and low flows with return periods of 2, 20, 100 and 300 years, "RT" to represent "Return period". The change is presented as the ensemble mean difference between 9 future periods (centered around the years shown on the X-axis) and the 1981-2011 reference period. The smaller

catchments are in red, the medium in blue, and the largest in green. The box plots represent the distribution of change for all catchments within each size class.



Near future
Far future
Latitude
Longitude
40°N
35°N
90°W
80°W
70°W
500 km
500 mi
200 mi
Q 0.1
Q 1
Q 10
Q 50
Q 90
Q 99
Q 99.9

Figure 4.8 Signal-to-noise ratios (SNR) for seven streamflow quantiles (Table 2, group1 indices) for the near (2030-2060) and far (2068-2098) future periods. Circles, square and triangles respectively represent catchments in the small, medium and large size classes.

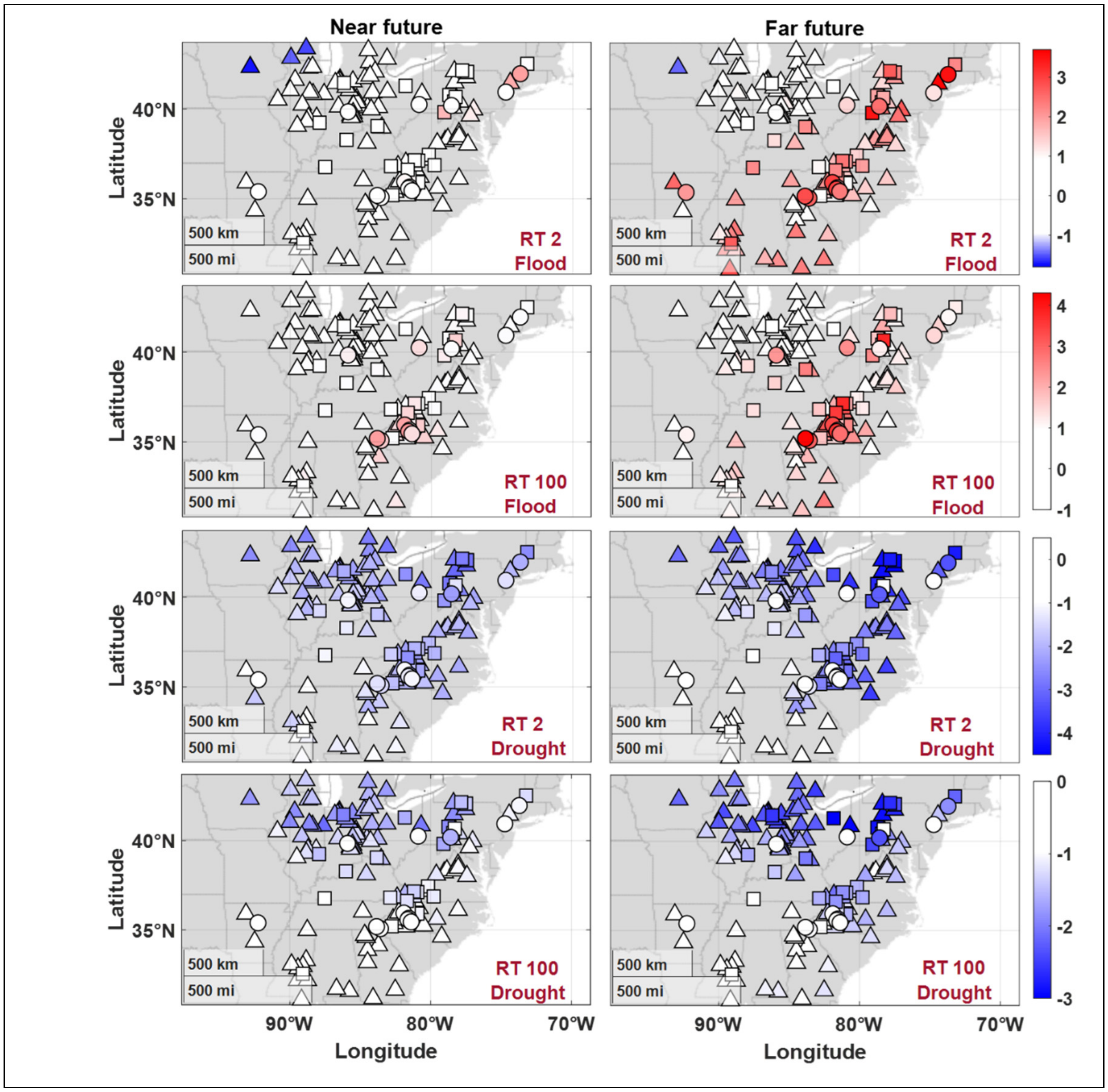


Figure 4.9 Signal-to-noise ratios (SNRs) for the 2- and 100-year return period floods (upper two rows) and droughts (lower two rows) for the near (2030-2060) and far (2068-2098) future periods (Table 2 indices from Group 2 and 3). Circles, square and triangles respectively represent catchments in the small, medium and large size classes.

Figures 4.10 and 4.11 present the projected time of emergence for the 8 quantiles of Figure 4.4 (Q0.1, Q1, Q10, Q50, Q70, Q90, Q99 and Q99.9). Figure 4.10 is a heatmap of the time of emergence, with dark colours representing an early time of emergence and light colours a more distant one. A white colour indicates that no time of emergence is projected to occur within the current century. The three columns represent the three catchment size classes, whereas the three rows correspond to the three different approaches used to estimate the time of emergence. To more clearly illustrate the variability across catchments from all three size classes, Figure 4.11 shows box plots of the time of emergence for the same quantiles. Several observations can be made from the graphs: 1-The central quantiles (Q10 to Q70) are the ones with the earliest times of emergence. 2-The high and low quantiles show much later times of emergence, although this changes with the 99.9 quantile, and especially so for the small catchments. 3-The small catchments differ by having a narrower range of quantiles showing early times of emergence, and a much larger number of quantiles with no emergence by the end of the century. 4- The KS-test and SEM approaches project extremely similar times of emergence, whereas the SNR method results in much later times of emergence. 5- The projected times of emergence are earlier for the medium and large catchments, with the exception of the 99.9 quantile, which see earlier times for the small catchments.

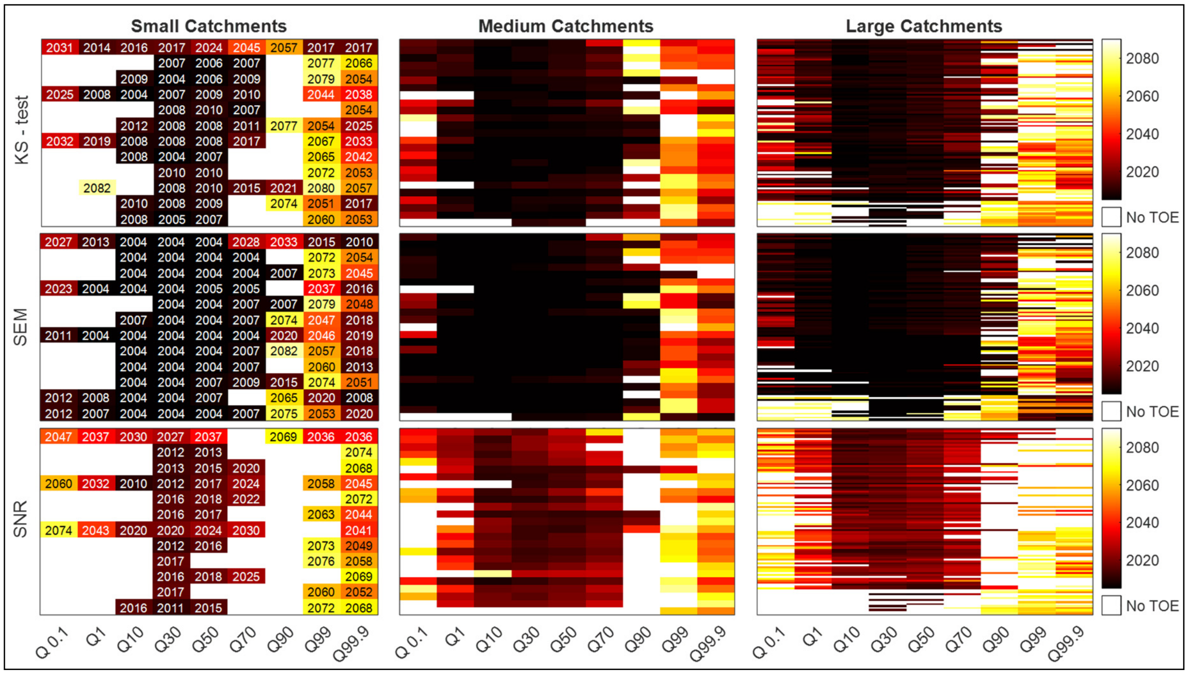


Figure 4.10 Time of emergence for the streamflow quantiles (Table 2, group 1) Q 0.1, Q1, Q10, Q30, Q50, Q70, Q90, Q99 and Q99.9). The three columns represent the three catchment size classes, whereas the three rows correspond to the three different approaches used to estimate the time of emergence: KS test, standard error of the mean (Leng et al., 2016), signal-to-noise ratio (SNR).

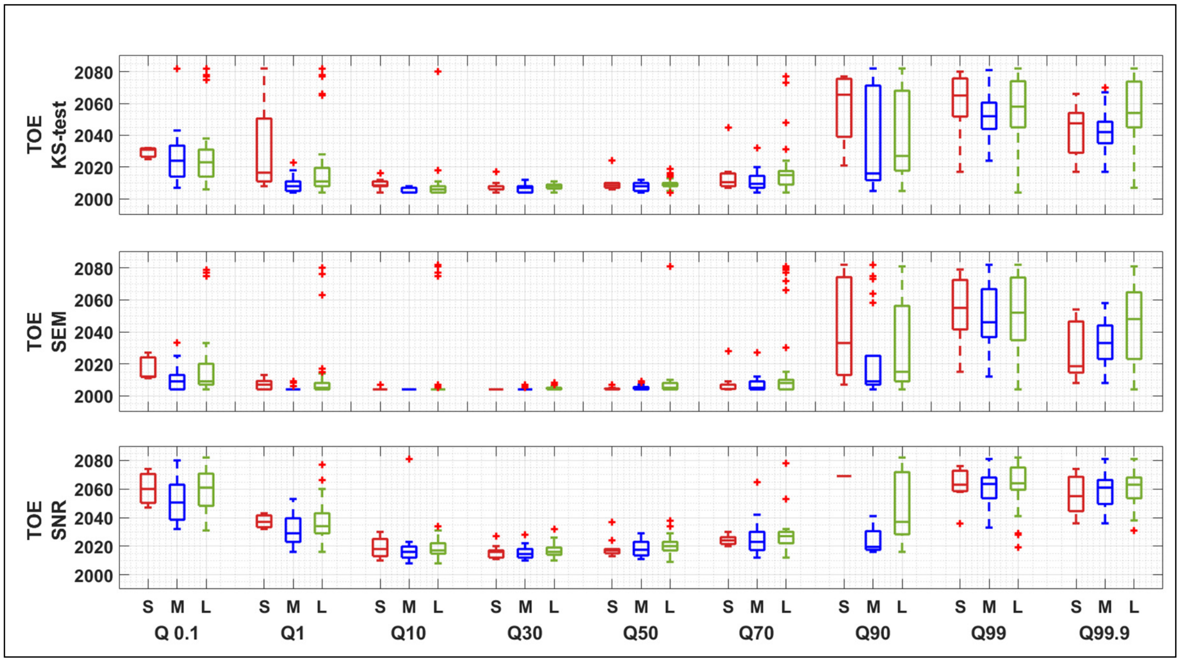


Figure 4.11 Box plots of the time of emergence of streamflow quantiles of Table 2 (group 1 streamflow indices) Q 0.1, Q1, Q10, Q30, Q50, Q70, Q90, Q99 and Q99.9. The three rows correspond to the three different approaches used to estimate the time of emergence - KS test, standard error of the mean (SME) (Leng et al.), signal-to-noise ratio (SNR). The smaller catchments are in red, the medium in blue, and the largest in green. Each box plot represents the distribution of the quantiles TOE for all catchments within each size class.

The large quantile earlier times of emergence for the smaller catchments (Figures 4.9 and 4.10) is further explored in Figures 4.12 and 4.13 by looking at extreme floods with return periods ranging from 2 to 300 years. These figures follow the format of Figures 4.10 and 4.11. In addition to the floods (top three rows), Figure 4.12 and 4.13 also show droughts with return periods ranging from 2 to 300 years. Results show that the catchment size has a clear impact on the time of emergence for floods, with small catchments having a consistently earlier time of emergence as compared to medium and large catchments. The times of emergence are relatively similar for all return periods, with the exception of the 2-year flood, which has a later time of emergence. The latitude has a clear impact on the large catchments, with northern catchments having a late time of emergence. Once again, the KS-test and SEM approaches project extremely similar times of emergence, whereas the SNR method results in much later time of emergence.

The results for droughts show an early time of emergence in most cases, although this gets progressively later for the larger drought return periods. For the larger size class, the southern catchments see a later time of emergence. Overall, the catchment size once again has a strong impact on the time of emergence of extreme droughts, with smaller catchments seeing a later time of emergence, which is the opposite of what was observed for floods.

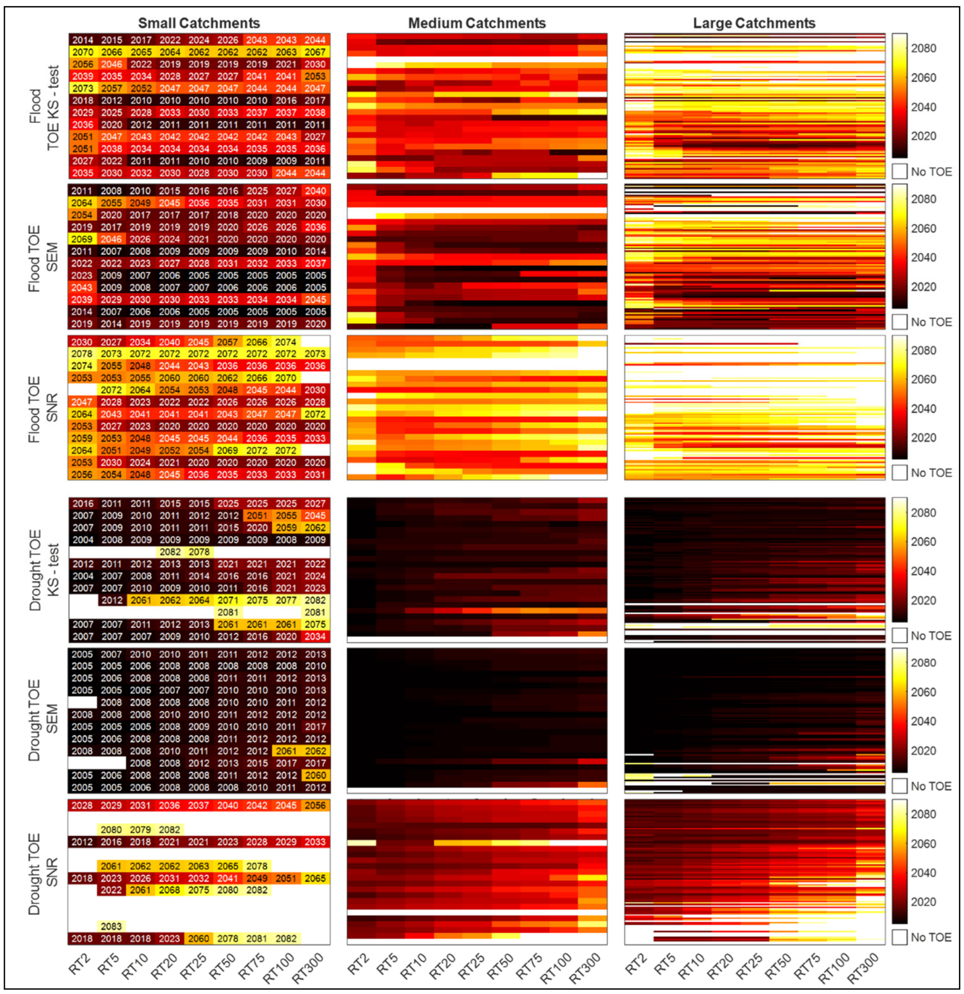


Figure 4.12 Time of emergence for extreme high (upper three rows) and low (lower three rows) flows with return periods between 2 and 300 years. The three columns represent the three catchment size classes. For both floods and droughts, the three rows correspond to the

three different approaches used to estimate the time of emergence - KS test, standard error of the mean (Leng et al.), signal-to-noise ratio (SNR).

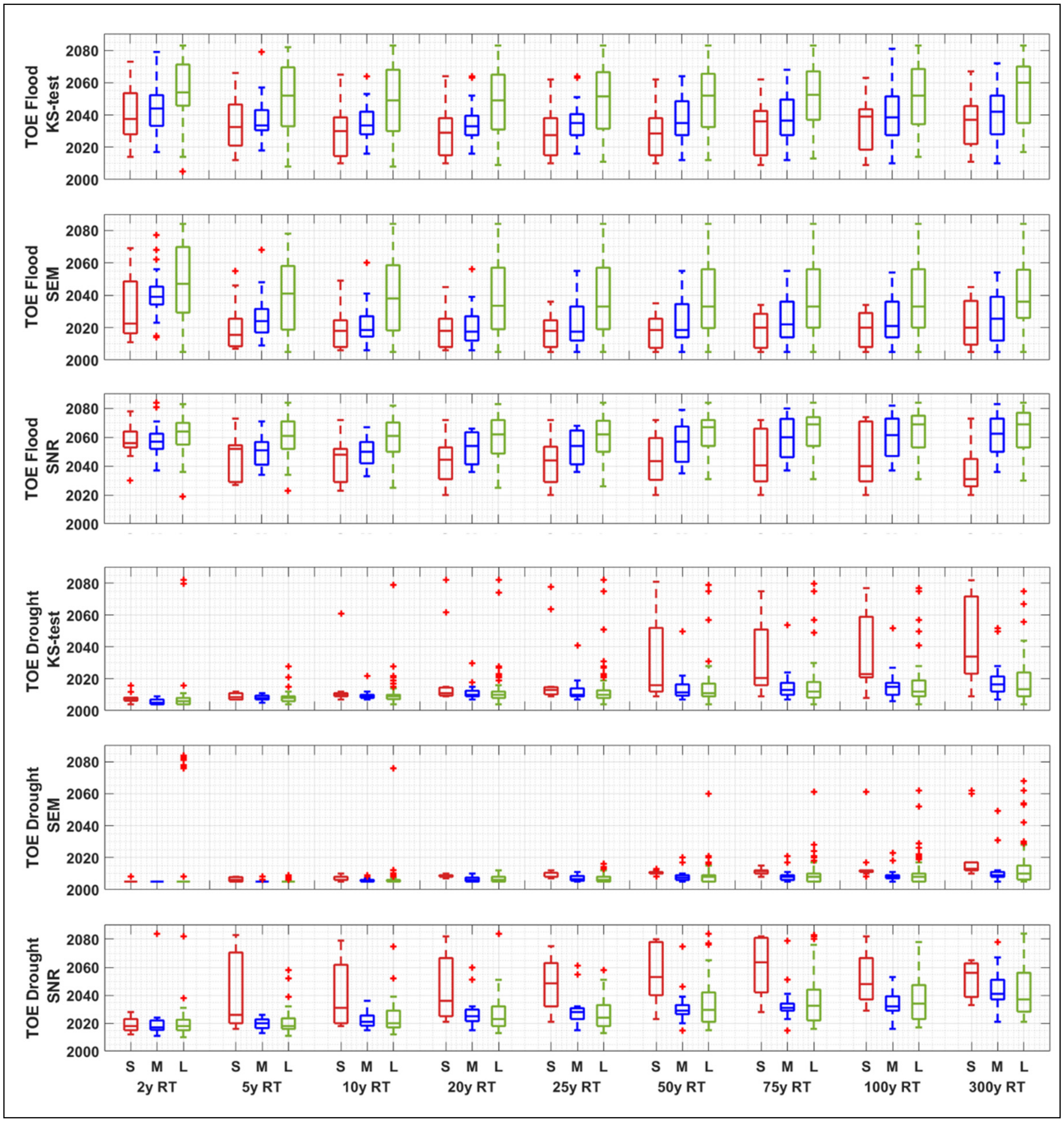


Figure 4.13 Box plots of the time of emergence for extreme high (upper three rows) and low (lower three rows) flows with return periods between 2 and 300 years. For both floods and droughts, the three rows correspond to the three different approaches used to estimate the time of emergence - KS test, standard error of the mean (Leng et al., 2016), signal-to-noise ratio (SNR). The smaller catchments are in red, the medium in blue, and the largest in green.

Each box plot represents the distribution of the TOE of flood/drought return periods for all catchments within each size class.

4.5 Discussion

Many impact studies performed over the past decade have outlined the critical need for adaptation measures to be put into place as rapidly and as efficiently as possible. This is particularly critical for the design of new infrastructures with long lifespans. This is the case with most water-related infrastructures, where the design considers various streamflow characteristics, and which typically have a long lifespan, often extending into the next century. Floodplain delineation is one area where considering climate change information is critical since history has shown that once the environment is built, it is incredibly difficult to turn back the clock in bad floodplain management cases. The vulnerability, impact and adaptation communities need good information to help prioritize the best adaptation measures and to avoid defaulting to a reactive mode in which actions are based largely on recent extreme events, without any study having been conducted to properly characterize the climate change signature of the said extreme events. Internal climate variability is a crucial factor to consider when dealing with climate projections, as acknowledged by many experts (e.g. Deser et al., 2012b; Hasselmann, 1979; Santer et al., 2019). Internal climate variability makes it difficult to directly relate any extreme events to climate change, without costly analyses such as are done in climate attribution studies (Schwarzwald and Lenssen, 2022). As a concept, the time of emergence can help guide decision makers in optimizing finite resources on more targeted adaptation measures. It can help identify the infrastructures that are most vulnerable and to prioritize adaptation actions.

Over the study catchments, most streamflow quantiles are projected to decrease by up to 20% by the end of the century, with the only exception being the larger streamflow quantiles (above quantile 90) and the very low quantiles (1% and below) for the southern catchments. For the extreme floods (very large quantiles) and droughts (very small quantiles) changes are consistent with a systematic worsening of both types of events, with droughts and floods becoming more severe in the future. To better understand these results, Figure 4.14 presents changes in mean future temperature and precipitation as projected by the ClimEx Ensemble, at both the annual and summer/fall (June to October) scales. The temperature is projected to rise significantly and consistently between 4 to 7 degrees, depending on the location and season. Projected future precipitations are expected to increase more modestly at the annual scale (between 1 to 12%) to and decrease over the summer-fall period for the upper half of the study domain, and by up to 15% for the northern basins.

The patterns presented in Figure 4.14 allow to interpret some of the results presented above. The general decreases observed for the median quantiles are indicative of a reduced mass balance resulting from the increased evapotranspiration brought about by the large temperature increases projected by ClimEx, a net loss not compensated by relatively modest increases in annual precipitation. They also explain why the southern catchments see smaller decreases as the temperature increases get relatively smaller in the south, combined with the largest relative precipitation increases. The spatial summer/fall precipitation patterns are consistent with a systematic increase in drought severity over most of the study domain, with the exception of its southernmost part, where precipitation is projected to increase and somewhat compensate for the added evapotranspiration due to increased temperature.

Catchment size clearly impacts future projected changes, and this is particularly obvious for extreme floods. Smaller catchments react more strongly to future flooding changes. This behaviour can be explained by considering projections of future extreme precipitation. Several studies have looked at the amplification of future extreme rainfall in a warmer climate (e.g., Fowler et al., 2021; Gensini and Mote, 2015; Prein et al., 2017). Results of these studies are consistent with those obtained from the ClimEx ensemble (Martel et al., 2018). There is strong consensus that the amplification of extreme rainfall will be skewed toward shorter duration, rarer and more localized events, with even the potential for Super-Clapeyron scaling in such cases (Guerreiro et al., 2018).

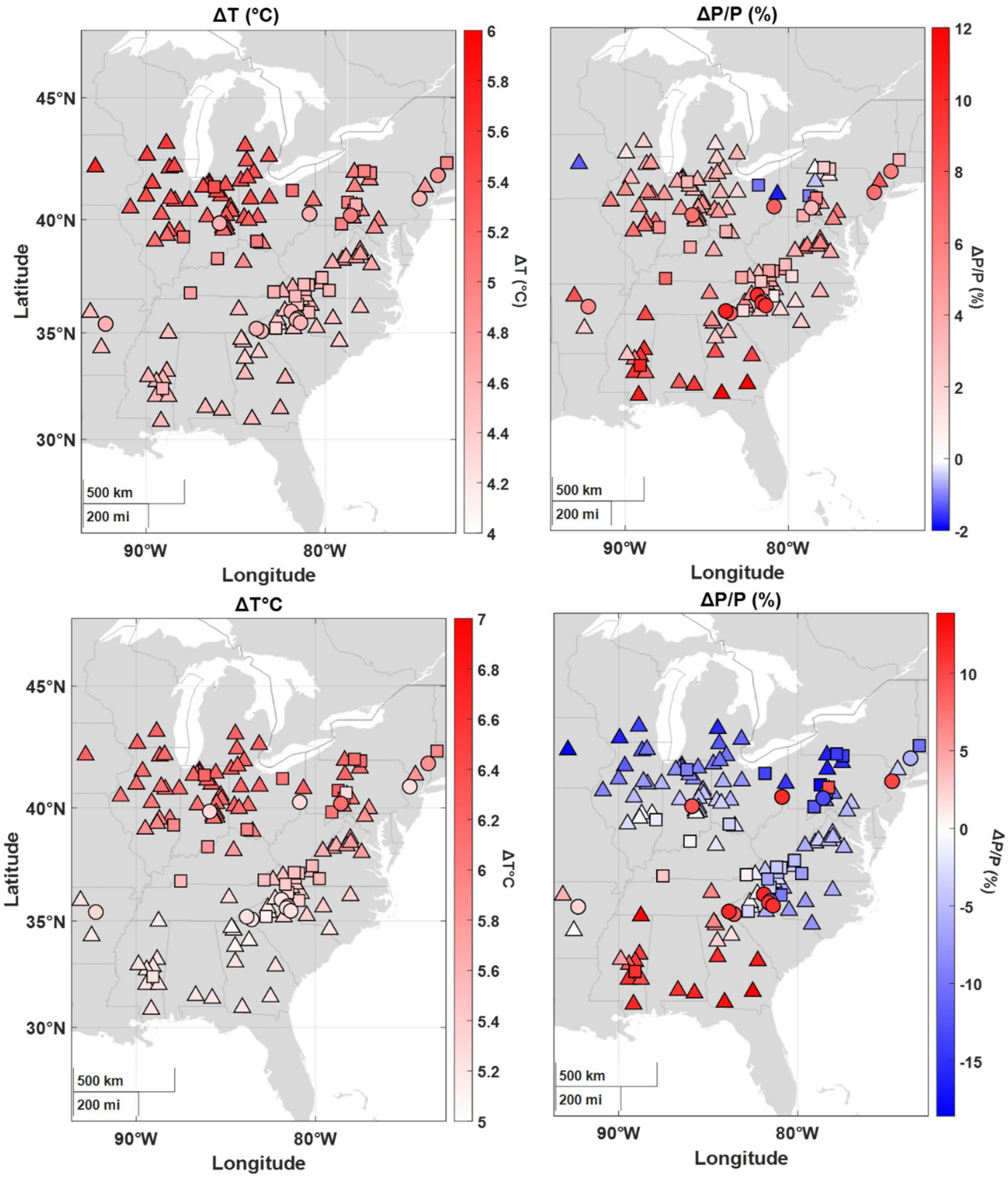


Figure 4.14 Future absolute temperature (ΔT) and relative precipitation (ΔP/P) change between the reference (1981-2011) and future (2068-2098) periods. First row – annual scale; second row, June to October period.

Such localized extreme events have a spatial scale that is more commensurate with that of smaller catchments, resulting in a much stronger potential for a large portion of the catchments to actively contribute to runoff during an extreme precipitation event. Comparatively, changes for future droughts are most consistent across all three catchment size classes, even though the increase in drought severity appears to be smaller for the small catchments. It is not clear why this is the case, and a more detailed analysis is needed to better understand hydrological drought-forming mechanisms on the smaller catchment. A lack of precipitation (meteorological drought) is always the leading factor in all types of droughts, but the link between meteorological and hydrological droughts, which appears to be loosely related to catchment size, is complex (Zhao et al., 2020). Catchment memory (related to the slower release of subsurface water) strongly impacts hydrological droughts and can affect forecasting skill and persistence (Sutanto and Van Lanen, 2022). Larger catchments are more likely to contain larger water storage potential (e.g., lakes and aquifers) and have a longer memory, and are therefore more resilient to short-term droughts (Hellwig and Stahl, 2018). On the other hand, catchments with a longer memory may recover more slowly from extreme droughts, and especially so for longer-duration droughts.

Finally, as discussed above, results appear to show an impact of catchment latitude, but only for the larger size classes. However, this apparent relationship is likely related to the bigger sample of large catchments in the latter, and especially, to the fact that the larger catchments cover a significantly wider range of latitudes as compared to the other 2 size classes. In fact, as shown in Figure 4.1, all but of 1 of the 20 catchments located below the 35^{o} latitude belong to the largest size class.

Based on the above results, it would seem that actions aimed at reducing the impact of future floods should therefore primarily target smaller catchments, whereas actions targeting droughts themselves should focus on larger catchments. Obviously, local vulnerability should also be considered, but all other factors begin equal, future flooding increases are particularly worrisome for smaller catchments.

The time of emergence (TOE) is an indicator that indicates how quickly we should be able to quantitatively discern the impact of climate change through measurements, and it also offers some measure of the urgency of the need to apply regional and local adaptation measures. Once again, local vulnerability should also be taken into account when deciding on final adaptation strategies. Since the time of emergence depends both on the projected change and on internal variability, a careful evaluation of both factors should always be considered. For example, extreme droughts were found to have earlier TOE as compared to extreme floods (Figure 4.12 and 4.13), for both the KS and SEM methods. However, Figures 4.8 and 4.9 show that is because the signal-to-noise ratio of droughts is larger in the near future, whereas we have to wait further in time for the flood signal to emerge, simply because floods are more affected by internal variability, even though the increase in flood magnitude may be much larger than for droughts.

For the streamflow indicators, results show that the TOE are earliest for the median quantiles of streamflow distributions, and then on to the largest quantiles, and finally, the smaller ones. The median quantile could therefore represent a good indicator of whether a climate change signature is already apparent in streamflow series. In comparison, Figure 4.15 shows the TOE for mean annual precipitation. It shows TOE that are very late as compared to those of streamflow. Comparatively, for the mean annual temperature (results not shown), TOE has been reached by 2004 for all catchments. These results are not surprising since it is well known that the signal-to-noise ratio is much smaller for precipitation (Sui et al., 2014), and therefore, it takes a much longer time for the climate change signal to emerge from the fog of internal variability in this case (King et al., 2015). The influence of the early TOE for temperature appears to impact streamflow more importantly than for precipitation, as shown by the early TOE for most studied streamflow quantiles.

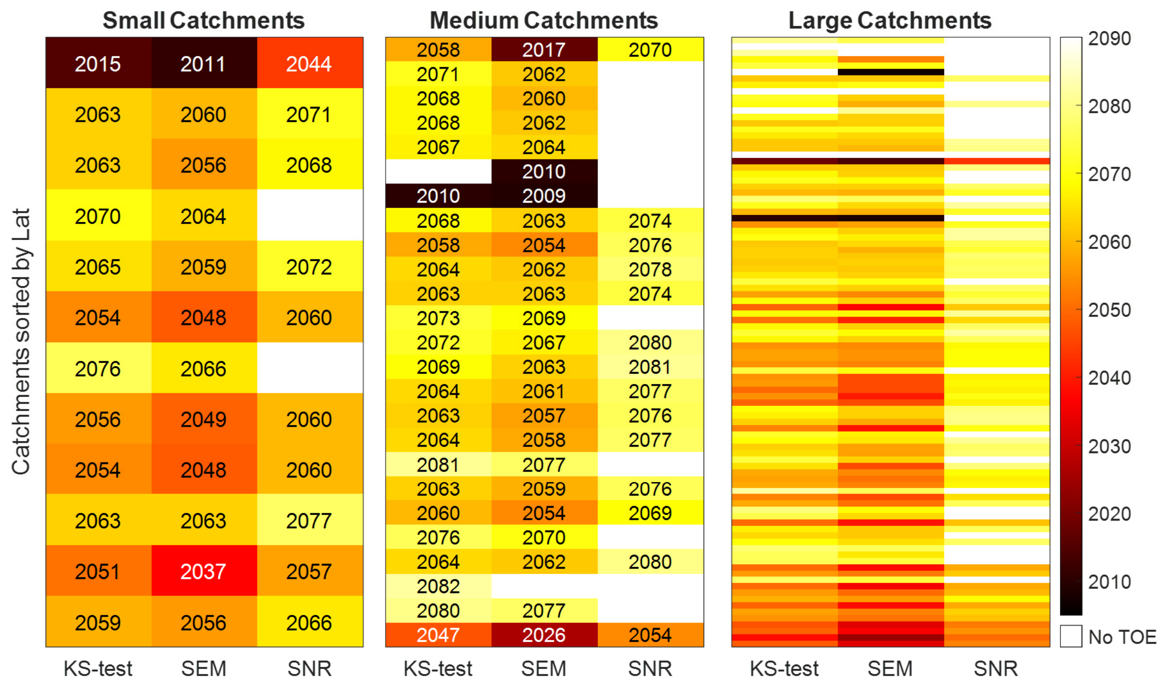


Figure 4.15 Projected time of emergence of mean annual precipitation using the KS-test, SEM and SNR.

This study uses three distinct methods to compute TOE, with all three generating heatmaps (Figures 4.10 and 4.12) with the same spatial patterns. The two statistical approaches give extremely similar TOE, whereas the signal-to-noise ratio method, with a 1σ threshold, provides significantly later TOE. This is to be expected given that the Deser method is equivalent to a signal-to-noise threshold of 2σ/7, as opposed to the 1σ commonly used in the signal-to-noise method, equation (4.4).

$$\frac{2\sigma}{\sqrt{n-1}} = \frac{2\sigma}{\sqrt{50-1}} = \frac{2\sigma}{7} \tag{4.4}$$

The Deser method is, however, not applicable in the real world since it relies on multiple realisations of the climate, whereas in the real world, we are stuck with a single realisation. However, it can be shown that the Deser method at the 0.95 confidence level is in fact essentially the same as a Student T-test (difference of the mean between two distributions) at the 0.99 level between the reference and the future periods. The fact that the two distribution-based methods give nearly identical TOE supports their use in TOE studies, and suggests that signal-to-noise approaches are too conservative. The KS test should be favoured as it is non-parametric and relies on the entire distribution.

There are several limitations to this study, with the most significant likely being that it was performed using a single ESM with a single greenhouse emission scenario (GHGES). Both the GHGES and the ESM have a large impact in the magnitude of the projected future changes. It also controls potential changes to internal variability in future horizons. Several studies have found that projected TOE are indeed sensitive to GHGES (e.g., Giorgi and Bi, 2009), and the different scenarios result in TOE that may differ by at least one decade (Hawkins and Sutton, 2012). In addition, the RCP8.5 scenario is considered by many as no longer being realistic (Van Vuuren et al., 2011), and CanESM2, the ESM on which ClimEx is based, is considered to be a hot and wet model (Yang Kam Wing et al., 2016). The ClimEx ensemble is therefore likely to overestimate future temperature and precipitation changes. However, internal variability may increase in warmer and wetter models, and previous studies (e.g., Chen and Brissette, 2019; Deser et al., 2020; Maher et al., 2020) have shown that estimates of internal variability may indeed differ from one SMILE to the next. This study should ideally be repeated with other SMILEs to confirm the TOE computed herein.

In the present work, hydrological simulations were performed using just one hydrological model. It is now well established that significant uncertainty may accompany this choice, especially for low flow calculations. In this regard, confidence in our results should be lower for the lowest flow quantiles (including extreme droughts) than for median and high flows, for which uncertainty is less a function of the hydrological model structure.

4.6 Conclusions

This study looked at the impact of anthropogenic climate change (ACC) on streamflow distribution in a warmer climate, as well as at the importance of internal natural climate variability in determining the time of emergence in hydrological climate change impact studies. All results presented in this work are contrasted for three different catchment size classes to better understand the relationship between catchment size, internal variability and the projected anthropogenic climate change signal. This was accomplished by combining the ClimEx SMILE's high temporal and spatial resolution with a hydrological model to project future streamflows on 133 northeastern US catchments.

The following are the main conclusions to be drawn from the study:

1- Most catchments will see a decrease in future flows for all quantiles up to quantile Q90, while increases are expected for the highest quantiles (above Q90, and especially for Q99 and Q99.9). These conclusions apply to all three catchment classes, although the largest decreases are observed for the medium and large catchments, while the largest increases are projected for the small catchments.

2- Flood and drought intensity will increase systematically through the end of the century. Catchment size has a significant impact on projected increases in flood and drought signals, with small catchments experiencing significantly greater increases in flooding than the others. Conversely, they will experience a weaker increase in severe extreme droughts.

3- Future projections of all hydrological indices, at least through the middle of the century, are significantly influenced by natural climate variability. In general, the signal-to-noise ratio of the studies streamflow indices increases with time from the near future to the far future. This is because the climate change signal is amplified in a warmer climate.

4- The fastest time of emergence is observed for the central quantiles (Q10 to Q70), and was reached at the beginning of the current century for the majority of catchments. The time of emergence of the high and low quantiles is expected to be later, around the middle of the present century in most cases, and even towards the end of the century and the beginning of the next century for small catchments.

5- The time of emergence of extreme floods and droughts is strongly influenced by the catchment size. The signal for extreme floods clearly appears earlier than for larger basins, while the opposite is observed for extreme droughts. The time of emergence appears earlier for droughts, despite the fact that the climate change signal is more significant for extreme floods, especially in small catchments.

6- The results show that both the internal variability and the climate change signal have impacts that depend on the size of the catchment, which also translates into a dependence of the emergence time on the size of the catchment.

7- It is recommended that the KS test method be used for emergence time determination in climate change studies. The SNR method is too conservative, and gives outlier results compared to the distribution-based methods, which give very similar results.

4.7 Acknowledgements

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4.8 Data availability

The MOPEX climate and streamflow datasets is available at:
https://hydrology.nws.noaa.gov/pub/gcip/mopex/US Data(Duan et al., 2006b). The Copernicus Climate Change Service (C3S) Climate Data Store provide ERA5 data at the following URL: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysisera5-single-levels?tab=form
(Hersbach et Dee, 2016).
ClimEx data may be downloaded from: https://www.climex-project.org/en/data-access/
It can also be obtained from the Matlab File Exchange, which can be accessed at:
https://github.com/TBenkHyd2 Models, the GR4J model (Perrin, Michel et Andréassian, 2003) and CemaNeige snow module (Valéry, Andréassian et Perrin, 2014) are accessible.
The SCE-UA global optimization algorithm, for its part is available at:
https://www.mathworks.com/matlabcentral/fileexchange/7671-shuffled-complex-evolution-sce-ua-method (Duan et Qingqyun, 1992).

CHAPTER 5

GENERAL DISCUSSION

This chapter presents an overview of the key findings from the research conducted in this thesis. It summarizes the most significant results that pertain to the main objective of the thesis, which is to improve our understanding of how natural variability and climate change affect hydroclimatic mean and extreme conditions at sub-daily intervals in relation to catchment size. Additionally, the chapter aims to explain the significance of these results and any limitations they may have. Finally, the chapter suggests possible methods for adaptation and areas for further research.

5.1 Projection of the change in extreme precipitation

The findings of Chapter 3 (the second paper) in this thesis have revealed the impact that climate change is having on extreme precipitation events. It has been observed that there is an amplification of extreme precipitation as a function of duration and return period in the future. The results show that higher return periods (rarer events) are projected to have greater relative changes. These results are consistent with previous studies, such as Li et al. (2019a), who showed larger increases in more extreme events than in less extreme events over most of North America. The findings are also in line with the intensification of extreme daily precipitation from CMIP5 (Kharin et al., 2018), sub-daily precipitation (Kuo, Gan et Gizaw, 2015; Tabari et al., 2016), and results from CPMs (Dai et al., 2020; Prein et al., 2017b). Furthermore, the results suggest that precipitation with shorter durations will produce larger relative changes. This is supported by result of convection-permitting model, which showed that shorter duration extremes may increase more than longer duration extremes (O'Gorman, 2015). Similar results have been observed for sub-daily time scales (e.g., Forestieri et al., 2018; Morrison et al., 2019; Moustakis et al., 2021). Additionally, the amplification of extreme precipitation is also found to be a function of catchment size. Extreme precipitation is expected to increase more across small catchments with a sub-daily hydrological response time. These results indicate that smaller storm cells in convective rain are strengthened more quickly than larger ones and may have a greater impact on small catchments than large ones. The findings are supported by the research of Kim et al. (2019), who discovered that ARF is inversely related to storm area and that increasing the area decreases ARF. Overall, the results demonstrate that small catchments are more sensitive and vulnerable to summer convective rainfall and its transformation into flash floods.

5.2 Projection of future streamflow

5.2.1 High flow

The findings of this research indicate that there is a comparable pattern of change for extreme high flows and extreme rainfall due to their relationship. Increases are a function of duration, return period, and catchment size. A larger increase corresponds with a shorter duration, a longer return period, and a smaller catchment size. The research also suggests that extreme flows typically have a higher relative amplification than extreme rainfall. However, the change in return periods is lower, which means the tails of both distributions are different with a steeper tail for precipitation. This is in accordance with the study of Zhang et al. (2022a) over the Eastern US, South America, South-East Asia, and Africa. Additionally, the flood quantiles show larger increases in small catchments than in larger catchments. These results are similar to the findings of Yu, Wright et Li (2020) and Sharma, Wasko et Lettenmaier (2018), who indicated that discharges increase more for smaller catchments because the storm covers the entire catchment and leads to soil moisture saturation. Furthermore, the results of Chapter 4 show that the rarer a flood, the more it will increase, which is consistent with the results of recent research (Roudier et al., 2016; Sharma, Wasko et Lettenmaier, 2018).

5.2.2 Low flow

The findings of Chapter 4 reveal that extreme droughts will be amplified as a result of climate change. These results align with the research of Zhao et al. (2020) and Tavakoli et al. (2014)

which predict that future hydrological droughts in North America and Belgium, respectively, will be more severe and more frequent. Additionally, the results of this study are similar to the findings of Roudier et al. (2016) which indicate that low floods (QlowRP10) are expected to decrease for many countries mainly located in the southern part of Europe. This is mainly due to less rainfall (Rajczak, Pall et Schär, 2013) and also higher potential evapotranspiration. Furthermore, Yu, Liu et Li (2020) have shown that hydrological droughts are sensitive to the spatial scales of catchments. For smaller catchments, meteorological droughts induced by less precipitation directly results into hydrological droughts. For larger catchments, hydrological droughts are affected by the effective rainfall, antecedent soil moisture, and the travelling time of surface runoff and subsurface runoff. The study finds that the trends for future droughts are mostly consistent across the three catchment size classes. However, the increase in drought severity appears to be smaller for the small catchments.

5.3 Uncertainty

The demand for studies on how to reduce uncertainty at a sub-daily scale is increasing as more applications of a climate model with a sub-daily time scale are required to better understand convective rainfall and subsequent flooding. However, there are differences between observed and modeled data. This study has investigated the importance and impacts of two sources of uncertainty in extreme events: diurnal cycle biases of variables (observation error and structural error in the modeling) and internal natural variability. These sources of uncertainty play a key role in the understanding of extreme events and need to be considered in future research.

5.3.1 Diurnal cycle biases

Our research has found that the diurnal cycle of climate models in smaller catchments, which have a sub-daily response, is biased. As a result, it is logical that correcting the diurnal cycle should improve impact model simulations. Through our work, we have determined that correcting the diurnal cycle results in improvements to the hydrological cycle in some catchments, but has much larger impacts on smaller catchments. Although the improvements are small, no negative impact has been observed. There are several research studies that point out diurnal uncertainties, but the effect of diurnal cycle bias correction on streamflow (and other impacts) had not, to our knowledge, been investigated before.

The diurnal cycle pattern of water flow in a river or stream is influenced by both temperature and precipitation changes throughout the day. A key factor in this pattern is evapotranspiration, the process by which water is lost to the atmosphere through the combined effects of evaporation from the soil and transpiration from plants. During the day, when it's warm and sunny, evapotranspiration rates tend to be high, which can reduce the amount of water available for streamflow. At night, when temperatures cool and there's less sunlight, evapotranspiration rates tend to be lower, which can increase the amount of water available for discharge.

This diurnal cycle of evapotranspiration can have a significant impact on the timing and magnitude of discharge flow in a watershed. To gain a deeper understanding of the significance of correcting diurnal cycle bias in small catchments, Figure 5.1 below illustrates a comparison of evapotranspiration amounts with and without diurnal bias correction (DBC and SBC) for both small and medium catchments.

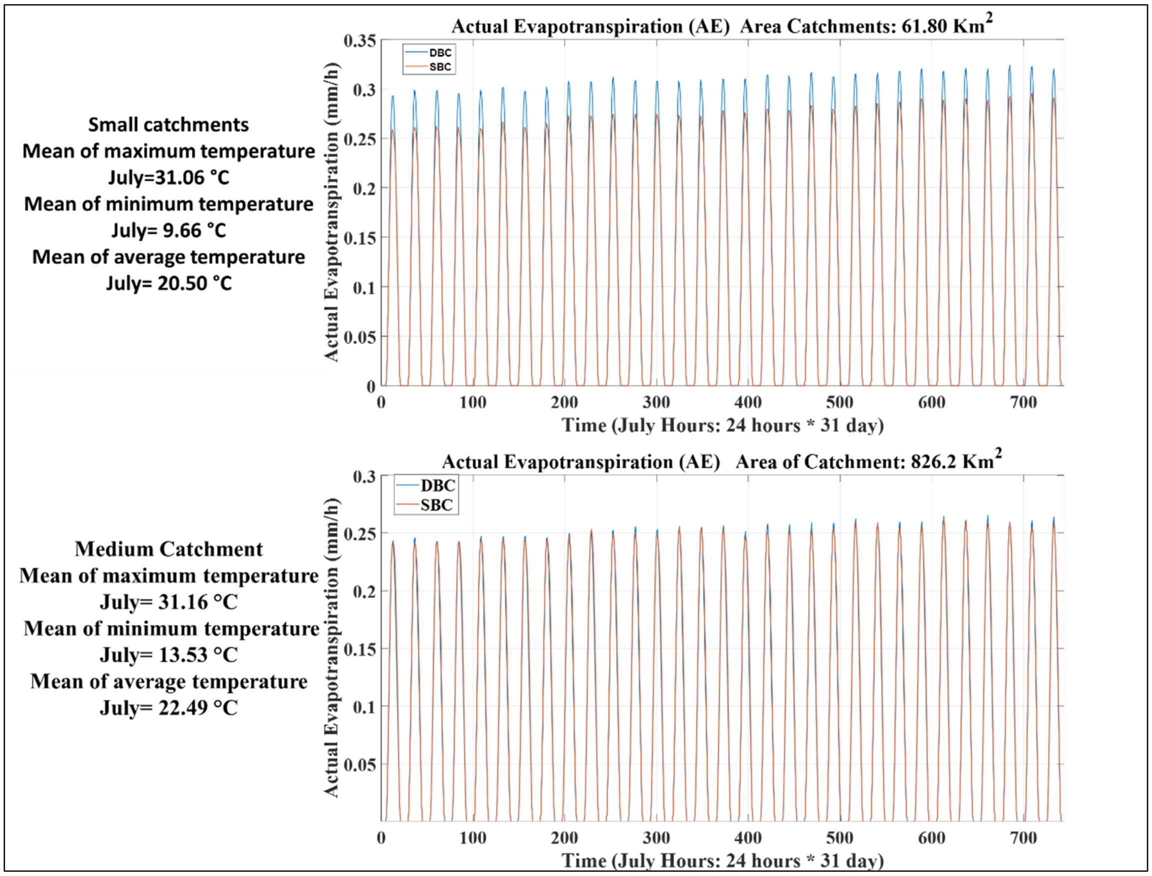

Figure 5.1 Comparing July actual evapotranspiration of small and medium catchments with and without diurnal cycle bias correction

According to those findings, we therefore recommend the sub-daily multivariate bias correction for all study dealing with sub-daily climate model data, and do stress that this can be particularly critical for small catchments.

5.3.2 Internal climate variability: detecting the signal of anthropogenic climate change (time of emergence)

Our results have shown that precipitation has a much stronger signal-to-noise ratio than temperature, meaning that the signal of climate change takes longer to break through the fog internal variability. The time of emergence (TOE) of temperature has already been met for all studied catchments, while precipitation TOE will only occur much later in this century and even the next for some catchments. These results are in line with recent studies such as Almazroui et al. (2021a), Barrow et Sauchyn (2019), and King et al. (2015). The overall TOE of streamflow tends to emerge earlier than precipitation, but later than temperature. This is perhaps not surprising since streamflow signatures come from the combination of both variables. A study by Leng et al. (2016) supports the view that runoff is a more effective indicator of global warming than precipitation. They displayed that runoff changes happen much earlier than that of precipitation. However, this also contradicts the findings of Zhuan et al. (2018), who claimed that with the joint contributions of temperature and precipitation, streamflow TOE occurs later than for both precipitation and temperature in China's Hanjiang River.

The median quantiles of streamflow distributions have the earliest TOE compared to other quantiles. These findings are in line with those presented by King et al. (2015) for temperature and precipitation. Our results show that extreme floods have a later TOE than extreme droughts, and that catchment size impacts the TOE with earlier (later) TOE for floods (droughts) over small catchments.

This study has also shown that the determination of the TOE depends on the statistical method chosen to estimate it. Earlier TOE are found when using distribution-based methods, which is in line with Gaetani et al. (2020) who indicated that TOE of precipitation occurs earlier in KS test and robustness is the largest when the 'KS test' method is used. Based on these findings, the thesis recommends using distribution-based methods to determine the TOE, as they make no assumptions about data distributions. This is particularly crucial in the case of extremes for which it is difficult to reliably estimate the parameters of a distribution.

Finding TOE has implications for planners and decision makers. Davenport, Burke et Diffenbaugh (2021) provide the framework that presents empirical proof that climate change has impacted the national average cost of flood damages in the USA. According to their calculations, applying empirical analysis to historical precipitation and flood damage accounts for around one-third (36%) of the cost of flood damages from 1988 to 2017, while detecting TOE provides a sign of human-induced climate change and could help mitigate this cost. Estimating TOE is relevant, and its significance for decision-making is also mentioned in recent studies, particularly when implementing adaptation and mitigation programmes (Barrow et Sauchyn, 2019; Chadwick et al., 2019; Nguyen et al., 2018; Zhou et al., 2018)et al. 2018; Zhou et al. 2018). Knowledge of TOE can also be used to inform water management decisions. For example, it can help in determining when to release water from dams or irrigation systems to ensure that the timing of water releases aligns with the TOE of aquatic organisms, which can help to maintain healthy populations.

5.4 Limitations of this work

5.4.1 Using a single climate model with a single greenhouse emission scenario

In order to better understand and reduce the uncertainty of climate models, it is recommended to use more than one climate model in climate change impact studies. Climate models use different structures and parameter sets, which result in various realizations of the future climate system. This work focused on hydro-meteorological extreme events and the role of internal climate variability, for which a large ensemble is recommended. However, there are currently not many ensembles of climate models with high spatial and temporal resolution. Climate change impact studies are sensitive to greenhouse gas emission scenarios, and in this study, only RCP 8.5 was examined. Although it is now considered a very pessimistic scenario, it has the benefit of highlighting the climate change signal with respect to internal variability, which is useful for examining precipitation, which has a low anthropogenic forcing to internal variability ratio. Overall, it is not expected that the main conclusions of this thesis would be different if it was redone with another climate model, since many of the results are in line with the work of others. However, using other climate models would very likely affect the magnitude of change and help to better outline future uncertainty related to climate model structure and climate sensitivity.

5.4.2 Using a single lumped hydrological model

Hydrological models can be a significant source of uncertainty, and particularly so in the case of low flows (Demirel, Booij et Hoekstra, 2013). The main reason for this is that most hydrological models have been designed for rainfall-runoff calculations, as is the case for GR4J/H used in this work. Low flows result from significant rainfall deficit over a long period and have a strong contribution from the water table. As such, using hydrological model specifically targeting low flows would probably help reduce the structural uncertainty of hydrological models in climate change low flow studies.

For median and large flows, using additional hydrology models is unlikely to change anything since research has shown that in these cases, uncertainty is dominated by the climate models.

5.4.3 Bias correction method

Bias correction method is a crucial aspect in our analysis, and while it's usually not a major contributor to uncertainty, we employed one of the best multivariate methods available. Although, it's worth mentioning that there are other bias correction methods that could be explored in future studies to further minimize uncertainty.

5.4.4 Method of finding signal of climate change

In this work, epoch differences were used to examine signal of climate change while different definitions of signal and noise may result in slightly different conclusions about hydroclimatic analysis in impact studies and detecting the timing of emergence. Epoch differences, linear trends, and polynomial trends are suggested by current scientific communities to characterize the anthropogenic climate signal. However, there isn't enough information to determine which pattern is most likely to occur, how much uncertainty it contributes to climate studies, or how internal variability influences the trend removal process. Factors such as data quality, temporal and spatial scales, and the sensitivity of the method to different types of signals, noise, and internal variability can all play a role in determining which signal definition and trend removal method is most appropriate for a given study. Therefore, it's important for researchers to carefully consider these factors when selecting a signal definition and trend removal method for their study in order to obtain accurate and reliable results for climatological analysis and time of emergence detection in impact studies.

5.5 Recommandations for future works

Future research could address the limitations mentioned above and therefore contribute to the body of knowledge needed to adapt to extreme events in the warmer climate. The results of this work suggest that a diurnal bias correction of precipitation and temperature should be applied in hydrological studies. To verify the importance of diurnal bias correction, it would be beneficial to examine its impact on other indexes of discharge flow, such as seasonal flows. For example, Zhu, Wright et Yu (2018) showed that summer and winter regulated flows tend to show a greater sensitivity to climate change.

In this research, the frequency and intensities of changes in meteorological and hydrological extremes were predicted independently without taking into account the transmission from one type to the other. Therefore, it is recommended to examine the relationship between extreme precipitation and flood and drought in current and future climates to better understand the potential effects and current vulnerability. Furthermore, this work shows that forecasting the time of emergence of a flood is more important for risk management over small catchments such as urban and suburban areas. It is recommended to examine the change of other variables and their impacts on the TOE flood signal in more detail, for example, slope, soil, changing land cover, land use, urban planning, and population. Future research should focus on the complexity of relationships among the processes that generate flood extremes.

CONCLUSION

The objective of this research was to gain a more comprehensive understanding of the potential effects of climate change on extreme hydroclimatic variables in the future. In pursuit of this aim, the study focused on the examination of diurnal cycle bias correction of climate variables and the consideration of natural climate variability. The ultimate goal was to decrease the uncertainty in projecting hydrological variables, and to enhance our comprehension of the intricate relationship between climate change, internal climate variability, catchment size, and hydrological projections to aid in decision-making and the creation of adaptation strategies.

A Single Model Initial condition Large Ensemble (SMILE) with 50 members was utilized in the research to evaluate the effect of climate change on extreme events and investigate the role of internal climate variability. Analyses were conducted across three different catchment sizes, including small (< 500 km^2), medium (between 500 and 1000 km^2), and large (> 1000 km^2) surface area catchments.

The study evaluated the future change of hydroclimatic variables for various durations, return periods, and catchment sizes. It also explored the role of internal climate variability in the examination of hydrological variables, particularly extreme floods and droughts, through the use of three different methods for detecting time of emergence. Additionally, the impact of diurnal cycle bias correction of climate variables on the simulation of streamflow was studied across three different catchment sizes in order to link the efficiency of diurnal cycle bias correction and catchment area. The main conclusions of the study are summarized as follows.

- The present study observes variations in the timing and intensity of the diurnal cycle, as observed through both climate model simulations and actual observations. These variations are attributed to a variety of factors including observational errors, natural internal climate variability, and incomplete representation of physical processes within the models. Through the implementation of a diurnal cycle multivariate quantile mapping bias correction method, the accuracy of temperature and precipitation projections was effectively improved. Additionally, the correction of diurnal cycle biases in precipitation and temperature resulted in noteworthy enhancements in streamflow simulations, particularly in small catchments.

- The research conducted in this study found that the intensity of both extreme precipitation and extreme flow is projected to increase across a majority of the 133 studied catchments. It was determined that the change in extreme precipitation and streamflow due to shifting climate conditions is dependent on factors such as duration, return period, and catchment area. Specifically, the greatest increase in future extreme precipitation was observed for the shortest duration and longest return period, specifically within small catchments.

- The study also found that while a majority of catchments will experience a decline in future flows for all quantiles up to Q90, an increase is expected for the highest quantiles. The largest decreases were observed in medium and large catchments, while small catchments are projected to see the largest increases. When comparing future changes in streamflow to increasing rainfall, it was found that the relative increases in streamflow were larger. Furthermore, the study found that catchment size plays a significant role in projecting an increase in extreme flow, with small catchments experiencing a greater increase in flooding and weaker increases in severe droughts.

- The research discovered that internal climate variability has a substantial impact on future hydrological variables, at least through the middle of the century. As time progresses, the impact of internal climate variability decreases, allowing the signals of change to become more prominent. The signals of change were observed to emerge for central, high and low quantiles of streamflow respectively. Additionally, the study found that there is a clear relationship between catchment size and the timing of emergence (TOE) of changes in extreme events, with small catchments experiencing an earlier TOE for floods and a later one for droughts.

It is important to note that the impact of climate change and internal climate variability are both functions of catchment area in hydrological studies and should be given more attention in future research to better understand and anticipate the changes that will happen in the future.

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