Using a Stochastic Weather Generator to Account for Climate Non-stationarity in Extended Streamflow Forecasts

by

Samaneh SOHRABI MOLLA YOUSEF

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Utilisation d'un générateur météorologique stochastique pour tenir compte de la non-stationnarité climatique dans les prévisions de débit étendues

Samaneh SOHRABI MOLLA YOUSEF

RÉSUMÉ

Des prévisions fiables de débit à long terme sont essentielles à la gestion des ressources en eau et jouent un rôle clé dans la gestion des réservoirs et la production hydroélectrique. Cadrer correctement l'incertitude est la question clé pour fournir une prévision fiable du débit à long terme. La principale approche pour couvrir les différentes sources d'incertitudes est d'utiliser une approche probabiliste contrairement à déterministe. Dans l'approche probabiliste, chaque donnée historique observée est considérée comme une réalisation possible de l'avenir. En outre, la non-stationnarité des variables hydrométéorologiques, soit en raison de la variabilité interne ou des changements anthropiques, est un autre problème important car il devient de plus en plus clair que les données historiques passées peuvent ne pas représenter adéquatement le climat actuel.

Par conséquent, il est nécessaire de développer des approches flexibles prenant en compte la non-stationnarité dans un contexte probabiliste. Le rééchantillonnage des séries chronologiques historiques passées est l'approche probabiliste la plus couramment utilisée dans le processus de prévision du débit à long terme. Cependant, les méthodes de rééchantillonnage souffrent de leur hypothèse de stationnarité dans les séries observées. Une autre approche possible consiste à utiliser un générateur météorologique stochastique couplé à un modèle hydrologique pour générer des prévisions probabilistes de débit à long terme. Les générateurs météorologiques peuvent facilement être modifiés pour tenir compte des tendances climatiques récentes et ont donc le potentiel de prendre en compte la non-stationnarité.

Cependant, avant que les générateurs météorologiques puissent être modifiés pour tenir compte des non-stationnarités climatiques, il est d'abord nécessaire d'évaluer si la chaîne de modélisation composée d'un générateur météorologique stochastique et d'un modèle hydrologique peut générer des prévisions de débit probabilistes dans la même mesure que les approches de rééchantillonnage plus traditionnelles. Le premier objectif de cette étude était donc de comparer les performances d'un générateur météorologique stochastique avec celles du rééchantillonnage de séries chronologiques météorologiques historiques afin de produire des prévisions d'ensemble de débit. Les résultats indiquent que s'il existe des différences entre les deux méthodes, elles fonctionnent néanmoins largement de façon similaire, ce qui montre que les générateurs météorologiques peuvent être utilisés comme substituts pour rééchantillonner le passé historique. Sur la base des résultats positifs de la première étape de cette étude, deux approches pour la prise en compte de la non-stationnarité basée sur la capacité de modification du générateur météo stochastique ont été proposées. La première approche a exploré une méthode de perturbation simple dans les paramètres d'un générateur météorologique stochastique. Dans le schéma de perturbation, toute la longueur de l'historique est utilisée pour quantifier la variabilité interne, tandis qu'un sous-ensemble des dernières années est utilisé pour caractériser les valeurs climatiques moyennes pour les précipitations, les températures minimales et maximales. Les résultats montrent que la méthode proposée améliore systématiquement la précision des prévisions de débit à long terme, bien que les mêmes résultats dépendent de la fenêtre temporelle utilisée pour estimer les estimations climatiques moyennes actuelles.

La deuxième approche a conditionné les paramètres d'un générateur météorologique stochastique à des indices climatiques à grande échelle. Dans cette approche, les indices climatiques les plus importants sont identifiés en examinant les corrélations annuelles entre un ensemble de 40 indices et les précipitations et la température. Un modèle linéaire est ensuite construit pour identifier les anomalies de précipitation et de température afin d'induire des perturbations dans le générateur météorologique stochastique. Pour faire face à la non-stationnarité dans les indices climatiques à grande échelle et la relation des séries chronologiques météorologiques, 5 fenêtres temporelles différentes sont définies pour déterminer le modèle linéaire optimal. Les résultats montrent que les températures sont significativement corrélées avec les indices climatiques à grande échelle, tandis que les précipitations ne sont que faiblement liées aux mêmes indices. La longueur de la fenêtre temporelle a un impact considérable sur la capacité de prédiction des modèles linéaires. Les modèles de précipitations basés sur des fenêtres temporelles de courte durée ont donné de meilleurs résultats que ceux basés sur des fenêtres plus longues, tandis que l'inverse a été constaté pour les modèles de température. Les résultats montrent que la méthode proposée améliore les prévisions de débit à long terme, en particulier autour de la crue printanière.

Mots-clés: prévision à long terme du débit, générateur météorologique stochastique, non-stationnarité, variabilité naturelle, changement climatique.

Using a stochastic weather generator to account for climate non-stationarity in extended streamflow forecasts

Samaneh SOHRABI MOLLA YOUSEF

ABSTRACT

Reliable long-term streamflow forecast is essential in water resources management and plays a key role in reservoir management and hydropower generation. Properly framing the uncertainty is the key issue in providing a reliable long-term streamflow forecast, and probabilistic forecasts have been used to this effect. In a probabilistic approach, each observed historical data is taken as a possible realization of the future. Non-stationarity of hydro-meteorological variables, either due to the climate internal variability or anthropogenic change, is another important problem for long-term streamflow forecasts as it is becoming increasingly clearer that past historical data may not adequately represent the current climate.

Therefore, there is a need to develop flexible approaches taking into account non-stationarity for long-term streamflow forecasts. Resampling past historical time series is the main approach used for probabilistic long-term streamflow forecasts. However, non-stationarity is a key issue of resampling approaches. One possible approach is to make use of a stochastic weather generator coupled to a hydrological model to generate long-term probabilistic streamflow forecasts. Weather generators can easily be modified to account for climatic trends and therefore have the potential to take non-stationarity into account.

However, before weather generators can be modified to account for climate non-stationarity, it is first necessary to evaluate whether the modeling chain consisting of a stochastic weather generator and a hydrological model can generate probabilistic streamflow forecasts with a performance similar to that of more traditional resampling approaches. The first objective of this study is therefore, to compare the performance of a stochastic weather generator against that of resampling historical meteorological time series in order to produce ensemble streamflow forecasts. Results indicate that while there are differences between both methods, they nevertheless largely both perform similarly, thus showing that weather generators can be used as substitutes to resampling the historical past. Based on these results, two approaches for taking non-stationarity into account have been proposed. Both approaches are based on a climate-based perturbation of the stochastic weather generator parameters. The first approach explored a simple perturbation method in which the entire length of the historical record is used to quantify internal variability, while a subset of recent years is used to characterize mean climatic values for precipitation, minimum and maximum temperatures. Results show that the approach systematically improves long-term streamflow forecasts accuracy, and that results are dependent on the time window used to estimate current mean climatic estimates.

The second approach conditioned the parameters of a stochastic weather generator on large-scale climate indices. In this approach, the most important climate indices are identified by looking at yearly correlations between a set of 40 indices and precipitation and temperature. A linear model is then constructed to identify precipitation and temperature anomalies which are then used to induce perturbations in the stochastic weather generator. Five different time windows are defined to determine the optimal linear model. Results show that temperatures are significantly correlated with large-scale climate indices, whereas precipitation is only weakly related to the same indices. The length of the time window has a considerable impact on the prediction ability of the linear models. The precipitation models based on short-duration time windows performed better than those based on longer windows, while the reverse was found for the temperature models. Results show that the proposed method improves long-term streamflow forecasting, particularly around the spring flood.

Keywords: Long-term streamflow forecast, stochastic weather generator, non-stationarity, natural variability, climate change

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LIST OF ABREVIATIONS

AAO	Antarctic Oscillation
AMM	Atlantic Meridional Mode
AMO-Nsmoothed	Atlantic Multi decadal Oscillation unsmoothed
AMO-smoothed	Atlantic Multi decadal Oscillation unsmoothed
AO	Antarctic Oscillation
ATSST	Atlantic Triple SST EOF
BEST	Bivariate ENSO Time Series
CAR	Caribbean Index
CRPS	Continuous Ranked Probability Score
EA-WR	Eastern Asia/Western Russia
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	ENSO precipitation index
EP_NP	East Pacific/North Pacific Oscillation
ESP	Ensemble Streamflow Prediction
EWF	Ensemble Weather Forecast
GLAAM	Globally Integrated Angular Momentum
GMLOT	Global Mean Lan/Ocean Temperature
HA	Monthly totals Atlantic hurricanes
MEI	Multivariate ENSO Index
NAO	North Atlantic Oscillation from NOAA
NAO_J	North Atlantic Oscillation from CRU
NBRA	Northeast Brazil Rainfall Anomaly
NCEP	National Centers for Environmental Prediction
NINO 1+2	Extreme Eastern Tropical Pacific SST
NINO 3.4	Eastern Central Tropical Pacific SST
NINO 4	Central Tropical Pacific SST
NINO3	Eastern Tropical Pacific SST
NOI	Northern Oscillation Index
NP	North Pacific Pattern

NTA	North Tropical Atlantic Index
ONI	Oceanic Niño Index
PDO	Pacific Decadal Oscillation
PNA	Pacific North American Index
Pr	Precipitation
PSD	Western Pacific Index
PW	Pacific Warm pool
QBO	Quasi-Biennial Oscillation
Reg-Res	Regression – Resampling
Reg-WG	Regression - Weather Generator
Res	Resampling
SF	Solar Flux
SOI	Southern Oscillation Index
SR	Sahel Standardized Rainfall
SWG	Stochastic Weather Generator
SWMRR	SW Monsoon Region Rainfall
Tmax	Maximum Temperature
Tmin	Minimum Temperature
TNA	Tropical Northern Atlantic Index
TNI	Indices of El Niño Index
TPSST	Tropical Pacific SST EOF
TSA	Tropical Southern Atlantic Index
WG	Weather Generator
WHWP	Western Hemisphere Warm Pool

INTRODUCTION

The development of human settlements and cities is closely linked to water. Well-being and survival of human population are both depended on water availability. In particular, human society is vulnerable to large fluctuations in the amount of available water. Variability in the water cycle in the form of floods and droughts can threaten infrastructures, food supplies and even human lives. Therefore, planning, developing and managing water resources have a great importance.

To manage water resources, thousands of dams and reservoirs have been built all over the world. Dams and reservoir systems have been built to provide a reliable water supply for agriculture, municipal and industrial consumers, as well as for power generation. According to the World Dam Commission, many large reservoir projects worldwide have failed at producing the expected level of economic benefits. One of the main reasons for this failure is inadequate consideration of management aspects. Operational planning and management of reservoirs are one important problem for operators and decision makers. A water resources system is often comprised of several different physical components and management of such complex systems is a challenging task. Successful management practices are required to increase economic benefits and satisfy demands. Of all relevant variables, streamflow play a determinant role in water resources management, and therefore, accurate streamflow forecasts directly benefit water resource management.

In reservoir management a proper short-term streamflow forecast between 1 to 15 days can help to decrease the impact of floods, whereas providing long-term streamflow forecasts (more than 2 weeks to the annual time scale) can impact the overall management of water resources system in terms of irrigation, power generation, environmental and ecosystem protection. The main challenge in providing a long-term streamflow forecast in reservoir management is dealing with various sources of uncertainties which are increasing over the lead time of forecast. Deterministic forecasts have long been used and remain common for streamflow forecasting. However, due to the inability of deterministic approaches at providing information about uncertainties, probabilistic forecasts have become more common.

In recent decades, climate change due to the human activities is one of the main sources of uncertainties which affect long term streamflow forecasts. According to the Inter-Governmental Panel on Climate Change global mean temperature has increased by 0.85 C over the 1800-2012 period which is an “unequivocal” sign of warming (Allen et al. 2014). The combined effects of anthropogenic climate change and natural climate variability challenge the assumption of stationarity for hydrometeorology time series Therefore, adequate streamflow forecasts should account for non-stationarity as a key additional source of uncertainty.

CHAPITRE 1

LITRATURE REVIEW

This literature review covers the many aspects relevant to streamflow forecasting. The first section discusses the importance and advantages of probabilistic approaches compared to their deterministic counterparts. It also covers the origin of ensemble weather and streamflow forecasts. The second section introduces the most common methods to generate ensemble streamflow forecasts and outlines the advantages and disadvantages of each method. The main problems of resampling approaches for long-term streamflow forecasts are then presented. The use of stochastic weather generators for long-terms streamflow forecasts is then discussed.

The last part of the literature review focuses on issue related to the non-stationarity of climate data in hydrological studies. The causes of non-stationarity as well as approaches to capture non-stationarity in streamflow modeling are reviewed and discussed.

1.1 Probabilistic Vs. Deterministic

The main classification of weather and streamflow forecasts is based on their deterministic or probabilistic nature. Many hydrological studies and efforts have been conducted in order to find the optimal deterministic forecast and a large number of operational hydrological forecasting systems produce deterministic forecasts. Typically, end users and decision makers prefer to have access to a single value forecast due to ease of use rather than having to deal with the uncertainty of probabilistic forecasts (Duan et al. 2019).

Despite the work on finding the best deterministic forecasts, the inability of deterministic approaches to provide long term forecasts capturing temporal and spatial uncertainties, forced researches to focus on probabilistic approaches. This is reflected by the use of ensemble prediction systems concept (Boucher and Ramos 2018; Zappa et al. 2018).

1.2 Ensemble Prediction System

An Ensemble Prediction System is a collection of two or more forecasts over the same future horizon. Ensemble Prediction Systems represent the probabilities and therefore uncertainties associated with a forecast. The main purpose of developing ESPs, in contrast to deterministic forecasts, was to assess and communicate the inherent uncertainty of the forecasts in an envelope (Zappa et al. 2018).

The first probabilistic studies were in the domain of weather forecasting, and date back to the sixties when Lorenz research demonstrated the chaotic nature of the fluid dynamics equations in weather forecasting (Lorenz 1965). In several papers, Lorenz (Lorenz 1963; Lorenz 1965; Lorenz 1969) investigated the predictability of the atmosphere and weather patterns and showed that the fundamental limit of atmospheric predictability is related to the initial conditions. Following the work of Lorenz, the 1970s was a decade of initiation and development of probabilistic approaches in weather forecasting. Epstein (1969) and Gleeson (1970) all proposed probabilistic approaches in forecasting. However, due to the complexity of these techniques and lack of enough computing power, they couldn't generate operational weather ensemble forecasts. The first official ensemble prediction systems date back to the 1980s. Hoffman and Kalnay (1983) computed the first simple ensemble weather prediction system with a technique called the Lagged Average Forecast method. In 1992, the US National Centers for Environmental Prediction computed a first operational ensemble weather forecast consisting of a 14-member ensemble forecast (Toth and Kalnay 1993). In the same year, European Center for Medium Range Weather Forecast (ECMWF) started generating and using ensemble weather forecasts (Molteni et al. 1996). As the computational power increased, the number and length of forecasts as well as complexity and resolution of the generating model increased, and by 1997, NCEP (National Centers for Environmental Prediction) and ECMWF (European Centre for Medium-Range Weather Forecasts) were able to compute global ensemble weather forecasts where each member was generated from different initial conditions. They demonstrated the usefulness of ensemble weather forecasts. Following the success of these two centers in applying ensemble weather forecasting, the use of ensembles in weather forecasting became prevalent around the world. By the late 1990s, the US navy and the meteorological service of Canada, Japan, South Africa, Australia and India were all using ensemble forecasts (Sivillo et al. 1997).

Ensemble weather forecasts contain important information about the uncertainties. Following the advances of ensemble prediction systems by the meteorological community, hydrologists started to apply ensemble prediction in hydrologic studies and especially in streamflow forecasting (Cloke and Pappenberger 2009).

Generating probabilistic forecasts in hydrology as well as assessing the skill of those forecasts is a complex task, especially in the context of streamflow forecasting. In practice, deterministic forecasts provide a single streamflow value per time step without giving any information about the uncertainty associated to the forecast. In many cases, assessing and communicating the uncertainty in order to make the best decision is essential. Hence, probabilistic approaches were proposed in order to overcome this important drawback of deterministic approaches (Krzysztofowicz 2001).

The first studies on ensemble prediction systems for streamflow forecasting began in the early 1970s and followed the success obtained in ensemble weather forecasting. The National Weather Service (NWS) applied the concept in the 1975 Extended Streamflow Program (Curtis and Schaake 1979; Twedt et al. 1977). As a result of the usefulness of the Extended Streamflow Program, the National Weather Service (NWS) redesigned the Program in 1979 to eliminate deficiencies and officially introduced ensemble streamflow prediction in 1984 (Day 1985).

The potential of ESP (Ensemble System Prediction) in water supply management was examined by Day in a 1985 study. He generated ESP by coupling past observed weather data to a hydrologic model. This study demonstrated that ESPs can be used for water supply management in the form of inflow hydrographs forecasts for reservoir operation as well as to forecast maximum and minimum streamflow. Likewise, Georgakakos (1989) demonstrated that ESP can significantly improve the planning of reservoir operation; however, it is system specific. Following the demonstration of the added value of using ESP, the Natural Resources Conservation Service (NRCS) implemented ESP in their forecasting system and, since 2000, the use of ESPs in hydrological forecasting became more prevalent by international bodies such as the European Commission joint Research Center and the World Meteorological Organization (WMO) (Cloke and Pappenberger 2009). Nowadays, the use of ESP in hydrological forecasting is prevalent and ESP can be used for various purposes such as flash flood forecasting (Alfieri and Thielen 2015), flood forecasting (Mueller et al. 2016; Schumann et al. 2013) and hydropower generation (Fan et al. 2016; Schwanenberg et al. 2015).

1.3 Methods for Generating ESP

Improving ensemble weather forecast as well as ensemble streamflow forecasts still remains an active problem. Since many ESPs in hydrological studies are first derived from weather forecasts, it follows that the choice of weather forecasting method has important impacts on ESP. Different methods for weather forecasting and generating the ensemble weather forecast (EWF) have been developed. These methods can be classified in three main categories that are Numerical Weather Prediction systems (NWPs), resampling methods, and Stochastic Weather Generators. The following section will briefly explain each method as well as their advantages and disadvantages.

1.3.1 Numerical Weather Prediction Methods (NWPs)

Numerical weather prediction (NWP) can be considered as a modern and most accurate tool to forecast the weather (Done et al. 2004; Roberts 2008). A first attempt to develop EWF dates back to the 1920s. However, due to the lack of enough computational power, the first NWP forecast was launched in the 1950s (Lynch 2008). Numerical weather prediction (NWP) employs a set of mathematical equations of the atmosphere and oceans in order to predict the weather according to current weather conditions (Pielke Sr 2013). Although NWP is considered as the best and most accurate forecasting method, studies have shown that in a best case scenario, NWP forecast have skill only up to a 6-day horizon for low precipitation (lower than 2 mm) and up to 4 days for high precipitation (between 2 and 10 mm,) . Some meteorological departments nonetheless use NWP for lead times up to 10 days (De Roo et al. 2003). Many studies have shown that the uncertainty in NWP is the largest source of uncertainty in NWP-driven hydrological forecasts (Coulibaly 2003). Therefore, it can be concluded that for short-term forecasting (up to 10 days), the NWP can be used for ensemble streamflow forecasts, but for lead times exceeding 10 days the skill of NWP is extremely limited at best. Therefore, in hydrological studies needing long-term forecasts, other methods should be considered.

1.3.2 Resampling Methods

Resampling is a non-parametric method which consists of using past meterorological time series as possible representations of the climate over the forecasting period. Resampling is present under many variants depending on how to draw samples from the entire pool of past time series.
Resampling methods consist of several variants such as the persistence, trends, climatology and analog methods. The persistence method is the simplest weather forecasting approach. It assumes that the conditions prevailing at the forecast time will not change and that weather patterns will change very slowly. The trend method is based on the determination of the speed and direction of fronts, pressure centers, areas of clouds and precipitation. Trend methods are suitable for weather systems which move at constant speed and direction over a long period. The climatology method is based on representing the past uncertinty of weather statistics accumulated over several years. The method assumes that the probability of any weather pattern is the same as it was in the past record. The analog method involves estimating today's weather according to similar weather conditions observed in the past. All of the above methods have limitations. Weather systems are very dynamic and it is sometimes difficult to find a perfect analog.

All resampling methods are based on using historical weather data and suffer for the same drawbacks. The main weaknesses of resampling methods can be summarized into two main points: First, since resampling methods are based on the historical record, any deficiency in past data will be represented in the quality of the ensuing weather forecast. The forecast horizon is also limited by the length of the existing records. Finally, since resampling methods are based on past data, they cannot take into account non-stationarity in the climatic record, such as induced by anthropogenic climate change. Therefore, trying to forecast the future only using past data is a very difficult task in non-stationary conditions. As a result, it can be implied that the raw forecasts based on resampling methods are always biased (Lall and Sharma 1996; Moniz et al. 2017).

1.3.3 Stochastic Weather Generators

Stochastic weather generators were developed in the early eighties to palliate for historical records which were often too short for many environmental applications. Stochastic weather generators are used to produce long time series with the same statistical properties as that of observations. Observed records of weather data are fundamental inputs to many environmental models in agriculture and hydrology. Many environmental models require several years of data for their proper calibrations. Therefore, the main reason for the development of stochastic weather generators was to generate synthetic weather time-series that were long enough to be used in hydrologic models and risk assessment studies. Another important reason for the development of stochastic weather generators is to extend and simulate weather time series at locations with no observation. Access to weather data at all locations is not always feasible and in some cases, due to instrumental issues, weather time-series are incomplete (Wilks and Wilby 1999). In such cases, stochastic weather generators can be used to generate long time series and therefore provide probabilistic weather forecasts needed for ESP. They can also incorporate climate change uncertainty in the forecasts and generate extremes outside of the observed range of the historical record. These are significant advantages compared to traditional historical resampling methods.

1.4 Stochastic Weather Generators

The concept of weather generators dates back to the 1800s. The earliest work of Quetelet in 1852 was related to the development of probabilistic modeling of precipitation occurrence and based on the concept of wet and dry day persistence. From 1916 to 1938 it was demonstrated that the probability of a rainy day is greater if it is preceded by a wet day. Longley (1953) modeled dry and wet spells by using geometric series and Gabriel and Neuman (1962) used a Markov Chain to reproduce the distribution of wet and dry spell lengths and therefore presented the first statistical model of daily rainfall occurrence. Tordorvic and Woolhiser (1975) combined the Markov Chain occurrence model with an exponential distribution to generate rainfall amounts. Finally, Richardson (1981) combined the above and built a stochastic weather generator able to generate precipitation, maximum and minimum temperature as well as solar radiation conditioned on the previous day wet/dry state. Wilks (1992) adapted a stochastic weather generator as a downscaling method in climate change studies and the results showed that weather generators could be used as a downscaling tool suitable to investigate the impacts of climate change. Wilks (1999a) used a simple stochastic weather generator to downscale and disaggregate precipitation, and showed that it could be readily used for simulating climate change scenarios at the local scale. In the same year, Corte-Real (1999) applied a stochastic weather generator as a downscaling tool conditioned on daily circulation patterns in southern Portugal. He showed that the weather generator could reproduce observed weather statistics very well. It could therefore produce reliable climate change scenarios, provided that that the present-time relationship between local precipitation and large scale atmospheric circulation remains valid in the future. Wilks and Wilby (1999) produced a complete review of the development of stochastic weather generators. They described common applications of weather generators, discussed the main deficiencies and suggested solutions to overcome them.

Following the success of stochastic weather generators at producing time series of weather variables, various studies have attempted to improve the performance of stochastic weather generators. To improve the low-frequency variability of stochastic weather generators, several methods such as perturbing monthly parameters using a low-frequency stochastic model (Hansen and Mavromatis 2001), correcting daily precipitation using power spectra of observed time series (Chen, Brissette et al. 2010) were introduced. To be able to assess the spatial variability of hydrological time series, multisite weather generators were then developed (Apipattanavis et al. 2007; Breinl et al. 2015). Various approaches to enhance the representation of intervariable correlations along with spatial correlations were also developed (Chen and Brissette 2015; Chen et al. 2018).

1.4.1 Types of Stochastic Weather Generators

Hydrologists classify stochastic weather generators into three main categories based on the precipitation model. They are parametric, semi-parametric and non-parametric weather generators.

WGEN (Richardson 1981) is the best example of a parametric weather generator and is likely the most widely used weather generator. WGEN applies a first-order Markov chain to describe the occurrence of wet and dry days and a distribution function for precipitation amounts (typically the exponential or gamma distribution). Various parametric weather generators were developed based on the Richardson approach such as WXGEN (Nicks et al. 1990), GEM (Hanson and Johnson 1998), ClimGen (Stöckle et al. 1999), extended WGEN (Parlange and Katz 2000) and WeaGETS (Chen et al. 2012a). The main problem of using a Markov chain in parametric weather generators is its ‘limited memory’ of rare and extreme events which could lead to inaccurate estimation of dry series such as droughts or prolonged rainfall. To overcome this issue, semi parametric weather generators were developed. In semi parametric weather generators, precipitation occurrence is based on distributions of the length of continuous sequences of wet and dry series. Semi parametric weather generators were developed by Rackso (1991) and Semenov and Barrow (1997) who introduced LARS-WG, a widely-used semi parametric stochastic weather generator. Semenov et al (1998) compared the parametric WGEN to LARS-WG. Results show that while LARS-WG used more complex distributions and tended to better match the observations over the calibration period, the overall performance of LARS-WG was similar to that of WGEN. The same study also showed that there were certain statistics of weather variables that neither stochastic weather generators could reproduce accurately. Since neither parametric and semi parametric weather generators were able to reproduce all statistics of observed time series, non-parametric approaches in precipitation modeling such as bootstrap resampling methods were proposed (Apipattanavis et al. 2007; Caraway et al. 2014; Goyal et al. 2011b; Leander and Buishand 2009b; Sharif and Burn 2007). The K-Nearest Neighbor algorithm introduced by Young (1994) was used in many studies. On the other hand, various studies demonstrated that non-parametric approaches could not produce new values for precipitation as they merely reshuffle historical data to generate realistic weather sequences. In addition, non-parametric approaches underestimate wet and dry spells. Several studies suggested approaches to improve the performance of non-parametric weather generators (Apipattanavis et al. 2007; Caraway et al. 2014; Goyal et al. 2011a; Leander and Buishand 2009a; Sharif and Burn 2007).

1.5 Non-stationarity in hydrometeorological variables

There is an increasing body of evidence supporting that climate change have critical impacts on regional ecosystems, water supply, agriculture and hydropower generation (González-Zeas et al. 2019). The behavior of hydrological systems is already changing in accordance to the changing climate and consideration of this impact is required for hydrological modeling studies about climate change adaptation strategies (Byun et al. 2019). Most hydrological models are developed based on the assumption that the climate and hydrological time series are stationary. In the absence of changes in external forcing (such as increases in greenhouse gases emissions), natural climate variability is considered a key source of uncertainty in hydrological modeling. The increase in external forcing due to anthropogenic activities is an additional source of uncertainty (Milly et al. 2008).

Non-stationarity in hydrological time series can arise due to the combined effect of the anthropogenic climate change and natural climate variability (IPCC 2007). A failure to take non-stationarity into account can lead to biased streamflow forecasts which can negatively impact the management of water resources systems (El Adlouni et al. 2007; Strupczewski et al. 2001; Villarini et al. 2010). Non-stationarity can cause changes in the probability distribution of hydrological time series over time. This is characterized by distribution parameters, such as mean and variance, changing with time (Gagniuc 2017). In the last 10 years, many studies have proposed approaches to deal with the non-stationarity of hydrometeorological data.

1.6 Non-stationarity modeling

In parametric approaches, covariates are typically used to describe the non-stationarity. A covariate can be defined as a variable that represents the climate variability and that is related to distribution parameters. The covariates that are used in non-stationarity modeling can be generally divided into four main groups: in the first group, time is a main covariate. In time-varying models, the parameters of a distribution are modelled as a function of time. Various methods to fit distributions to non-stationary data are presented such as incorporating the trends in statistical moments, incorporating the trends in moments, using local likelihood approach, quantile regression methods, generalized extreme value (GEV) and or generalized Pareto distributions (Katz 2013; Khaliq et al. 2006; Ouarda and Charron 2019). In the second group, large-scale climate indices are taken as covariates to translate the changes onto hydrological time series. Many studies have found that large-scale modes of climate variability such as El Niño Southern Oscillation (ENSO), North Atlantic Oscillation and Pacific Decadal Oscillation (PDO), can be used to identify patterns of low variability in non-stationarity conditions (Ouarda and Charron 2018; Ouarda and Charron 2019). A third group of studies use covariates which have a clear physical meaning such as population (Villarini et al. 2010) or modified reservoir index (Su and Chen 2019). In the fourth and last group, a combination of covariates such as population and large scale climate indices are used simultaneously to reflect the non-stationarity (Stasinopoulos and Rigby 2007).

Non-parametric approaches for non-stationarity studies are developed based on the calibration of a hydrological model and updating of model parameters. A few methods are developed based on “differential split-sample test” proposed by KlemeŠ (1986). In this approach, the historical data is usually divided into consecutive subsets and the model are calibrated separately for each subset period (Gharari et al. 2013; Thirel et al. 2015). Another approach is using periods that are supposed to be similar to the expected future hydroclimatic condition to calibrate the hydrological model (Vaze et al. 2010). Recently, sequential data assimilation (DA) techniques, such as ensemble Kalman filter (EnKF) have been used to estimate model parameters and states as a strategy to deal with non-stationarity (Pathiraja et al. 2016). Despite all of those recent efforts, many challenges remain on how to properly account for non-stationarity in hydrological science (Mondal and Mujumdar 2015; Su and Chen 2019; Westra and Sisson 2011).

1.7 Incorporating the Large – Scale Climate Indices in Hydro-Meteorological Forecasts

In the recent decade, various approaches have been proposed to consider non-stationarity in the hydrological modeling process. The proposed methods are mostly based on incorporating the temporal change of key variables into hydrological models. One of the main approaches is employing large-scale climate indices as covariates. Large-scale climate indices can represent patterns of internal variability and reflect that into hydrological time series distributions (Ouarda and Charron 2018; Ouarda and Charron 2019). A large and growing body of literature has investigated the value of using large scale climate indices in hydrology. One of the earliest studies on the interaction between large scale climate indices and streamflow forecasts was conducted by and Hamlet and Lettenmaier (1999). They incorporated climate information in ensemble streamflow forecasts of the Columbia River in the US by restricting the ensemble members to years that were similar in terms of El Nino-Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO). They demonstrated that the forecast can be improved by conditioning the forecasts on PDO and ENSO. Hidalgo and Dracup (2003) explored the influence of ENSO and PDO on precipitation and streamflow in the Upper Colorado River Basin. Their results demonstrated a significant impact of ENSO on precipitation and showed that changes in precipitation and streamflow coincided with PDO shifts. Grantz et al. (2005) incorporated climate indices in ensemble streamflow forecasts over the western United States to improve the skill and lead-time of seasonal forecasts. The results of this study showed that incorporating climate indices could increase the skill of forecasts by up to 4 months. Najfi et al (2012), compared five parametric and nonparametric ESP weighting methods based on 18 large scale climate indices. The results of this study showed that the weighted ensemble forecast improved the range of streamflow estimates and uncertainty bounds. Kalra and Ahamd (2013), applied an artificial intelligence data-driven model called Support Vector Machine (SVM) to incorporate large-scale climate indices (including ENSO, PDO, AMO and NAO) to improve the skill of long-term forecasts. Beckers (2016) evaluated the skill of ENSO-conditioned ESP over 59 years of streamflow forecasts in the Columbia River basin. They reported a 5 to 10% improvement in forecast skill for two test stations out of three. Chen and Lee (2016) looked at the correlation between runoff and an extensive subset of large-scale climate indices for a watershed in Taiwan. They have verified two main shifts in summer streamflows in accordance with large scale climate indices. Lauro et al (2019) found a direct relationship between the Niño 3.4 index and streamflows in Argentinean basins .

1.8 Large – scale climate indices incorporation methods

The methods for incorporating large-scale climate indices into hydrological forecasts can be classified into pre- and post-processing schemes. In pre-processing schemes, the inputs of hydrological models are modified based on the phase of a set of large scale climate indices. In this scheme, the historical years or months that share similarity with the current configuration of climate indices at the forecast time are selected (Hamlet and Lettenmaier 1999; Werner et al. 2004; Wood et al. 2002). Post processing schemes are mainly based on weighting the forecasts according to the climate indices. In this approach, all of the historical record is used for the ensemble weather forecasts, and the outputs of the hydrological model are weighted based on the relevant climate indices at the time of the forecast (Najafi et al. 2012; Werner et al. 2004).

Building a statistical model is another approach involving large scale climate indices in hydrological forecasting. In this approach, large scale climate indices are taken as main predictors and hydro-meteorological variables are taken as predictants. Methods such as simple and multiple regressions (Esha and Imteaz 2019; Mekanik et al. 2013) principal component analysis (PCA) (Hua et al. 2007; Sagarika et al. 2015), singular value decomposition (SVD) (Tootle and Piechota 2006) and canonical correlation analysis (Forootan et al. 2019) are among the proposed methods to incorporate climate indices in the hydrological forecasting process.

In the recent decade, the use of black-box models for defining the relationship between large scale climate indices and hydro meteorological variables has become more frequent among hydrologists. Methods such as artificial neural network (ANNs), Genetic Programming and machine learning have been used to find non-linear relationships between large-scale climate indices and hydrometeorological variables (Choubin et al. 2016; Esha and Imteaz 2019; Kim et al. 2019).

However, despite the growing literature on the topic, identifying the key large scale climate indices and finding the best approach to use information from these indices within the hydrological forecasting process remain active research areas (Kim et al. 2019).

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CHAPITRE 2

OBJECTIVES, APPROCH AND ORGANIZATION OF THE DOCUMENT

The principal objective of this project is to improve the forecasting skill of long-term streamflow forecasts. To meet the main objective, the three following specific objectives are defined:

1- Evaluate and compare the performance of “stochastic weather generators” against that of historical resampling in terms of generating long-term ensemble streamflow forecasts;

2- Incorporate recent climate trends in long-term ensemble streamflow forecasts by using a stochastic weather generator in order to take climate non-stationarity into account;

3- Identify and incorporate large-scale climate indices in long term ensemble streamflow forecasts using a stochastic weather generator in order to take non-stationarity into account.

Each of those specific objectives was organized into a journal paper and presented in the following chapters.

There is no doubt that for short term meteorological forecasts, Numerical Weather Prediction (NWP) systems are the best method. However, these forecasts are limited in time and are typically, valid for up to 6 days for low precipitation and up to 4 days for high precipitation. In many applications, there is a demand for long lead time forecasts. The most common approach for making long term forecasts is based on the re-sampling of available historical data. This approach implicitely assumes stationarity of historical time series. As such, resampling methods have two main drawbacks; (1) the climate is changing and therefore future events are not necessarily well represented by past data and (2) the availability and length of available historical data imposes limitations on the approach. In this respect, stochastic weather generators can potentially overcome both limitations and be considered as an alternative approach to the traditional resampling method. Thus, in the first paper (chapter 3), the performance of a stochastic weather generator is evaluated in comparison to the performance of historical resampling in providing long-term streamflow forecasts.

Most of the resampling methods assume that past observed streamflows are the best estimates of future mean conditions and variability. However, the Earth's climate is changing and this non-stationarity has likely impacts on the performance of resampling methods. The second paper (chapter 4) of this thesis presents a method to capture the recent trends of climate variables into the streamflow forecasts, without any covariates. The observed trends are used to condition the parameters of the stochastic generator. The results of this method are assessed with a comparison against traditional resampling and the unconditioned stochastic weather generator.

Research has shown that large scale climate indices have a strong influence on hydro climatological variables (Chen and Lee 2016; Hamlet and Lettenmaier 1999; Kim et al. 2019). Large scale climate indices are mainly used as covariates to capture the temporal variability in climate variables. Linking hydrological time series statistical properties to a subset of relevant large scale climate indices could help capture non-stationarity to provide better streamflow forecasts. In the third paper (chapter 5), a method to identify relevant climate indices and incorporate them into long-term forecasts is presented. The method first defines linear models between a relevant subset of climate indices and climate variables. A stochastic weather generators is then conditioned based on the defined linear model to produce ensemble weather forecasts. The results of the propsed method are once again assessed with a comparison against traditional resampling and the unconditioned stochastic weather generator.

A general discussion (chapter 5) of the results of this thesis, as well as a discussion of the advantages, disadvantages and limitations of the proposed long-term forecasting methods follows the presentation of the three papers. Recommendations and suggestions for future work are then presented, followed by a general conclusion (chapter 6).

CHAPITRE 3

EVALUATION OF A STOCHASTIC WEATHER GENERATOR FOR LONG-TERM ENSEMBLE STREAMFLOW FORECAST

Samaneh Sohrabi [a] and François P. Brissette [b]

[a,b] Department of Construction Engineering, École de Technologie Supérieure, 1100 rue Notre-Dame West, Montreal, Québec, Canada H3C 1K3

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Abstract

Accurate and reliable long-term streamflow forecasts are important for many water resource applications, such as reservoir management. The potential impacts of climate change on water resources and non-stationarities in hydroclimatic time series are raising important questions on the ability of historical time series to be representative of current climate conditions. Since resampling historical time series remains one of the main approaches used to generate long-term probabilistic streamflow forecasts, there is a need to develop more flexible approaches taking into account non-stationarities in weather and streamflow records. One possible approach is to make use of a stochastic weather generator coupled to a hydrological model to generate long-term streamflow forecasts. Weather generators can easily be modified to account for recent climatic trends and therefore generate potentially better ensemble streamflow forecasts. However, while there is a large body of literature on stochastic weather generators and their ability to produce accurate meteorological time series, much fewer works have examined how this performance translates into streamflows, and even fewer have looked at probabilistic streamflow forecasts. Accordingly, before weather generators can be modified to account for climate non-stationarities, it is first necessary to evaluate whether the modeling chain consisting of a stochastic weather generator and a hydrological model can generate

probabilistic streamflow forecasts to a similar extent as more traditional resampling approaches. The aim of this paper is therefore to compare the performance of a stochastic weather generator against that of resampling historical meteorological time series in order to produce ensemble streamflow forecasts. The comparison framework is based on 30 years of forecasts (in hindcast mode) on a single Canadian watershed. Forecasts resulting from both methods are evaluated with respect to CRPS and rank histograms. Results of this paper indicate that while there are differences between both methods, they nevertheless largely both perform similarly, thus showing that weather generators can be used as substitutes in resampling the historical past. Potential approaches modifying weather generators to consider non-stationarities are discussed.

3.1 Introduction

Long-term streamflow forecasting (1 to 12 months ahead) is important to various water resource sectors, such as hydropower generation and optimal reservoir operation (Georgakakos 1989; Hamlet et al. 2002; Markoff and Cullen 2008). Consequently, providing reliable long-term streamflow forecasts has long been a concern for the hydrological science community.

A main issue with long-term streamflow forecasts involves properly incorporating uncertainties which grow larger as the forecast lead time increases (Georgakakos 1989). Deterministic forecasts have long been used, but have proven to be inadequate for long-term forecasts, and this has led researchers to focus on probabilistic approaches to properly encompass the large uncertainties associated with distant forecasts. An Ensemble Prediction System (Brier 1944; Cooke 1906; Day 1985; Murphy and Winkler 1984) is a collection of two or more forecasts over the same future horizon, which represents the various probability states and uncertainties associated with the forecasting process (Sivillo et al. 1997). Various studies have demonstrated the benefit of using ESP in reservoir management and in the decision-making process (Faber and Stedinger 2001; Kim et al. 2007; Zhao et al. 2013). ESP is now widely used in research and operational forecasts around the world (Cloke and Pappenberger 2009).

The methods for making probabilistic forecasts can be classified into three main categories, namely, Numerical Weather Prediction systems (NWPs), resampling methods and Stochastic Weather Generators. NWPs, obtained by assimilating current atmospheric and oceanic conditions into a coupled numerical mathematical model, are the most accurate tool for forecasting future weather conditions (Pielke Sr 2013). However, forecasts from NWPs typically have skill up to a 6-day horizon for low precipitation (lower than 2 mm) and for up to 4 days for high precipitation (between 2 and 10 mm) (Chen et al. 2010). NWPs are therefore not well-suited for hydrological forecasts with longer time horizons as they cannot adequately represent long-term forecast uncertainty (Cloke and Pappenberger 2009; Coulibaly 2003). Accordingly, long-term forecasts typically favor resampling of the historical past as well as the use of weather generators. Resampling is by far the most commonly used approach when it comes to generating long-term forecast and to estimating forecast uncertainties (King et al. 2014; Leander and Buishand 2009b; Todorovic and Woolhiser 1975; Young 1994).

Resampling approaches were developed around 1990 to alleviate the problems inherent in parametric models (Lall and Sharma 1996), with one main such problem being the assumption of normality, which is not realized for most hydrological variables. This assumption requires data transformation, which is a primary cause of bias (Lall and Sharma 1996; Prairie et al. 2006; Sharma et al. 1997). Furthermore, the complex distribution of natural variables nonlinear relationship in historical records cannot be fully captured by most parametric methods. This weakness is what led to the development of nonparametric resampling methods, such as the index sequential method (ISM), the kernel-based approach and K-NN bootstrapping methods (Kendall and Dracup 1991; Khaki et al. 2018; Li et al. 2017; Salas and Lee 2009; Sharifazari and Araghinejad 2015). Despite their widespread use thanks their relative ease of implementation, most resampling approaches do, however, suffer from the same potential drawbacks.

Resampling methods are based on the historical record, and any deficiency in this record will affect the forecast quality. The methods are also unable to generate weather values larger (or smaller) than observed values (Rajagopalan and Lall 1999), which limits their ability to properly assess uncertainty related to rare events. The length of the historical record also brings limitations when it comes to appropriately sampling forecast uncertainty. Finally, non-stationarities due to internal climate variability and anthropogenic change calls into question the validity of using the historical past for accurate long-term streamflow forecasts (Clark et al. 2004a; Clark et al. 2004b; Murphy and Winkler 1984). Despite all the different methods and techniques that have been proposed over the years, additional research is still needed to fully address these issues (Lall 1995; Lee et al. 2010; Prairie et al. 2007; Prairie et al. 2006) .

Stochastic weather generators were developed in the 1980s with the aim of generating long-enough synthetic weather time series with specific statistical properties to be used in hydrologic models and risk assessments studies, and to extend and simulate weather time series at locations with no observed data (Wilks and Wilby 1999). Many studies have focused on improving weather generators to represent higher statistical moments of both univariate and multivariate statistics of observed weather data (Brissette et al. 2007; Chen et al. 2012a; Hansen and Mavromatis 2001; Hayhoe 2000; Kyselý and Dubrovský 2005). Other studies have also looked into using weather generators as constituting a downscaling tool in climate change impact studies because of the relative ease with which their parameters can be modified to represent climate variability (Keller et al. 2017; Kilsby et al. 2007; Semenov and Barrow 1997; Zhuang et al. 2016). Despite this advantage, only a few studies have looked at the potential of using stochastic weather generators for long-term streamflow forecasting (Breinl et al. 2015; Li et al. 2013; Shield and Dai 2015). Weather generators have the potential to overcome the main drawbacks of resampling approaches, and notably, to take into account non-stationarities. Therefore, the goal of this paper is to compare the performance of ensemble streamflow forecasts built from resampling the historical record against that of a stochastic weather generator when coupled with a hydrological model to provide long-term probabilistic streamflow forecasts.

The remainder of this paper is divided into four sections. The watershed and data are first described, followed by the methodology employed. Results are then presented and discussed in the last two sections.

3.2 Watershed and data description

The Lac Saint-Jean watershed (Figure 3.1) was selected as a test case for this study. It is located in the eastern Canadian province of Quebec. It has a surface area of 73,800 km^2 and consists of four main rivers flowing into a 1000 km^2 lake (Lac Saint-Jean), which is regulated at its outlet by a large hydropower dam. Rio Tinto, the world's largest producer of aluminum, operates six power plants on this watershed, with an annual averaged capacity of 2000 megawatts, feeding a large aluminum plant. Economic development around Lac St-Jean is therefore closely linked to its hydropower potential (Dibike and Coulibaly 2005). Overall, the watershed is sparsely inhabited, and its land cover mostly consists of a homogeneous boreal forest.

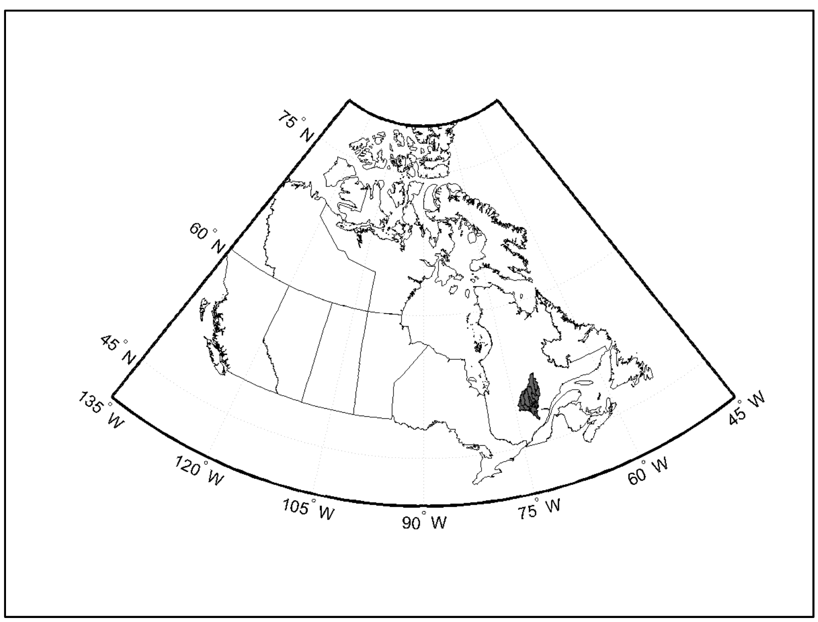

Figure 3.1 Lac Saint-Jean watershed

Daily precipitation, daily maximum and minimum temperatures are provided in gridded format from the NRCAN dataset. The NRCAN dataset. is a Canada-wide daily-scale precipitation and temperature gridded dataset with a 10-km spatial resolution (Hutchinson et al. 2009). The study period covered in this work spans the 1950 to 2010 period. Naturalized streamflow data for Lac St-Jean was provided by Rio-Tinto, and covers the same time period. Figure 3.2 presents the annual cycle (and variability) of the hydrometeorological variables used in this study. Temperature and streamflow values are characterized by a strong seasonal pattern typical of a northern latitude climate, whereas the precipitation values show a weaker cycle with increased mean monthly totals in the summer and early fall.

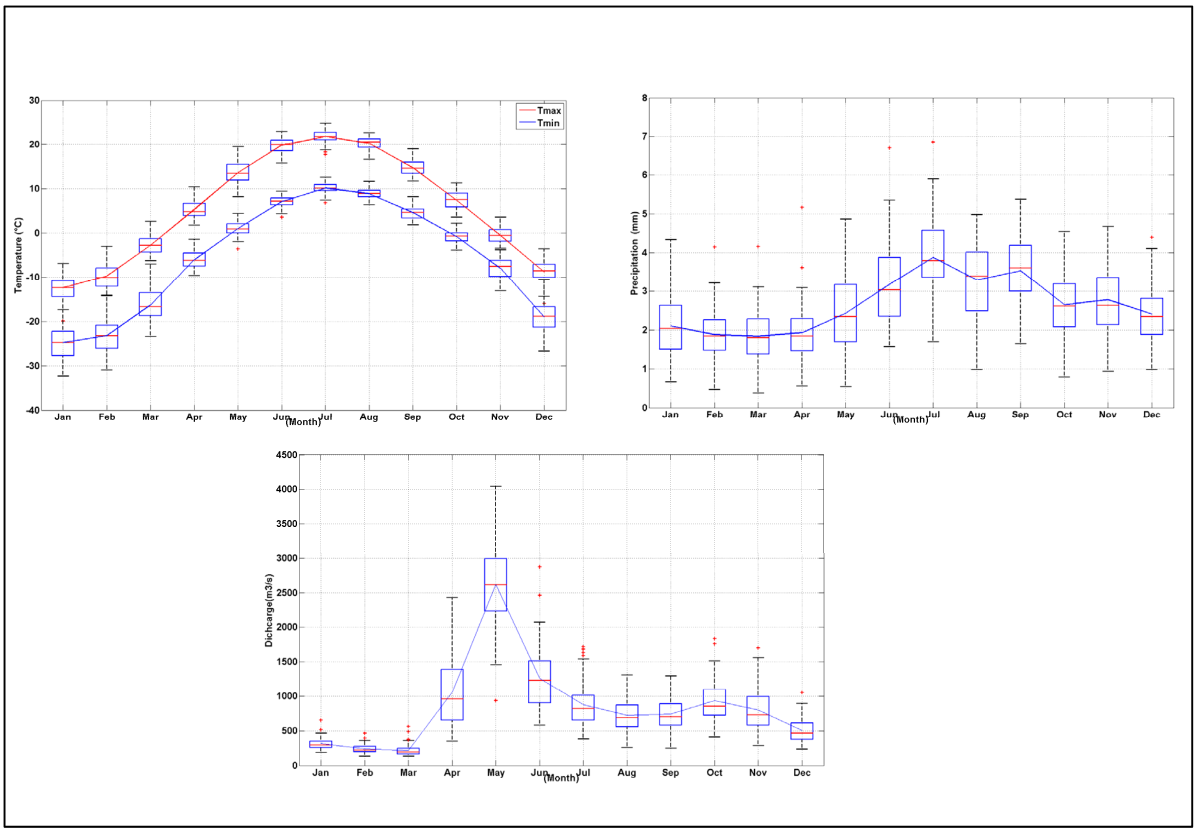

Figure 3.2 Annual cycle of key hydrometeorological variables used in this study A) Minimal and maximal temperatures, B) Precipitation, C) Streamflow

3.3 Methodology

The aim of this project is to compare the performance of weather generators against the benchmark method of equiprobable resampling for long-term streamflow forecasting. To this end, the framework for this comparison consists of three main steps. In a first step, for each forecast date, ensemble weather forecasts are generated from both approaches. In the second step, these weather forecasts are used with a hydrological model to generate ensemble streamflow forecasts. In a last step, the forecasts from both methods are compared against observed past conditions. Details are provided below.

Both methods are evaluated in hindcast mode over the 30-year 1980 to 2009 period. The 1950 to 1979 time period is used as the initial historical record. Over the evaluation period, 1-year ahead forecasts are made 12 times per year, on the first day of each month. The evaluation period is therefore comprised of 360 1-year forecasts (30 years times 12 forecasts). Similarly to what would be done in the real world, the recalibration of the hydrological model and weather generator is performed at the beginning of every new year, adding the preceding year to the historical record. Figure 3.3 presents the methodological framework.

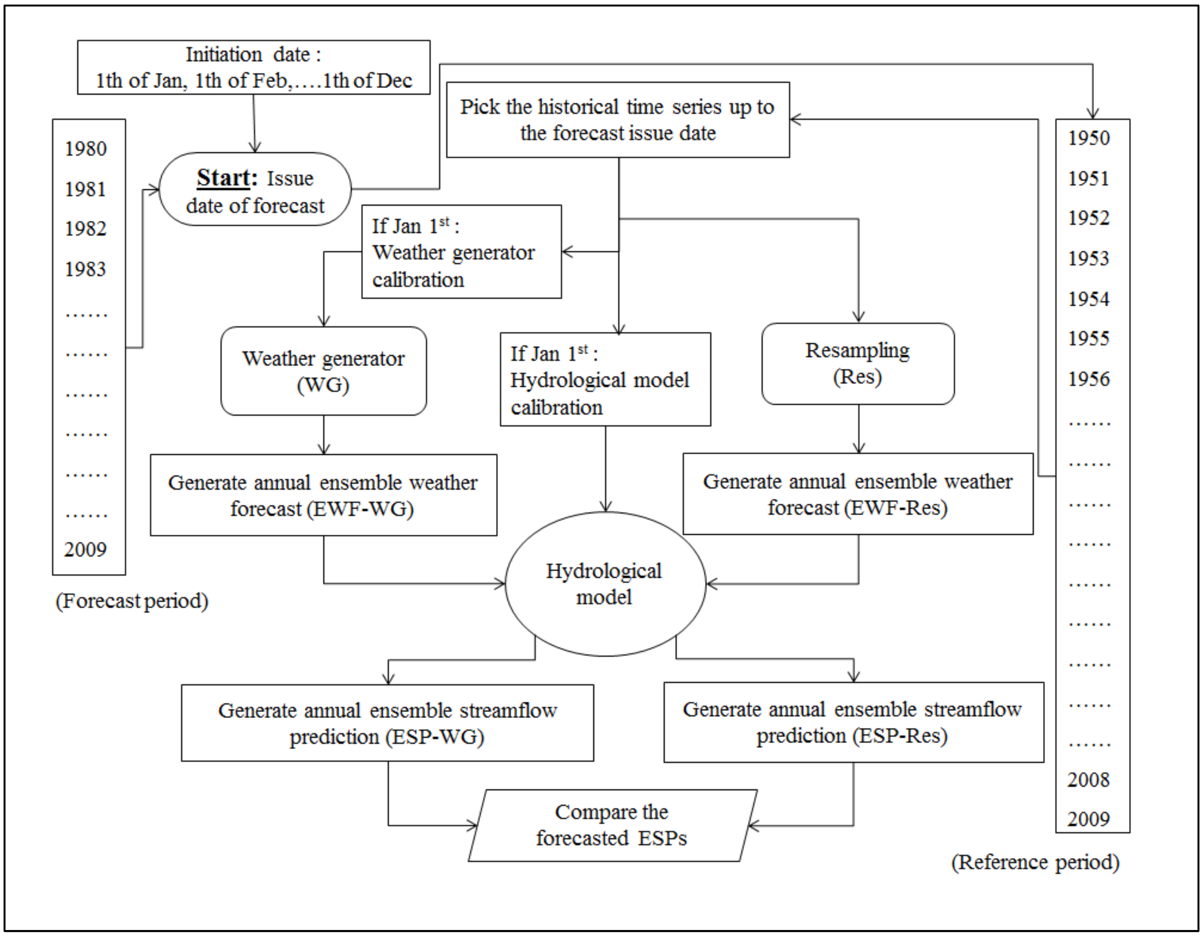

Figure 3.3 Methodological framework

3.3.1 Ensemble weather forecast – approach 1: Resampling

In this study, the simple method of resampling the past observed climatology data is used as the benchmark approach. As discussed earlier, resampling past climatology is the most commonly used approach for long-term ensemble weather forecasting. This work uses equiprobable resampling with no reshuffling between precipitation and temperature years. The number of members in each of the ensemble weather forecasts is therefore equal to the number of years in the historical period.

3.3.2 Ensemble weather forecast – approach 2: Stochastic Weather Generator

The Weather Generator used in this study is WeaGETS, the uni-site multivariate weather generator of (Chen et al. 2012a). WeaGETS is based on the original work of Richardson (1981) and Richardson and Wright (1984). It first generates precipitation occurrence using a first-, second- or third-order Markov chain. On wet days, precipitation is then generated using either an exponential or a gamma distribution. Minimal and maximal temperatures are generated conditionally on the wet/dry day status. Serial correlation and cross-correlations between precipitation and temperature are preserved using a first-order regressive process. Inter-annual variability is preserved by using the spectral approach of Chen et al (2010). All WeaGETS parameters are first computed on a monthly basis, and are then interpolated to the daily scale with Fourier harmonics, as proposed by Richardson (1981). More details can be found in Chen et al (Chen et al. 2012b; Chen et al. 2014). For this study, a 1st-order Markov chain is used to produce the precipitation occurrence and the 2-parameter gamma distribution is used for estimating precipitation amounts. Like most weather generators, WeaGETS can generate an extremely large number of years (limited by computer storage/memory), but in this study, to allow for a fair comparison, the number of members is identical to the number of years available in the historical past.

3.3.3 Hydrological Model

The hydrological model used in this study is the lumped conceptual HSAMI model. HSAMI was developed by Hydro-Québec, and is used to make hourly and daily operational forecasts for more than 80 watersheds with surface areas ranging between 160 Km^2 and 70,000 Km^2. It has also been used in many Canadian hydrological studies, including climate change impact studies (Chen et al. 2011; Minville et al. 2008), multi-model simulations (Arsenault et al. 2015), model calibration experiments (Arsenault et al. 2013) and regionalization studies (Arsenault and Brissette 2014a; Arsenault and Brissette 2014b). HSAMI is a conceptual rainfall-runoff lumped model with 23 parameters. Two parameters account for evapotranspiration, 6 parameters for snowmelt simulation, and 15 parameters for vertical and horizontal water movement. Vertical water flows are estimated by four interconnected linear reservoirs (snow on the ground, surface water, saturated and unsaturated zones). Horizontal routing is carried out by two unit hydrographs and one linear reservoir for low flows. The minimum required inputs are daily scale precipitation, maximum and minimum temperature, and flow discharge for the calibration period. If available, cloud cover fraction and snow water equivalent can also be used as inputs. The calibration of HSAMI was performed automatically using the CMA-ES algorithm (following the work of Arsenault et al. (2013)), with the Nash-Sutcliffe criterion used as an objective function. The calibration process followed the procedure outlined in Arsenault (2018), and bypassed the validation step.

To avoid any bias resulting from the hydrological model, and to forgo the complex assimilation process, simulated streamflows were used instead of observations. Doing so results in a 'perfect' hydrological model and eliminates all uncertainties resulting from the assimilation process and hydrological modeling biases. This ensures that all differences between the resampling and weather generator ensemble streamflow forecasts are entirely due to differences in the generation of both ensemble weather forecasts.

3.3.4 Evaluation Procedure

The challenge for all probabilistic forecasts is to provide an unbiased ensemble with the proper dispersion. Despite the steadily growing body of literature on ensemble streamflow forecasting, the number of evaluation metrics remains relatively small. The main probabilistic score broadly used in the meteorological and hydrological community for ensemble verification remains the Continuous Ranked Probability Score (CRPS) (Matheson and Winkler 1976). The CRPS generalizes the MAE (mean absolute error) to the case of probabilistic forecasts.

If F is the predictive CDF and y is the observation, the CRPS can be defined by Equation (3.1):

$$CRPS\ (F, y) = \int_{-\infty}^{\infty} [F(t) - H(t-y)]^2\, dt \tag{3.1}$$

$H(t-y)$: Heaviside function. It is 0 when $t < y$ otherwise is 1 (Hersbach 2000; Toth et al. 2003).

A perfect CRPS value is zero (all members of the ensemble predicting the same value, equal to the observation) and, therefore, the aim of a probabilistic forecast is to minimize the CRPS value. The CRPS allows for discrimination between different ensemble forecasts.

Another important part of ensemble verification is related to the dispersion of the forecast. To this end, the rank histogram (Talagrand diagram) has been widely used as a graphical evaluation method to visually assess the bias and spread of an ensemble forecast. The rank histogram measures how well the ensemble forecast represents the probabilistic distribution of observations (Hamill 2001). To plot the rank histogram, the forecast is typically separated into n+1 bins (with n being the number of members in an ensemble), and a count is tabulated for the number of times observations fall within each bin. For a perfect ensemble forecast, the rank histogram will be flat since the probability of the observation falling within each bin would be equal. Alternatively, the number of bins can be related to the CDF of the ensemble. An asymmetrical rank histogram is the result of a biased forecast, whereas concave or concave shapes respectively represent an under- or over-dispersed forecast (Hamill 2001; Hersbach 2000; Wilks 2006; Zalachori et al. 2012). To measure the deviation from the flat and uniform rank histogram, the flatness coefficient (δ) described in Equation (3.2) is used:

$$\delta = \frac{1}{n+1} \sum_{z=1}^{z=n+1} |f(z) - y| \tag{3.2}$$

With

$f(z)$= Relative frequency in rank z

$y = \frac{1}{n+1}$ = Theoretical relative frequency

n: Number of ensemble members

In a perfectly flat rank histogram, the value of δ is equal to 0 (Velázquez et al. 2010).

3.4 Results

Prior to using the modeled streamflows as pseudo-observations, it is nonetheless important to ensure that HASMI performs accurately over the Lac St-Jean watershed. Figure 3.4 shows the mean hydrograph derived from observation and modeled streamflows over the 1950 to 1980 period. The performance of HASMI is excellent (Nash Sutcliffe of mean daily hydrograph is 0.9885) and justifies the use of a conceptual lumped model, despite the large size of the Lac St-Jean watershed. This performance also justifies the use of a single-site weather generator, rather than its more complex multi-site version. (Brissette et al. 2007; Chen et al. 2014).

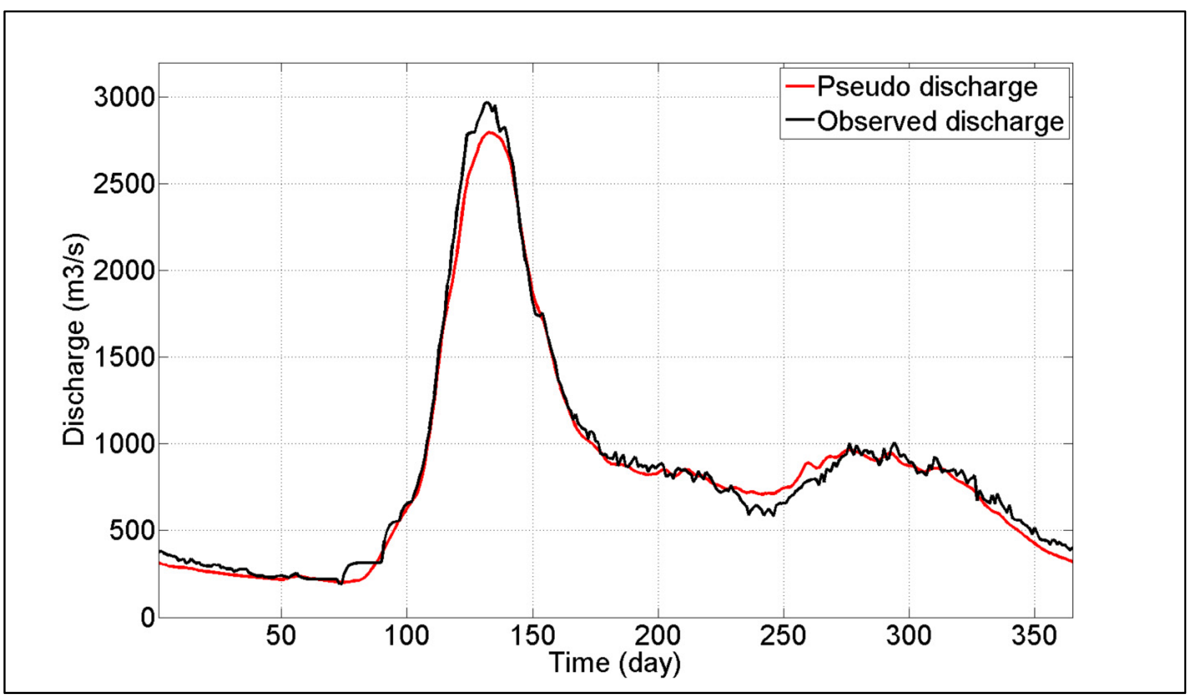

Figure 3.4 Mean annual hydrograph of simulated and observed inflows into Lac-St-Jean

As was shown in methodology framework, the ESP forecasts are made by two methods at each forecast date and over the entire forecast period. CRPS values are calculated daily for each forecast. Figure 3.5 shows the ensemble streamflow forecasts made on January 1st 1980, and the associated CRPS values for both forecast approaches. The larger apparent spread observed for the weather generator forecast is due to the larger number of members used in the forecast Thirty members are used for resampling, as compared to 500 for the weather generator. Otherwise, both approaches provide forecasts with similar CRPS values.

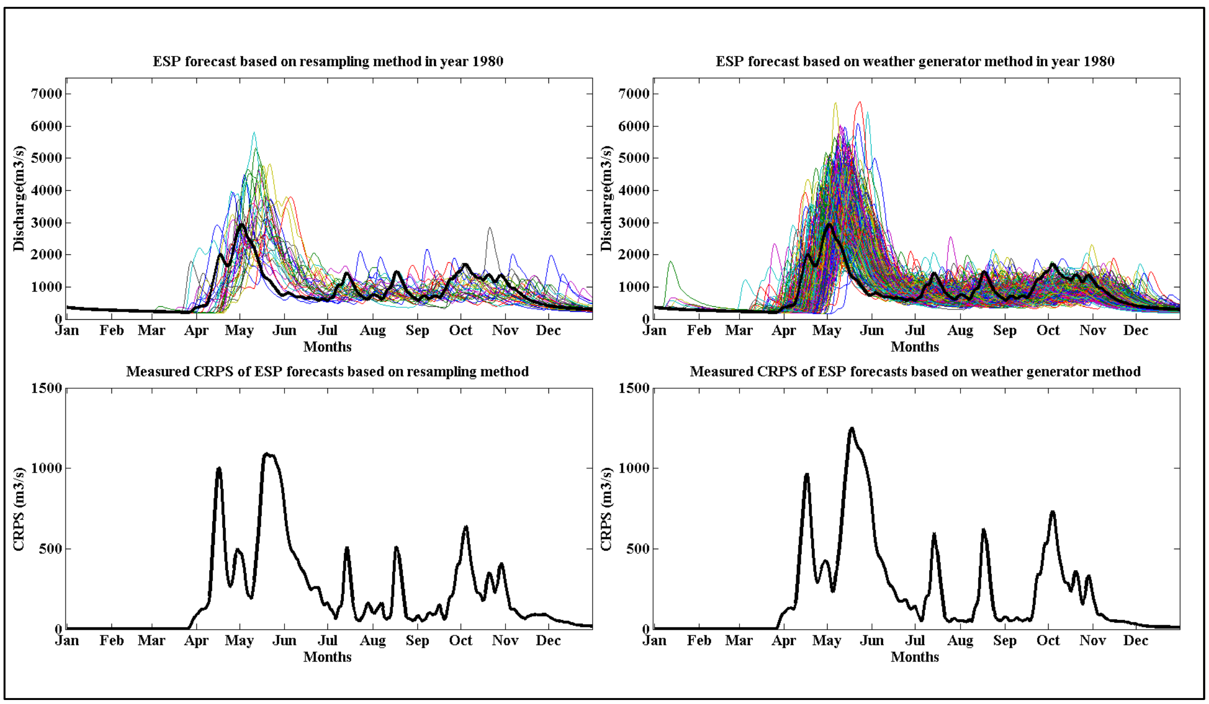

Figure 3.5 1-year ensemble streamflow forecasts made on January 1st 1980 using resampling (left) and weather generator (right) approaches. The black line represents observations. There are 30 members for resampling (1950 to 1979) and 500 members for the weather generator (first row). The CRPS values are shown in the second row

Figure 3.6 presents mean monthly CRPS values aggregated across all forecasts. For every year, there are twelve 1-year forecasts made on the first of each month. The mean monthly CRPS value is computed for each year by taking the mean of each daily CRPS (30 days times 12 forecasts). The boxplots presented in Figure 3.6 are made with the mean monthly CRPS values computed for each forecasted year (1980 to 2009). Values are then used to construct the boxplots. The solid boxplot rectangles represent the interquartile spread (25th and 75th quantiles), with the median near the middle, while the whiskers show the extent of the values. Outliers are identified with the + sign.

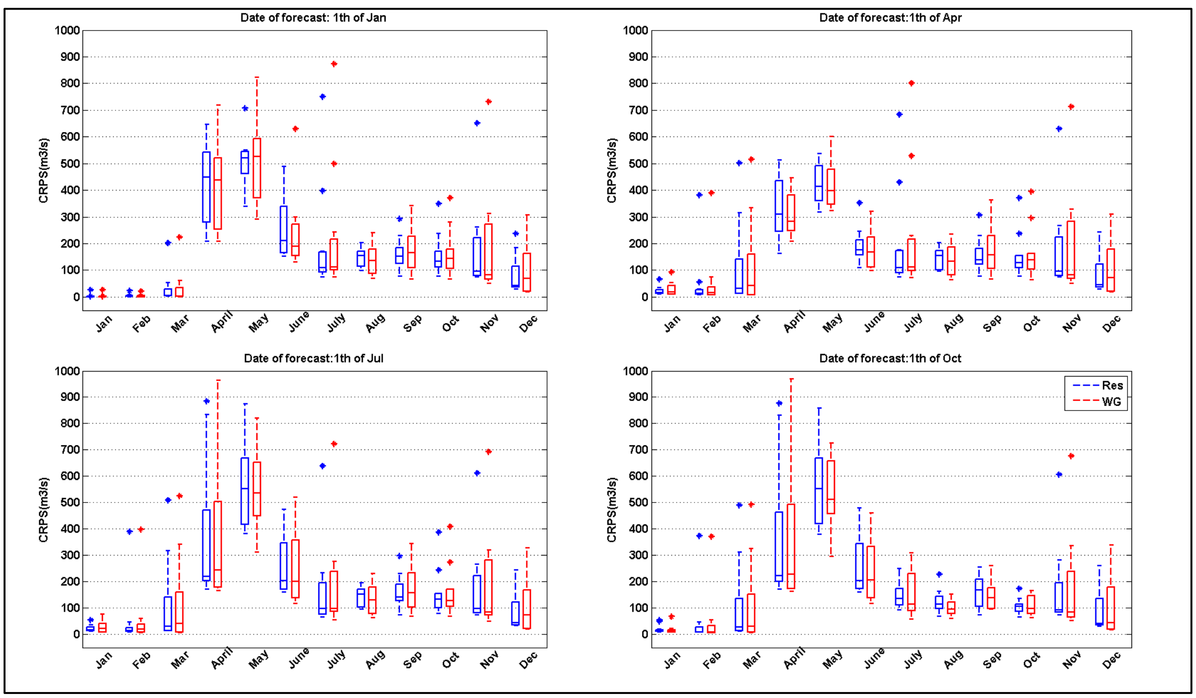

Figure 3.6 The boxplot results of monthly CRPS based on ESPs forecasted by resampling and weather generator method at Jan 1st, Apr 1st, Jul 1st and Oct 1st

These results indicate that both forecasting approaches perform similarly in all cases. The largest CRPS values are observed during the spring flood in April, May and June, when uncertainty and streamflow values are at their maximum, whereas the lowest values are related to the winter low flows, where uncertainty and streamflow values are relatively small. The impact of the forecast date on CRPS values is quite clear when looking at the April 1st forecast, which results in lower uncertainty in the spring flood. In order to better outline differences between both forecasting approaches, Figure 3.7 presents the 30-year average of all mean monthly CRPS values for all 12 forecast dates.

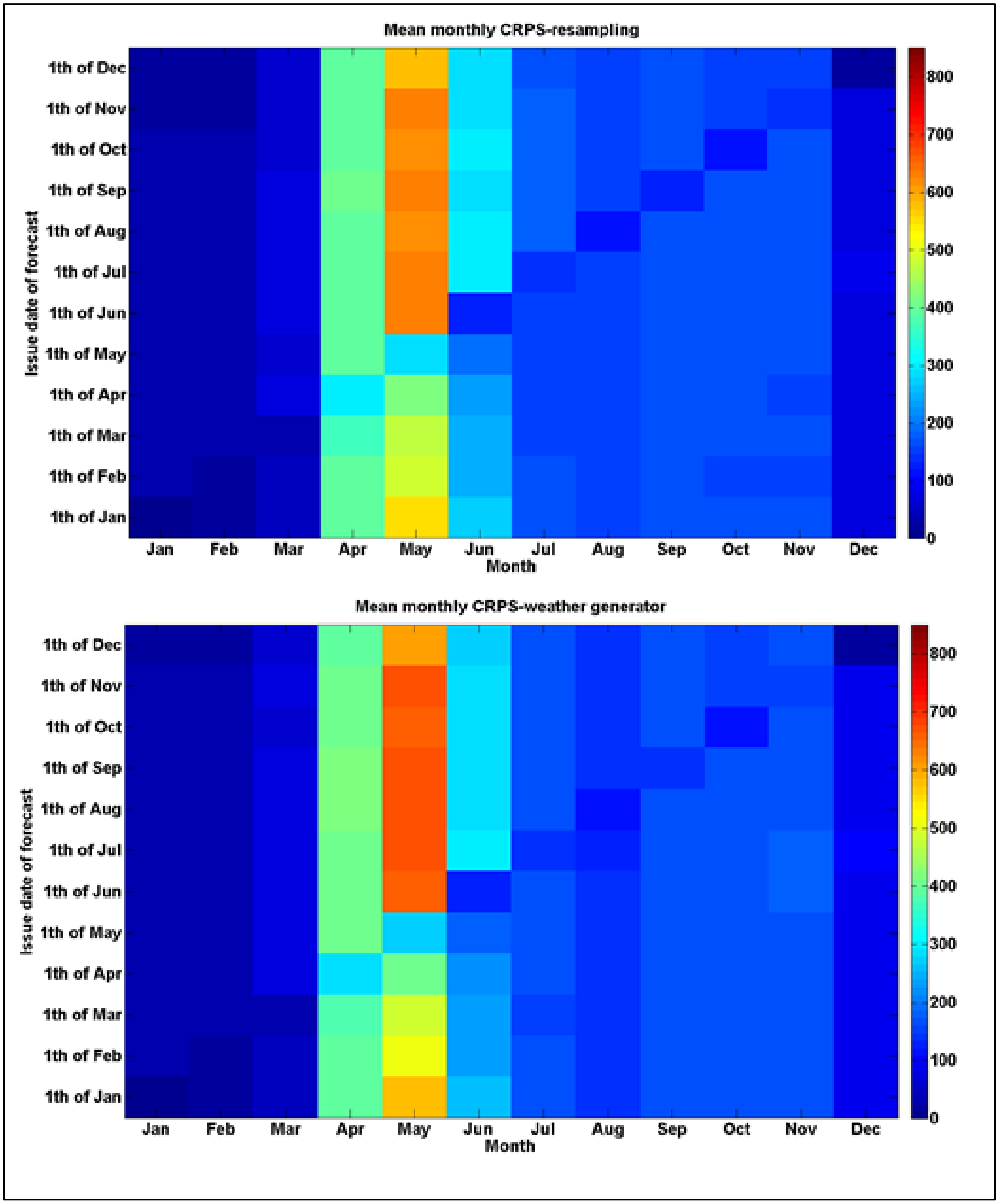

Figure 3.7 Mean monthly CRPS of ensemble streamflow forecasts using the resampling (left) and weather generator (right) approaches

As was the case for Figure 3.6, the mean monthly values are obtained by averaging daily CRSP values within each month, for all 30 years of the hindcasting period and 12 forecast dates. Therefore, each mean monthly value represents the average for 360 forecasted days. The vertical axis presents the date of the forecast, and the horizontal axis, the month of the forecast. Accordingly, the diagonal is distinctly darker since it corresponds to the first month of each forecasting date, when uncertainty is lowest. The general pattern of the mean monthly CRPS is very similar for both approaches. The lowest mean monthly CRPS values are consistently found in the winter, when the streamflows are consistently small. Mean monthly CRPS values are highest during the snowmelt period (April to June), when streamflow values and variability are highest. To better outline differences between both approaches, Figure 3.8 presents the difference between both estimates of mean monthly CRPS values. Red colors indicate that the resampling approach has a lower mean monthly CRPS, while the reverse is true for blue colors.

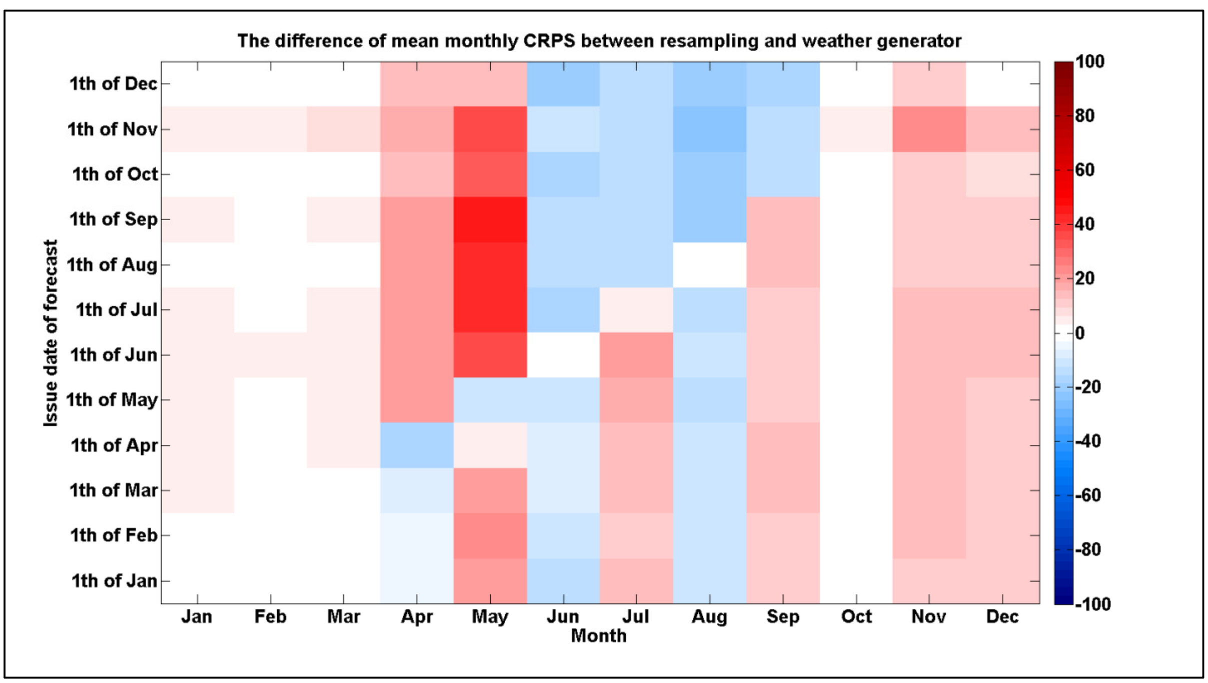

Figure 3.8 Difference of mean monthly CRPS values between the resampling and weather generator approaches

The difference between both approaches is minimal from January to March. The resampling forecast ensemble performs generally better in April and May, and especially for longer lead times (above the diagonal). The weather generator approach generally gives lower mean monthly CRPS values in the summer, but consistently larger ones in November and December. Nonetheless, differences remain small, with the exception of May forecasts issued 7 to 12 months in advance.

To further compare both approaches, rank histograms are presented in Figures 3.9 and 10. Each histogram is composed of 10,800 forecasted days (30 days per month x 12 1-year forecast x 30 years). The histogram flatness value (Equation 3.2) is presented within each histogram figure.

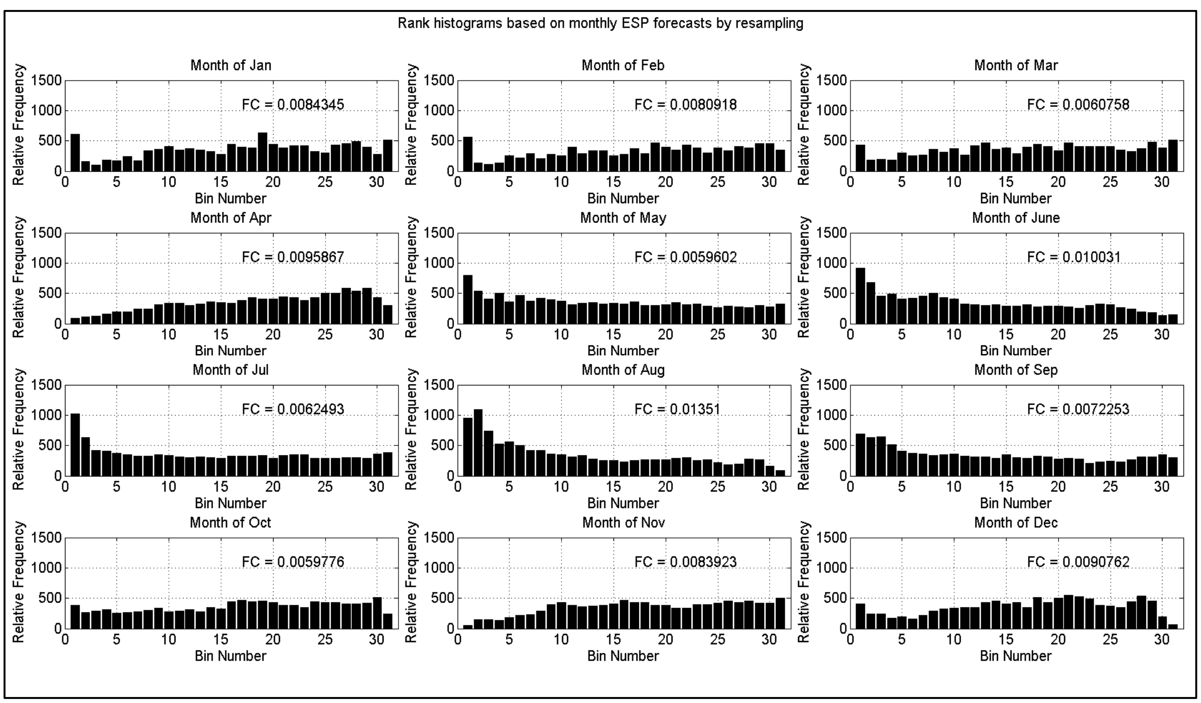

Figure 3.9 Plotted rank histograms based on monthly ESP forecasts of resampling method

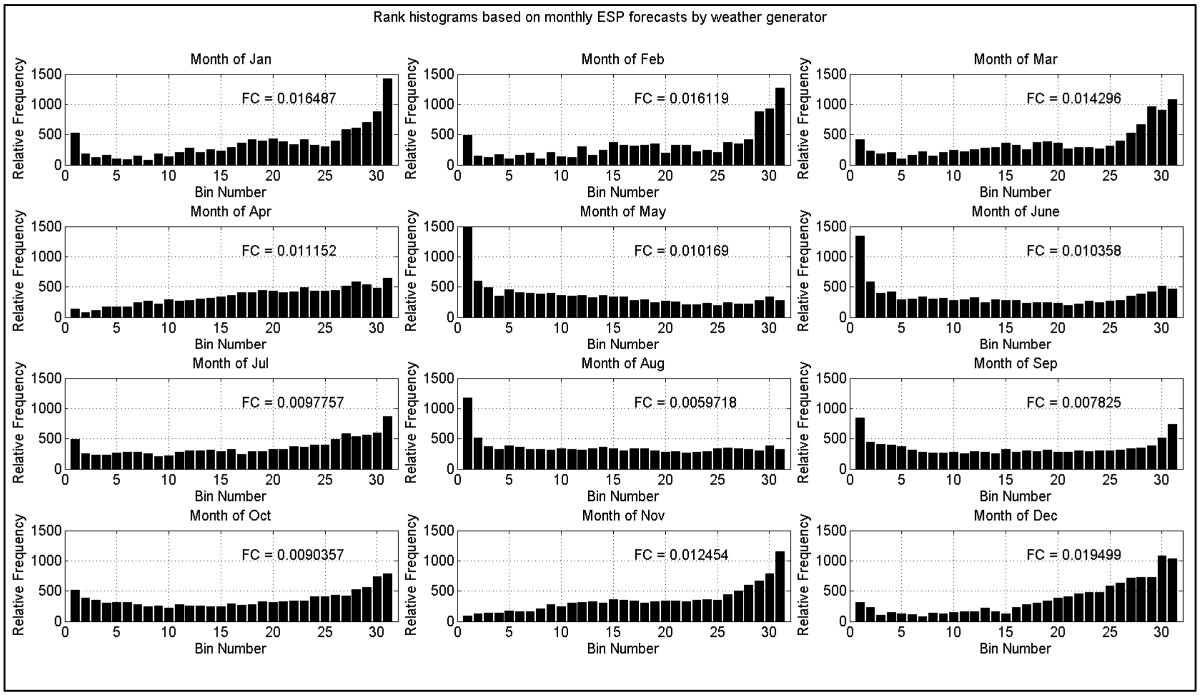

Figure 3.10 Plotted rank histograms based on monthly ESP forecasts of weather generator method

A constant number of 30 ensemble members were used for all forecasts. The weather generator randomly generated 30 years for each forecasting date. For resampling, when the number of historical years was larger than 30, the ensemble members were chosen randomly amongst all available years.

Overall, all histograms are relatively flat. All forecasts for both approaches are relatively well dispersed. There is, however, one main difference between both approaches. Despite having similar mean CRPS values (Figures 3.6 and 3.7), the rank histograms for the weather generator approach display a small but consistent negative bias for the winter months (November to March), with flatness values consistently higher than for the resampling values. Both approaches otherwise perform similarly during all other months, although resampling results in a larger positive bias during the post-flood period, from May to November.

To gain a better understanding of the year-to-year differences between both approaches, Figure 3.11 presents the year-to-year flatness ratio that is calculated based on a year-by-year rank histogram over the forecast period, from 1980 to 2009.

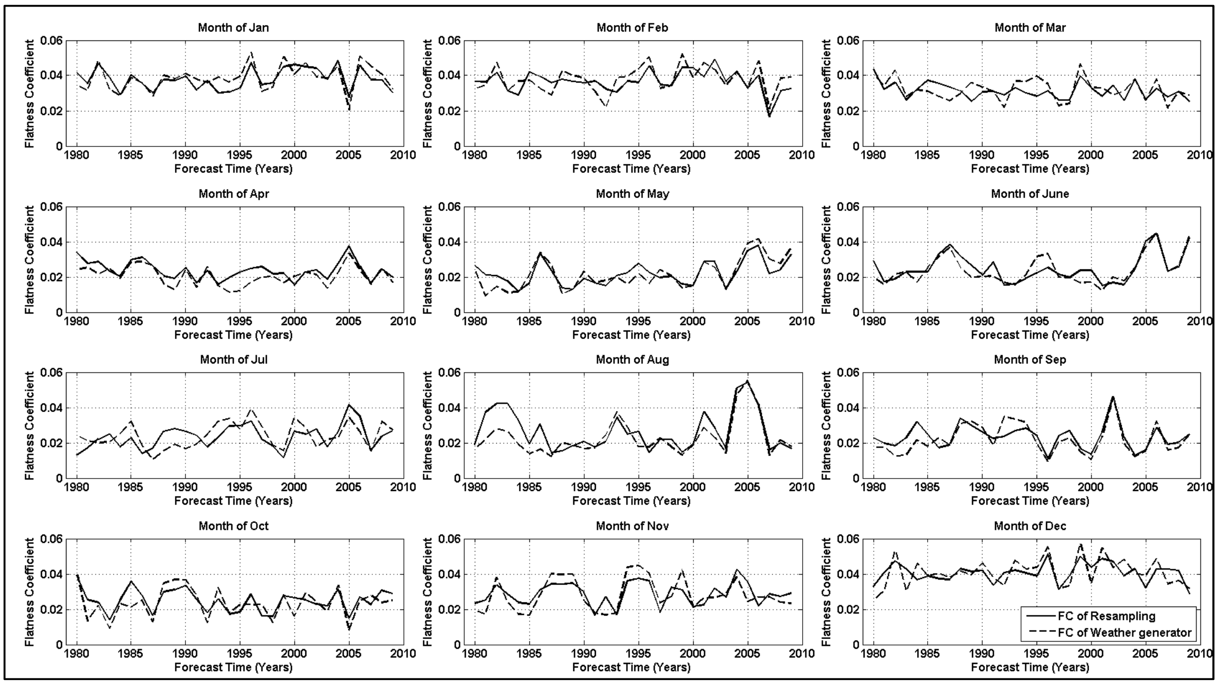

Figure 3.11 Calculated flatness coefficient of each individual rank histogram at each forecast year regardless of the issue date, from 1980 to 2009

To calculate the yearly flatness coefficient values for each month, the rank histogram is comprised of all January forecasted days for the 12 forecasts issued for each given year. For example, the flatness coefficient for January 1980 is calculated by pooling all the January forecasts for year 1980, which are made at 12 issue dates (31 days of January x 30 number of forecasts for each day x 12 issue dates). Results show that both methods perform similarly with respect to this metric.

Finally, Figure 3.12 presents the rank histogram of all 1-year monthly forecasts made from January 1st 1980 to December 31st 2009. The resampling rank histogram is flat, with a very slight positive bias. Taken globally, the results indicate that the weather generator performance is not nearly as good as resampling, as it is negatively biased and slightly under-dispersed.

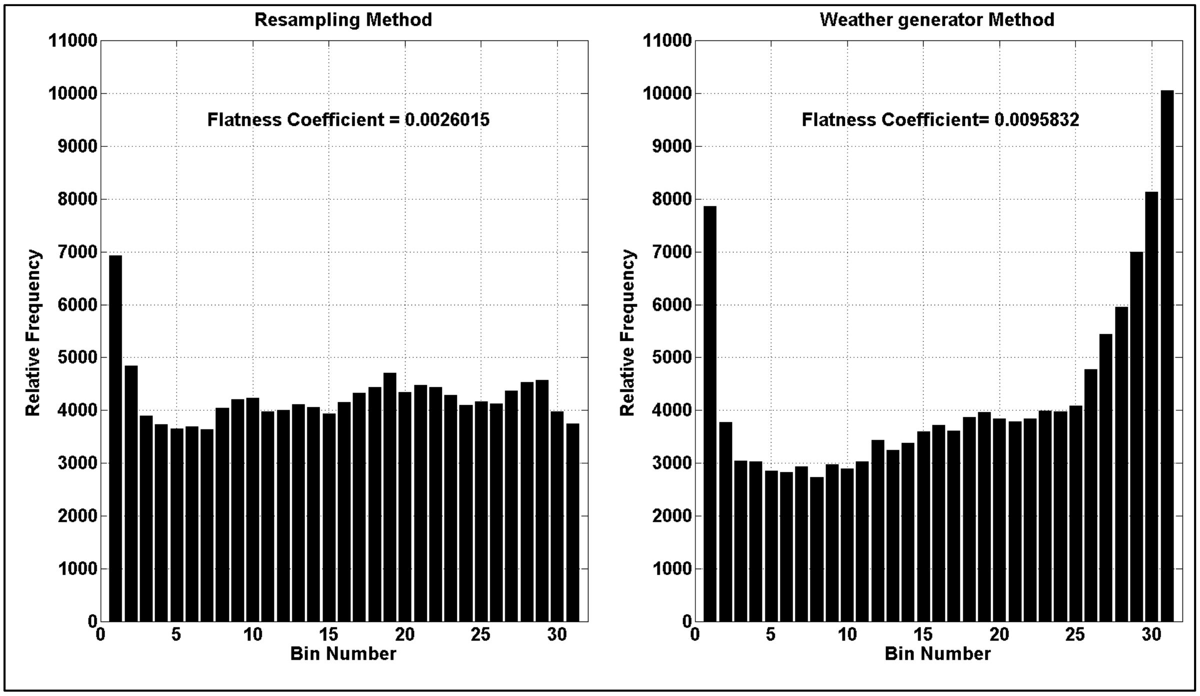

Figure 3.12 Global rank histogram pooled from all 1-year monthly forecasts for resampling (left) and weather generator (right)

3.5 Discussion

The results presented are based on 360 one-year forecasts issued on the first of each month, from January 1980 to December 2009. Overall, the results, presented in terms of CRPS and rank histograms, show that both approaches perform similarly. In terms of the CRPS metric, both approaches are globally equivalent. The WG method generates slightly better forecasts just before the flood (January to April), whereas resampling is generally slightly better for the forecasts issued after the flood. The performance is also similar when looking at bias and dispersion from rank histograms, although the WG forecasts are globally slightly under-dispersed and negatively biased. This shows the importance of using more than one metric to evaluate forecast quality (Demargne et al. 2010; Hamill 2001; Renner et al. 2009). The differences between both approaches remain small, and only become clearer after all forecasts are pooled together (Figure 3.12). The reasons behind the differences are difficult to explain. In principle, stochastic weather generators are built to reproduce uni- and multivariate statistics of observed time series. The WG used in this work has been extensively tested for its ability at reproducing characteristics of precipitation and temperature series (Caron et al. 2008; Chen et al. 2010; Chen et al. 2012b). The performance of WG outputs in terms of driving environmental models (such as a hydrology model) has been less studied in the literature, even though this is one of the main reasons why WG were developed in the first place. Such studies performed with hydrological models indicate that WG series provide realistic streamflow series for a wide variety of conditions. The small differences observed between WG and original observed series appear however to be slightly amplified by to impact model (Khalili et al. 2011; Li et al. 2013). The results presented in this work are consistent with these findings, in that WG streamflow forecasts appears to perform similarly to those from resampling, but with some relatively minor differences that are difficult to track back to the WG precipitation and temperature time series. The hydrological model acts as a complex non-linear filter of precipitation and temperature, and small changes in one or both series may result in somewhat larger differences. If the weather generator time series were statistically identical to the observed series, one would expect both streamflow ensembles to perform identically. Any differences can therefore be tracked back to minor inadequacies in the weather generator series characteristics.

The presence of biases in forecasts is typically rooted in uncertainties due to a combination of various input, output, model structure and parameter uncertainties (Han et al. 2007; Krzysztofowicz 2002; Li et al. 2009). Such biases have been noted in resampled time series in other studies (Bogner and Kalas 2008; Schaake et al. 2007; Seo et al. 2006). In particular, biases in long-term forecasts may be due to the non-stationarities present in historical time series (Ceola et al. 2014; Meng et al. 2019) due to internal climate variability and long-term trends linked to anthropogenic forcing.

Non-stationarity in hydro climatic time series is now well-documented in many regions of the world (Westra et al. 2013). Non-stationarity raises important questions about equiprobable historical resampling. Using non-equiprobable resampling is a complex endeavor, for which there are currently no easy solution. It is however relatively easy to incorporate non-stationarity into a stochastic weather generator. A few studies have provided frameworks which could be applied to the problem of generating long-term ensemble streamflow forecasts (Chen et al. 2012b; Jones et al. 2016; Keller et al. 2017; Li Liu et al. 2017; Semenov and Barrow 1997). For example, the variability structure of historical meteorological time series at the seasonal, monthly and daily scales could be preserved, while mean annual and seasonal values could be conditioned on large-scale teleconnection indices or by weighting years differently, with the more recent being more important. Resampling approaches are much less flexible due to the limited number of years available. Before moving on to the evaluation of such approaches, a necessary first step would be to evaluate the ability of a stochastic weather generator at generating ensemble streamflow forecasts, and this is what this work has presented.

3.6 Conclusion

This paper presents a comparison of two methods for generating long-term ensemble streamflow forecasts. Both methods make use of a hydrological model to transform precipitation and temperature time series into streamflows. The first approach resamples historical time series, while the second one makes use of a stochastic weather generator calibrated using the same historical series. The main goal of this paper is therefore to validate the use of a stochastic weather generator for ensemble streamflow forecasting. To this end, forecasts made from the combination of a stochastic weather generator and hydrological models are compared to those obtained from equiprobable resampling of past meteorological variables. The evaluation period consisted of 1-year long forecasts issued on the first day of each month over a 30-year (1980-2009) hindcast period. Forecasts resulting from both methods are evaluated with respect to CRPS and rank histograms. Results indicate that while there are differences between both methods, they largely perform similarly, which thus indicates that weather generators can be used as substitutes to resampling the historical past. Potential approaches to modify weather generators to take into account non-stationarities are discussed.

CHAPITRE 4

USING A STOCHASTIC WEATHER GENERATOR FOR LONG-TERM ENSEMBLE STREAMFLOW FORECAST IN NON-STATIONARITY CONDITIONS

Samaneh Sohrabi [a], François P. Brissette [b] and Richard Arsenault [c]

[a,b,c] Department of Construction Engineering, École de Technologie Supérieure, 1100 rue Notre-Dame West, Montreal, Québec, Canada H3C 1K3

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Abstract

Providing reliable long-term probabilistic streamflow forecasts is important for many applications, such as reservoir management. For long-term streamflow forecasts (up to 1-year ahead), properly framing uncertainty is a key issue. Non-stationarity of hydro-meteorological variables, either due to internal variability or anthropogenic change, is an important problem as it is becoming increasingly clearer that past historical data may not adequately represent the current climate. This paper explores a simple perturbation method to drive a stochastic weather generator to generate long-term probabilistic weather forecasts, which in turn are used to drive a hydrological model to generate an ensemble streamflow forecast. In the perturbation scheme, the entire length of the historical record is used to quantify internal variability, while a subset of recent years is used to characterize mean climatic values for precipitation, minimum and maximum temperatures. The performance of this method is evaluated in hindcast mode over a 30-year period against that of an equiprobable resampling of past climate values, as is done in many operational settings. Results show that the proposed method systematically improves forecast accuracy, although the same results are dependent on the time window used to estimate current mean climatic estimates. The best performance was obtained using a 1- to 5-year time

window. Using time windows longer than 10 years yielded results similar to those obtained using the entire historical record.

4.1 Introduction

There is an inseparable link between human society and the water cycle. The well-being and survival of human populations are heavily dependent on water. In particular, human society is highly vulnerable to large fluctuations in available water quantities. Water cycle variability due to floods and droughts can threaten infrastructures, food supplies, and ultimately, human lives. Therefore, planning, developing and managing water resources are absolutely vital. To manage water resources, thousands of dams and reservoirs have been built throughout the world; such systems are built to ensure a reliable water supply for use in agriculture and municipal and industrial consumption, as well as for power generation. Streamflow forecasting is important for managing and operating reservoir systems. While a proper short-term streamflow forecast of between 1 and 15 days can help decrease the effects of floods, providing a long-term streamflow forecast horizon ranging from a few weeks to the annual scale can have a significant impact on the management of water resource systems in terms of irrigation, power generation, environmental and ecosystem protections. The main challenge in providing a long-term streamflow forecast lies in dealing with different sources of uncertainties, which increase with the forecast lead time. Deterministic forecasts have long been used, and remain common for streamflow forecasting. However, because deterministic approaches are unable to provide information about uncertainties, probabilistic forecasts have become more common. In recent decades, climate change due to human activity has come to represent one important additional source of uncertainties affecting long-term streamflow forecasting. According to the Inter-governmental Panel on Climate Change, global mean temperature increased by 0.85 °C over the 1800-2012 period, which constitutes an unequivocal sign of warming (Bongaarts 2019). The combined effects of anthropogenic climate change and natural climate variability challenge the assumption of stationarity for hydrometeorologial time series. Therefore, adequate streamflow forecasts must account for non-stationarity. The aim of this study is to propose a simple approach for considering non-stationarity in long-term forecasting.

4.1.1 Literature review

Inflow forecasting plays an important role in real-time reservoir management. Many studies have demonstrated the value of inflow forecasts on the efficiency of reservoir management and operations (Anghileri et al. 2016). In reservoir management, determining the forecast lead-time is crucial, and depends mainly on the purpose of the forecast. However, in both short-term and long-term forecasting, the forecasting lead time must be long enough to provide sufficient information for efficient release decisions; similarly, it should also be as short as possible in order to reduce the uncertainties that grow as the forecasting lead time increases. In this context, short-term forecasting with a lead time of between 1 and 15 days is more valuable in meeting short-term operation objectives such as flood protection (Saavedra Valeriano et al. 2010), while long-term forecasting with a lead time ranging from a period of more than 15 days to the annual scale is more valuable for long-term operation, water supply and hydropower generation (Sankarasubramanian et al. 2009). However, various studies have confirmed that long-term forecasts are essential in reservoir operation models (Zhao et al. 2019). In particular, long-term forecasts can considerably improve the operation performance and potentially improve the power generation, as well as increase revenues (Turner et al. 2017).

The main issue surrounding long-term streamflow forecasting in real-time reservoir operation models is dealing with various sources of uncertainties. In general, uncertainty sources stem from meteorological forcing, hydrological initial conditions, model parameters, model structure and hydrometeorological modeling chain (Shamshirband et al. 2019). Although general principles and techniques have been proposed, the issue of how to adequately address the uncertainty in inflow forecasting remains a challenge (Seo et al. 2019). To cope with different sources of uncertainties in streamflow forecasting, an Ensemble Streamflow Prediction approach is preferred (Day 1985). An ESP forecast is a collection of deterministic predictions issued by a single or multiple hydrological models to simulate the same event in order to produce possible representative samples of the future. The ESP forecast provides an envelope of possible future states of a hydrometeorological system and offers a way to communicate uncertainties (Duan et al. 2019). The first use and adoption of ESP forecasts in reservoir management and operation date back to the 1970s. The National Weather Service (NWS) applied the concept for the first time in 1975 as an “Extended Streamflow Program”. The potential of ESP was examined by Day (1985) in water supply management by generating ESPs by coupling past observed weather data to a hydrologic model. Following the successes of ESPs in water supply management, hydrological communities started to explore the benefits of using ESPs forecasts for other applications. Nowadays, these forecasts are used by forecast centers around the world, and there is a scientific consensus on the operational value of probabilistic forecasts of ESP (Zappa et al. 2018).

Common long-term ESP forecasting methods can be divided into resampling and weather generator methods. Resampling methods represent the most common approach among hydrologists for generating a long-term forecast (King et al. 2014). These methods were originally developed in 1990 with the aim of solving problems associated with parametric methods. Finding a best fit on hydrological time series using parametric methods is often difficult. Observed hydrological time series usually exhibit a variety of features, such as unexpected skews or unusual long tail, which cannot be easily captured by parametric methods. The outliers in hydrological time series can also influence the parameters of parametric methods and lead to an unnecessarily high variance. As a result, the simulation by parametric methods may not be able to fully represent the observed data (Prairie et al. 2006). Thus, various non-parametric resampling methods, such as the index sequential method (ISM), the kernel-based approach and K-NN bootstrapping methods, have been developed (Khaki et al. 2018; Li et al. 2017). Despite the advantages and widespread use of these methods, most resampling methods do however suffer from the same potential drawbacks. Resampling methods rely on past observed climatology, and therefore, any deficiency in historical records can directly transfer to the forecast. In addition, the number of forecast members in an ensemble is limited to the length of existing records. Finally, resampling methods typically assume stationarity, and so a changing climate can affect forecast reliability (Clark et al. 2004a; Hamill et al. 2004).

Stochastic weather generators were developed in the 1980s, mainly in a bid to generate long synthetic weather time series (Wilks and Wilby 1999). These generators can take the key statistical properties of observational data and simulate weather time series of any desired length, which can be used in hydrological modeling and risk assessments studies (Breinl et al. 2015; Dubrovský 1997; Evin et al. 2019; Wilks 1999b). Following the success of stochastic weather generators in producing long weather time series, various studies have attempted to improve the performance of different aspects of the generators. To improve low-frequency variability, several methods involving, for instance, the perturbation of monthly parameters using a low-frequency stochastic model (Hansen and Mavromatis 2001) and the correction of daily precipitation using power spectra of observed time series (Chen, Brissette et al., 2010) have been introduced. Multisite weather generators have also been developed to allow assessing the spatial variability of hydrological time series (Apipattanavis et al. 2007; Breinl et al. 2015). As well, various approaches have been developed to enhance the representation of the intervariable correlations, along with spatial correlations (Chen and Brissette 2015; Chen et al. 2018). One of the main areas in which stochastic weather generators are predominantly used is in climate change impact studies. Wilks (1992) was the first to adapt a stochastic weather generator as a downscaling method in climate change studies. The approach was based on the modification of stochastic weather generator parameters according to climate scenarios, and produced time series consistent with climate change. Results showed that stochastic weather generators are reliable and computationally inexpensive downscaling tools for investigating climate change impacts.

While weather generators have been adapted for use in climate change impact studies, no attention has been given to this capacity in the field of hydrological forecasting. The ability to modify stochastic weather generator parameters may represent a promising avenue in the context of streamflow forecasting, and particularly in the case of non-stationary conditions.
There is an increasing body of evidence supporting the fact that climate change has critical impacts on regional ecosystems, water supplies, and agriculture and hydropower generation (Didovets et al. 2019; Kiesel et al. 2019; Mujumdar 2019). The behavior of a hydrological system changes with the climate, and hydrological modeling must consider climate change

adaptation strategies (Byun et al. 2019). Non-stationarity is therefore an important issue for hydrological modeling.

Non-stationarity in hydrological time series can arise due to a combination of anthropogenic forcing and natural climate variability (IPCC 2007). It has been proven that failure to take non-stationarity into account can lead to underestimation or overestimation in hydrological forecasting, such as streamflow forecasting, and consequently, can have an impact on water resource system management (Strupczewski et al. 2001; Villarini et al. 2010). Non-stationarity can lead to changes in the probability distribution of hydrological time series over time by time-shifting parameters such as the mean and the variance (Gagniuc 2017). In recent decades, many studies have proposed approaches to deal with non-stationarity in hydro meteorological data.

In parametric approaches, covariates are used to describe the non-stationarity. A covariate can be defined as a variable that represents the climate variability and reflects the phenomenon in distribution parameters. The covariates that are used in non-stationarity modeling can generally be divided into four main groups:

In the first group, time is a main covariate in hydrological modelling. In time-varying models, the distribution parameters are modeled as a function of the time trend, and can change over time. Various methods are presented to fit the distributions to non-stationary data; these include incorporating trends in statistical moments, incorporating trends in moments, using the local likelihood approach, quantile regression methods, using a generalized extreme value (GEV) or a generalized Pareto (Katz 2013; Khaliq et al. 2006; Ouarda and Charron 2019).

In the second group, low-variance large-scale climate indices are taken as covariates to transpose the changes to modeled hydrological time series. Recent studies have indicated that large-scale modes of climate variability, such as the El Niño Southern Oscillation (ENSO), the North Atlantic Oscillation and the Pacific Decadal Oscillation (PDO), can be used to identify low variability pattern in non-stationarity conditions (Ouarda and Charron 2018; Ouarda and Charron 2019).

The third group of studies uses covariates such as population, which have a physical meaning (Villarini et al. 2010) and a modified reservoir index (Su and Chen 2019).
In the fourth group, a combination of covariates, such as population and large scale climate indices, are used simultaneously to reflect the non-stationarity (Stasinopoulos and Rigby 2007).

Non-parametric approaches for non-stationary cases have been developed based on a calibration of the hydrological model and an updating of the model parameters. Some methods are based on the “differential split-sample test” proposed by Klemeš (1986). In this approach, either historical data is usually divided into consecutive subsets, and models are calibrated separately for each subset period (Thirel et al. 2015), or the periods that are supposed to be similar to the expected future hydro climatic condition are used to calibrate the hydrological model (Vaze et al. 2010). Recently, sequential data assimilation (DA) techniques, such as the ensemble Kalman filter (EnKF), have been used to estimate model parameters and states as part of a strategy to deal with the non-stationarity condition (Pathiraja et al. 2016).

Despite all recent efforts, many challenges remain as to how to properly account for non-stationarity issues in hydrological science (Mondal and Mujumdar 2015; Su and Chen 2019; Westra and Sisson 2011). This study aims to address this by proposing a simple long-term EPS forecasting method under a non-stationarity assumption. To develop this method, a stochastic weather generator is used as the main computational tool. The ability to modify the parameters of a stochastic weather generator is used to consider non-stationarity in the forecasting process.

The remainder of this paper is divided into four sections. The watershed and data are first described, followed by the methodology. Results are presented and discussed in the last two sections, followed by a conclusion.

4.2 Watershed and data description

The Lac-Saint-Jean watershed is selected as a case study watershed. The Lac-Saint-Jean is a sub-basin of the large Saguenay-Lac-Saint-Jean watershed located in the province of Quebec, Canada. The watershed has a surface area of 73,800 km2 from which four main rivers flow into the 1000 km2 Lac-Saint-Jean. The annual mean precipitation is 972 mm, while the annual mean maximum and minimum temperatures are 5.7 °C and -5.4 °C, respectively. The annual mean discharge is 861 m3/s. Figure 4.1 shows the Lac-Saint-Jean watershed.

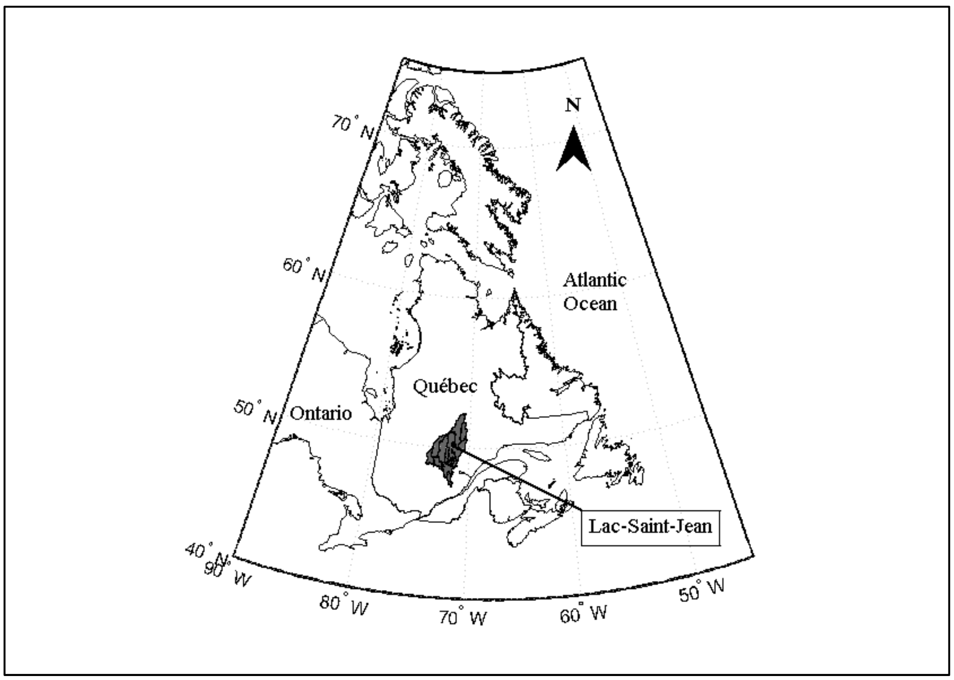

Figure 4.1 Location of Lac-Saint-Jean watershed in Quebec, Canada

The daily precipitation and maximum and minimum temperatures for this study are obtained from the NRCAN dataset. NRCAN is a Canadian-wide daily-scale precipitation and temperature gridded dataset with a 10-km spatial resolution (Hutchinson et al. 2009). The naturalized streamflow data are obtained from Rio-Tinto, the world's largest producer of aluminum, which operates six power plants on this watershed (Dibike and Coulibaly 2005). The hydrometeorological data from 1950 to 2009 were obtained for this study. The summary of the main annual hydrometeorological variables over the past 60 years are presented in Figure 4.2.

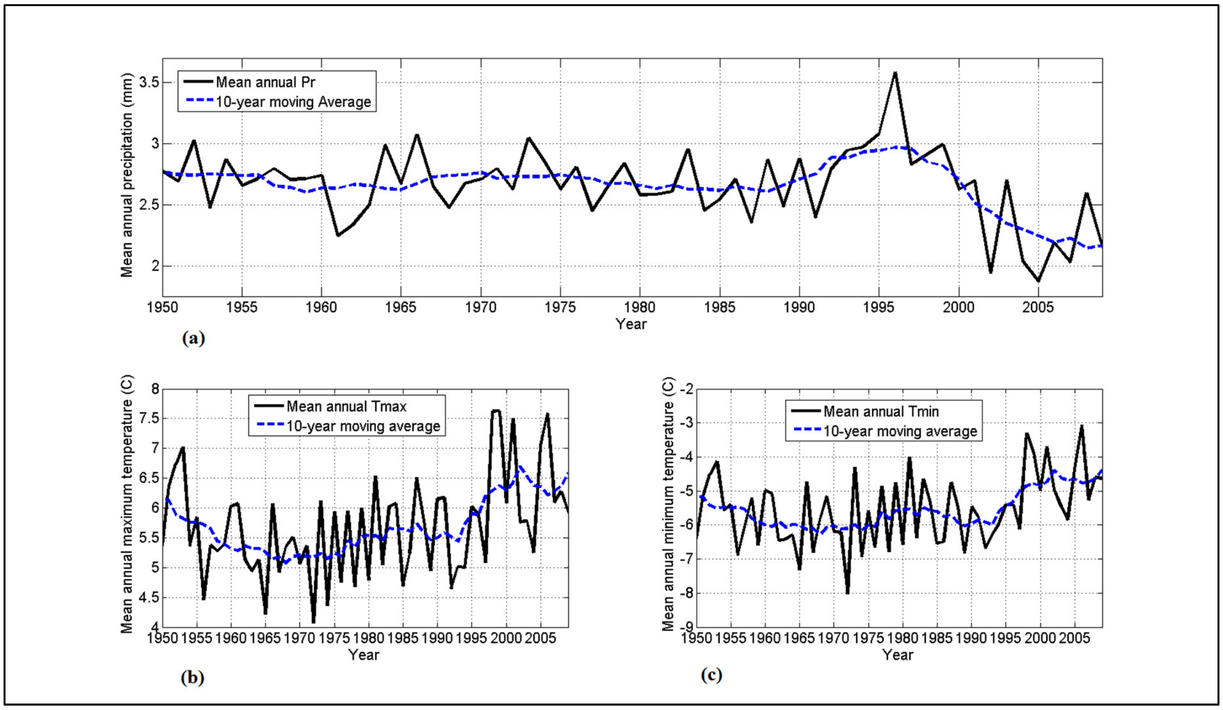

Figure 4.2 Mean daily and 10-year moving average for precipitation (a), mean daily and 10-year moving average for maximum temperature (b) and mean daily and 10-year moving average for minimum temperatures (c) over 60 years in Lac-Saint-Jean

The 10-year moving average for precipitation and maximum and minimum temperatures indicates clear trends for all three variables. There is a clear increase in temperature over the 1990-2010 periods, accompanied by a sharp decrease in precipitation.

4.3 Methodology

In this section, the ensemble weather and streamflow forecast methods are first described, and in a second step, the evaluation framework is presented.

4.3.1 Resampling method as a benchmark method

Since resampling past observed climatology is the most common long-term forecasting method, the method is used as the benchmark method for this study. Equiprobable resampling with no reshuffling between precipitation and temperature years is used as a main approach. In this approach, the number of members in each of the ensemble weather forecasts is therefore equal to the number of years in the reference period.

4.3.2 Stochastic weather generator

For this study, the WeaGETS weather generator is used (Chen et al. 2012a). WeaGETS is a single-site daily scale weather generator, and is based on the works of Richardson (1981) and Wright and Richardson (1984). Precipitation occurrence is first generated using a first-, second- or third-order Markov chain. On wet days, precipitation quantity is generated using either an exponential or a gamma distribution. Maximum and minimum temperatures are generated conditionally on the wet/dry day status. In this study, a first-order Markov chain is used, and the exponential distribution is used to estimate precipitation amounts on wet days. The exponential probability distribution function is as follows (4.1):

$$f(x) = \lambda e^{-\lambda x} \tag{4.1}$$

where x is the daily precipitation (in mm) and λ is the inverse of the mean daily precipitation. Serial correlations and cross-correlations between precipitation and temperature are preserved using a first-order regressive process. Inter-annual variability is also preserved using the spectral approach of Chen et al (2010).

4.3.3 Time window correction method

In this method, the monthly climatic mean values for both temperature and precipitation are computed based on the n previous years instead of using the entire length of the time series. The entire length of the time series is kept for all other statistics. The weather generator is modified based on the Change Factor method (Diaz-Nieto and Wilby 2005). For year x, the change factors are computed as follows (Equations (4.2) and (4.3)):

$$CFP_{n,m,x} = \frac{\sum_{j=x-n}^{x-1} \bar{P}_{j,m}}{\sum_{j=1950}^{x-1} \bar{P}_{j,m}} \tag{4.2}$$

$$\mathrm{CFT}_{n,m,x} = \sum_{j=x-n}^{x-1} \bar{T}_{j,m} - \sum_{j=1950}^{x-1} \bar{T}_{j,m} \tag{4.3}$$

Where $\bar{P}_{j,m}$ and $\bar{T}_{j,m}$ respectively represent the monthly mean precipitation and temperature for month m and year j. In essence, the change factors represent the ratio (precipitation) or difference (temperature) in monthly mean values between the last n years, compared to the climatology of the entire period starting in 1950. The parameters of the weather generator representing the monthly mean values for temperature and precipitation are modified by using the change factors computed above, and the ensemble weather forecasts are generated accordingly.

It should be noted that to define the number of step-back years from the year j, the term "time window" is defined and used in this study. The calculated change associated with each time window is called the impact of the time window. For example, the impact of a 3-year time window means that the average of the last 3 years' annual means is used to estimate the changes for year j.

4.3.4 The hydrological response simulation

The hydrological response of ensemble weather forecasts regarding the impact of each time window is simulated by using the HSAMI lumped hydrological model. HSAMI, as a lumped, conceptual, rainfall-runoff model is used as a hydrological model in this study. It was developed by Hydro-Québec with the aim of forecasting the natural inflows at hourly and daily scales. It is used on more than 80 watersheds with surface areas from ranging 160 Km2 to 70,000 Km2. It has also been used in many Canadian hydrological studies, such as climate change impact studies (Chen et al. 2011; Minville et al. 2008), multi-model simulations (Arsenault et al. 2015), model calibration experiments (Arsenault et al. 2013) and regionalization studies (Arsenault and Brissette 2014a; Arsenault and Brissette 2014b). HSAMI is a conceptual model with 23 parameters. Two of those parameters account for evapotranspiration, 6 for snowmelt simulation, and 15 for vertical and horizontal water movement. Vertical water flows are estimated by four interconnected linear reservoirs (snow on the ground, surface water, saturated and unsaturated zones). Horizontal routing is carried out by two unit hydrographs and one linear reservoir for low flows. Running the HSAMI requires a minimum of three time series of precipitation, maximum and minimum temperatures at the daily scale. The cloud cover fraction and snow water equivalent as complementary data can also be used (Brown 2010; Essou et al. 2016; Sveinsson et al. 2008).

HSAMI is calibrated automatically using the CMA-ES algorithm (following the work of Arsenault et al (2013)) and the Nash-Sutcliffe criterion is used as the objective function. Based on the work of Arsenault (2018), calibration is performed on all available years with no validation step. To eliminate the uncertainty linked to the hydrological modeling process; this study uses the simulated streamflow instead of observed values. Doing so results in a 'perfect' hydrological model, and eliminates all uncertainties resulting from the assimilation process and hydrological modeling biases. This ensures that all differences between the resampling and weather generator and the proposed method ensemble streamflow forecasts are entirely due to differences in the generation of ensemble weather forecasts.

4.3.5 Evaluation

The proposed method first evaluates the impact of using each time window on long-term streamflows, and then its long-term EPS forecasting performance is compared to that of the resampling and calibrated weather generator methods. The annual streamflow volume is considered for evaluation purposes.

4.3.6 Experimental setup

The proposed method is evaluated in hindcast mode over the 30-year 1980-2009 period. The 1950-1979 time period is used as the initial historical record. At each forecast date, the impacts of n-year time windows are assessed, with n varying from 1 to the entire length of the time series. Over the evaluation period, 1-year-ahead forecasts are made 12 times per year, on the first day of each month. The evaluation period is therefore comprised of 360 1-year forecasts (30 years times 12 forecasts). The hydrological model and weather generator are calibrated at the beginning of every new year, adding the preceding year to the historical record. The performance of the proposed method is evaluated in comparison to the resampling and weather generator approaches, both using the entire available historical record at the date of the issued forecast. The performance of all forecasting approaches is evaluated with respect to the forecast flood volume. Flood volume is calculated based on total inflow volume between April 1st and June 30th. Figure 4.3 presents the methodological framework.

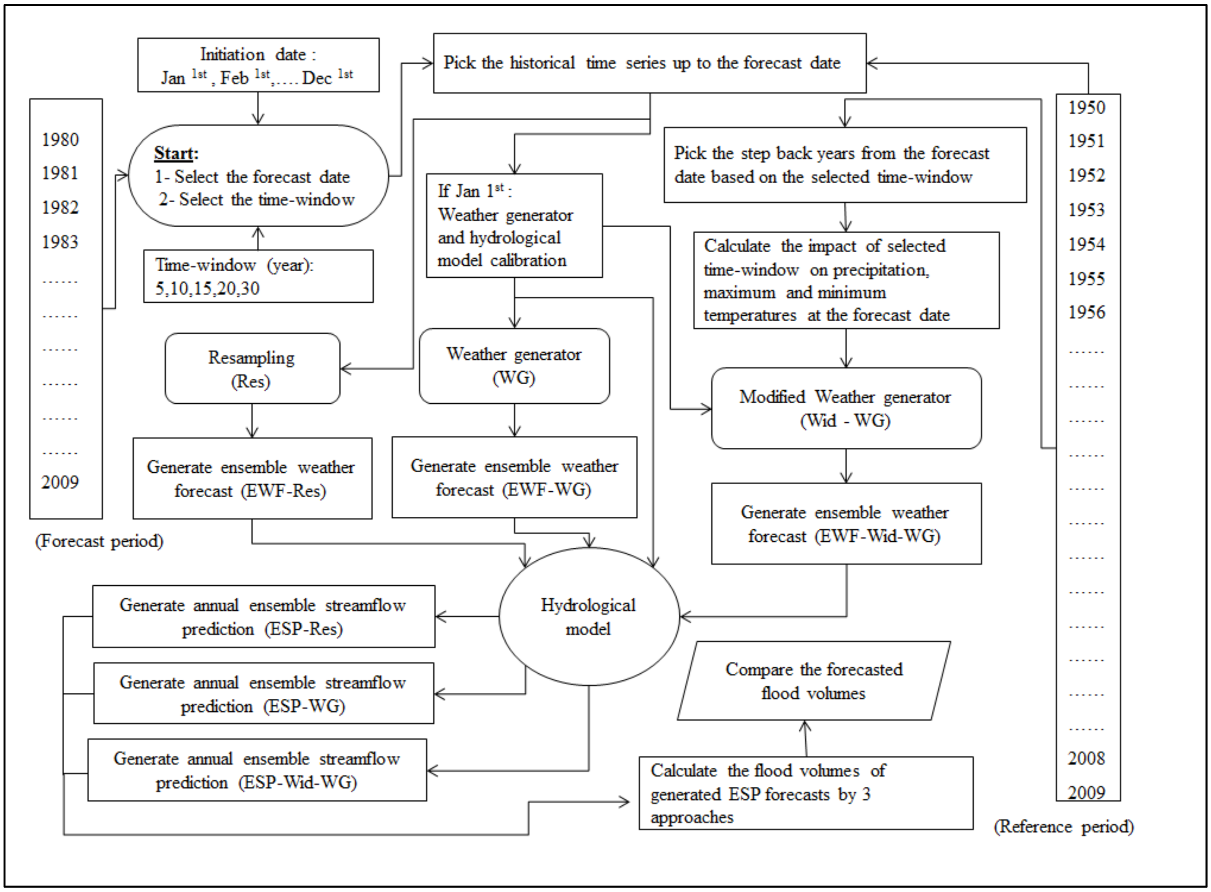

Figure 4.3 Methodological framework

4.4 Results

Figure 4.4 presents the biases between the forecast and observed flood volumes of the proposed method by using a 1-30-year time window. Results are presented as boxplots comprised of 30 bias values corresponding to each forecast year (1980-2009). The 9 graphs represent the forecast dates at the first day of each month. For each boxplot, the rectangular box outlines the 25th, median (in red) and 75th quantiles, whereas the whisker extents cover the entire distribution of biases. The red crosses are considered statistical outliers.

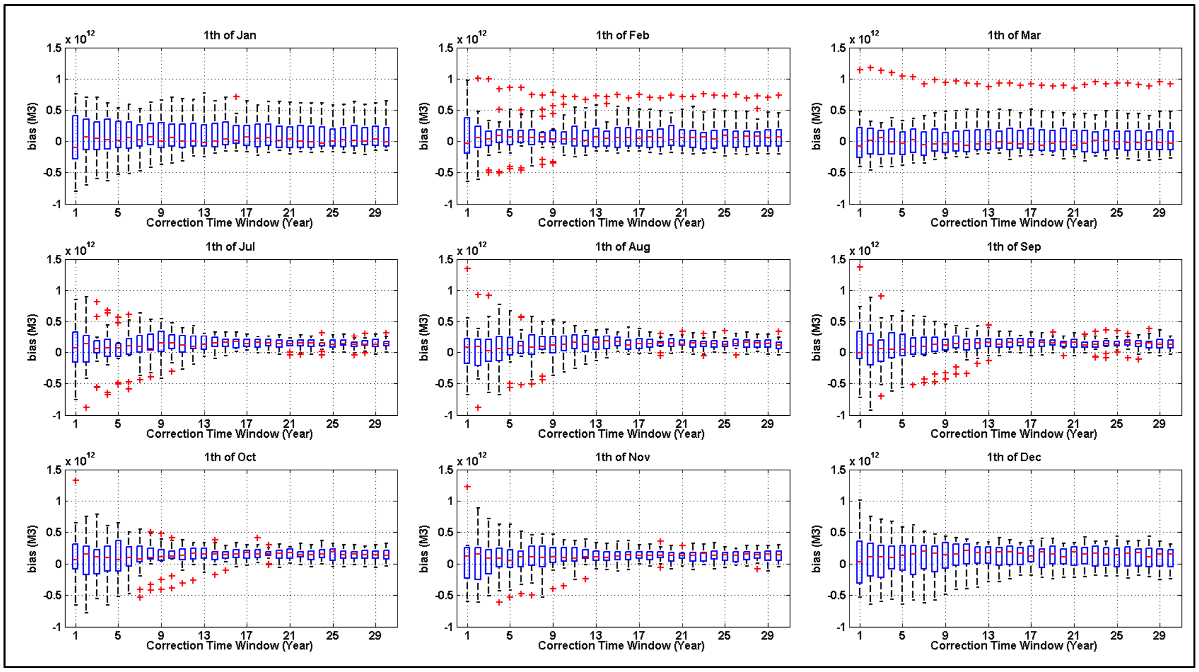

Figure 4.4 Results of calculated bias between forecast and observed flood volume using 1 to 30 time windows over 30 years of forecasts

Since the proposed method is applied one year in advance to floods, the three monthly forecast dates that occur during the freshet (i.e. April 1st, May 1st and June 1st) are eliminated from this assessment since they typically cover the end of one freshet and the beginning of the following year's freshet. According to Figure 4.4, the performance of the proposed method is considerably dependent on the forecast issue date and its closeness to the flood. The results can be broken down into two categories: results that are driven with the initiation date close to the flood (i.e. up to four months, including Dec 1st, Jan 1st, Feb 1st and Mar 1st), and far from the flood (i.e. the remaining months). To better outline the impact of the moving time window, Figure 4.5 presents the mean bias values for each graph of Figure 4.4.

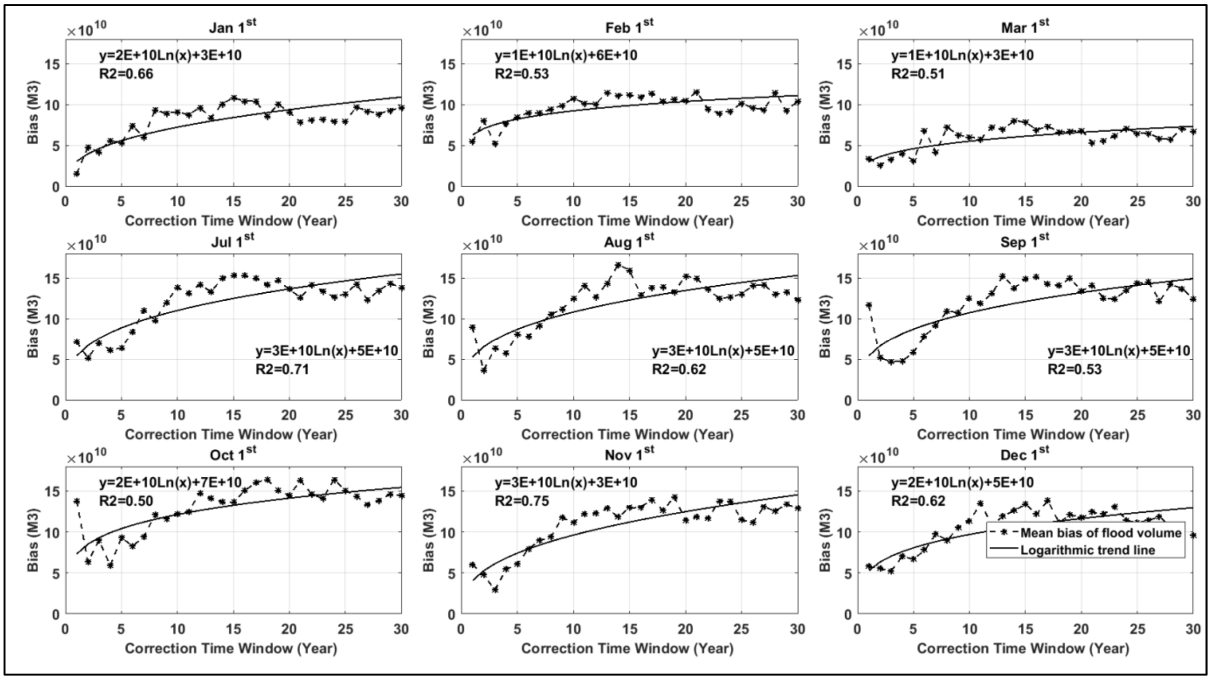

Figure 4.5 Results of calculated mean bias between forecast and observed flood volume using 1 to 30 time windows over 30 years of forecasts

Figure 4.5 shows that along with increasing the length of the time window comes an upward trend that progressively stabilizes after a certain number of years, suggesting the presence of a logarithmic trend. Accordingly, the logarithmic trend line, as well as logarithmic function and its associated r-square value, are displayed according to the results of mean biases at each forecast date in Figure 4.5. According to Figures 4.4 and 4.5, increasing the length of the time window decreases the bias spread but increases its amplitude. According to the suggested logarithmic trend line in Figure 4.5, the bias is stabilizing around a specific time window. This time window, during which the trend of mean bias becomes constant, can be considered as the best time window, during which the minimum bias spread and mean bias can be achieved.

To provide a better understanding of the impact of different time windows on the modeling of weather variables, Figure 4.6 shows the autocorrelation plots of three such weather variables. The autocorrelation plots can illustrate the correlation and dependency of weather variables on the precedent year's information. These plots show the persistence of internal variability over a few years.

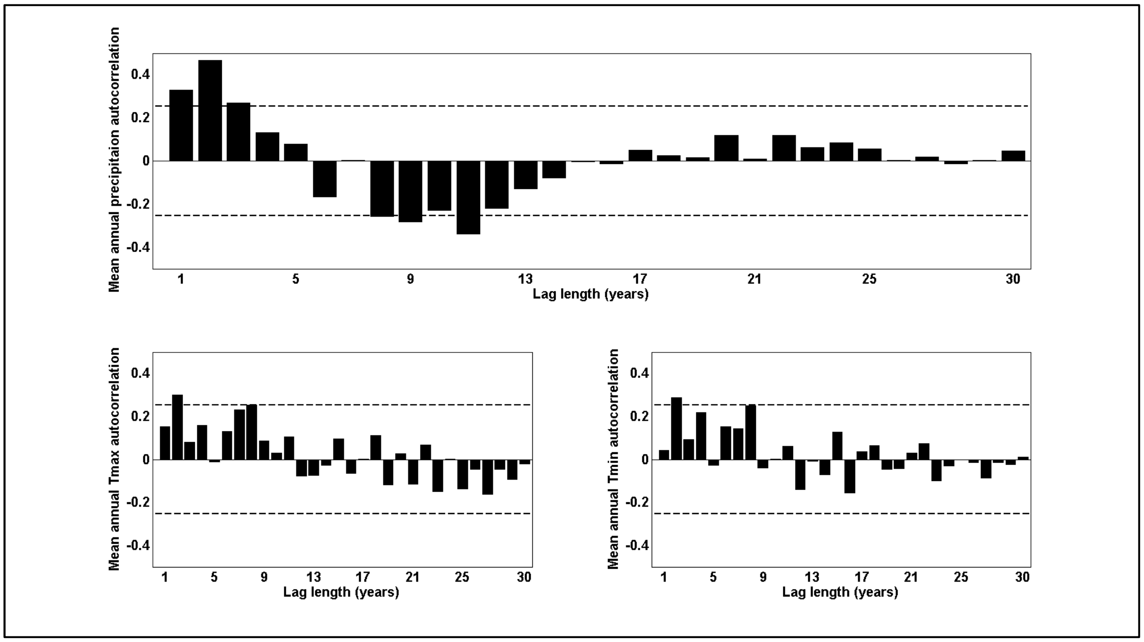

Figure 4.6 Autocorrelation of mean annual precipitation, maximum and minimum temperatures over 30 years from 1980 to 2009

The autocorrelation plot of mean annual precipitation shows a 10-15-year cycle. The autocorrelation plots of mean annual maximum and minimum temperatures show a similar, albeit less well defined, pattern. It can be interpreted that the previous 10 years are very influential at the time of forecasting. In particular, all three weather variables show a positive autocorrelation with the previous 5 years' time series. It can be summarized that climate information of up to the 5 previous years possesses valuable information that might have a significant correlation with the climate at the forecast time. The autocorrelation plots can partly explain the reason of the good performance of the proposed method when using the 1- to 5-year time windows in Figures (4.5) and (4.4).

Since the mean bias results show that the best performance of the proposed method can be achieved by using a 1-5-year time window depending on the forecast date, the performance of the proposed method is further evaluated using a 5-year time window. This was done by comparing its performance to those of the weather generator and resampling methods over the 1980-2009 periods. The mean annual simulated hydrographs obtained from the three forecasting methods are presented in Figure 4.7.

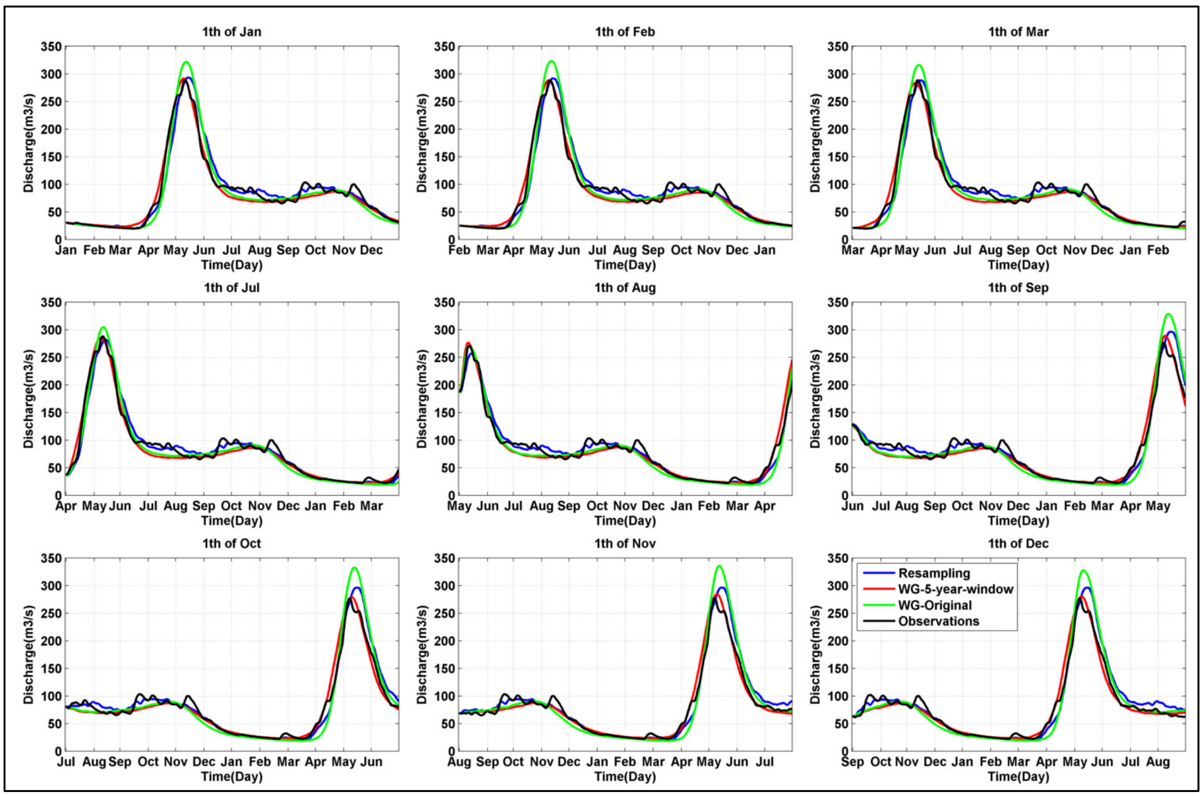

Figure 4.7 Forecast mean annual hydrograph of the proposed method obtained by using 5-year time window (WG-5-year-window), a calibrated weather generator (WG-Original) and a resampling method (Resampling) over the 1980-2009 period versus observed annual hydrograph

Figure 4.7 shows that all three methods perform well. The performance of the 5-year window in the proposed method is clearly the best at flood forecasting. The flood initiation, peak and end are well estimated this method, and outside the flood period, all three methods perform similarly.

Resampling works well for forecasts close to the beginning of the flood (January to March), but fails to accurately predict the flood onset for longer lead times. In addition, a flood volume overestimation can clearly be seen in the resampling method results. The weather generator performs similarly to the resampling method; however, the resampling method outperforms the calibrated weather generator around the freshet in all cases. The mean monthly biases of the flood volumes forecast by the three methods over 30 years are calculated and presented in Figure 4.8.

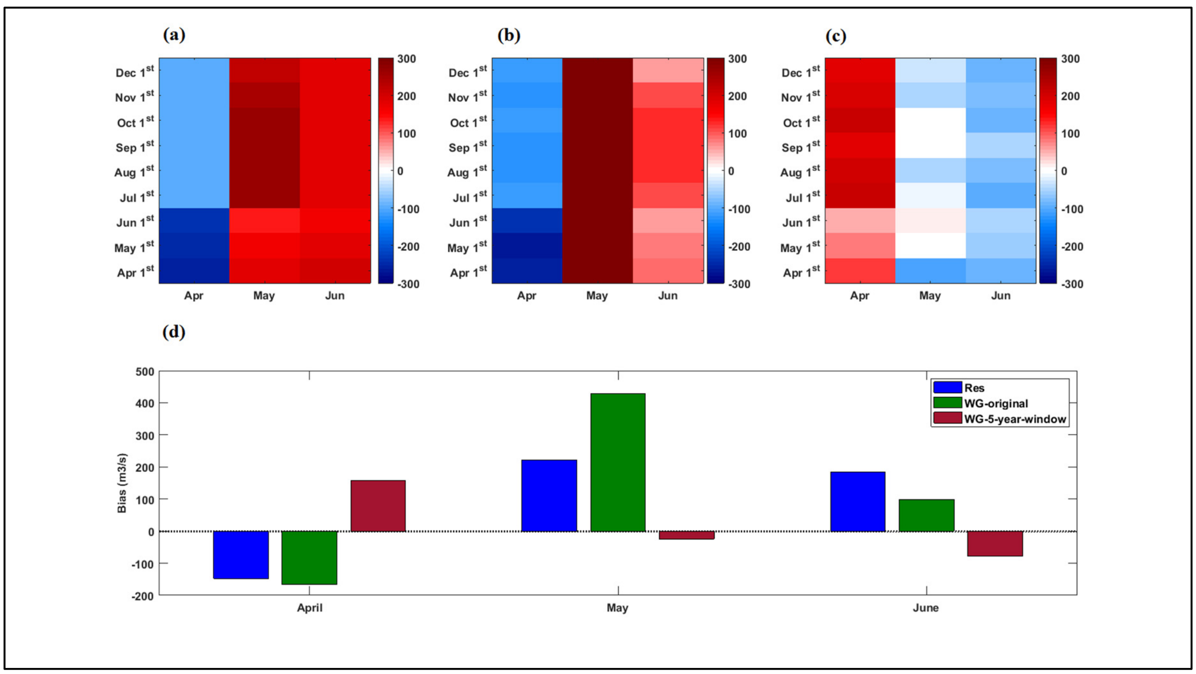

Figure 4.8 Mean monthly bias of simulated flood obtained by resampling (Res) (a), calibrated weather generator (WG-Original) (b) and proposed method using 5-year time window (WG-5-year-window) (c) over 30 years of forecast; Mean monthly bias over the 9 issue dates of simulated flow volumes in the three freshet months by the three methods (d)

At the top of Figure 4.8, the mean monthly biases of the three methods during the freshet (April, May and June) for 9 forecast issue dates are presented. The mean monthly bias pattern around the freshet based on the resampling method is almost invariable, and the forecast issue date has no significant impact on the pattern of bias. Regardless of the forecast issue date for the resampling method, there always seems to be an underestimation of flow volumes in the month of April (at the beginning of the freshet), and an overestimation in May (during the peak of the freshet) and June (as the freshet ends). The pattern of mean monthly biases for the weather generator is similar to that of the resampling method; however, the estimated bias around the freshet is slightly larger. In contrast, despite an overestimation at the initiation time of the freshet, the bias results of the proposed method by using a 5-year time window show a considerable improvement in flow volume estimation for the month of May, where the peak flow occurs, followed a slight underestimation for the month of June.

4.5 Discussion

In this study, a new approach is introduced to consider the non-stationarity in long-term streamflow forecasting. The proposed approach is developed based on a calibration of the stochastic weather generator up to the forecast date, and then conditioning the parameters to add more weight to the recent years. To capture and calculate recent climate information, different time lengths of historical data (precipitation, maximum and minimum temperatures), defined in terms of different time windows, are used. The impact of each time window on the streamflow forecasting performance is assessed and evaluated. The impact of the time window length is first evaluated, after which the optimal time window length is then determined, and the approach is compared to forecasts issued based on traditional resampling and weather generator approaches.

The importance of internal variability in predicting weather variables has been discussed in various studies (Dai and Bloecker 2019; Hegerl et al. 2018; Nath et al. 2018). To capture internal variability, access to long historical records is essential (Ludescher et al. 2016; Xie et al. 2019). On the other hand, the impact of anthropogenic forcing on climate variables is likely better represented by more recent years, as compared to the entire historical record. To take non-stationarity into account, it is essential to define a way to capture the temporal trend and concentrate on the most recent climate information (Ouarda and Charron 2019). Therefore, while there is a need to have long historical records in order to ensure a better estimation of the internal fluctuations of weather variables, the most recent historical data must also be emphasized in order to capture the temporal variability due to the combined effect of natural variability and anthropogenic climate change (Westra and Sisson 2011). In the proposed method, to avoid any potential loss of valuable historical information, long historical records are used to calibrate the weather generator. As such, the impact of internal variability can still be accurately simulated. Next, the recent changes in weather variables are calculated using the different time windows and introduced to the parameters of the calibrated weather generator. The parameters can thus vary according to the introduced changes, and temporal variability of weather variables in recent years can be captured and included in the forecasting process. Therefore, the proposed method attempts to consider internal variability and recent trends due to anthropogenic forcing.

As presented in Figure 4.2, the trend of weather variables, and especially of temperatures, have changed over the last 30 years, with increases seen that are consistent with anthropogenic forcing. Temperature is a key component in the onset of snowmelt-related flooding. Accordingly, any over- or underestimation of forecast temperatures can cause errors in flood timing estimation (Xiong et al. 2019; Yen et al. 2018). Temperatures mainly affect the snow melting onset process, and increasing temperature trend can cause early snow melting, and consequently, early flood initiation. Changes in the precipitation trend can impact the peak flood and total flood volume. The results of the resampling and weather generator methods clearly illustrate the consequence of relying on stationarity assumptions in streamflow forecasting. Both approaches result in a mean annual hydrograph with a late flood initiation date. This in turn results from the historical record containing too many cold years, which are not representative of a warming climate. Similar results can be seen in the overestimation of flood volumes, with colder years resulting in fewer early snowmelt episodes. The deficiencies of resampling approaches in considering taking non-stationarity have also been discussed in other recent studies. Liu et al (2019b) identified a delay in the timing of the annual maximum flood in the Wi River Basin (WRB) of China. Mediero et al (2014) documented a decreasing trend in flood magnitude in Spain, which could be explained by the non-stationarity of weather variables. Salvadori and Neila (2013) also confirmed the non-stationary of floods in Northeastern United States.

The length of the time window chosen to calculate mean monthly climatic values affects the mean bias and spread of forecast flood volumes. Using a shorter time window decreases the mean bias, at the expense of a larger spread. Using a 5-year window was found to represent an optimal compromise for this watershed case study. These results are in line with recent studies on the influence of the recent past on the weather variable and streamflow trends. Liu et al (2019a) identified that the most important time scales contributing to the trend of the original low flow series are 2-year and 4-year events, while in another study by Joshi (2016), the 2-8 year period was determined to be the most influential time scale on drought trends.

The proposed method is designed to consider non-stationarity within the hydrological modeling chain. This method is robust and simpler in comparison to other approaches that have attempted to capture and incorporate non-stationarity in hydrological modeling. While most of the approaches aimed at capturing non-stationarity are rooted in defining indirect covariates, such as large-scale climate indices, in the proposed method, temporal weather variable changes can directly be captured and calculated by using a shorter time window to calculate the mean monthly values of relevant climate variables. Employing covariates to reflect the non-stationarity condition in modeling can introduce new sources of uncertainties (Su and Chen 2019). In addition, choosing the best and a sufficient number of covariates remains a major challenge (Li and Tan 2015; Liu et al. 2017; Rashid and Beecham 2019). Moreover, employing and incorporating the proper time window in non-stationarity modeling can allow identifying the dominant time scales that can affect the trends or change points in hydrological time series. While most of non-stationarity studies are concerned with quantifying the contribution of climate change and human activities on non-stationarity (Huang et al. 2016; Liu et al. 2017; Mediero et al. 2014), the time window approach allows determining which period is predominantly responsible for trends and changes, and uses that information to refine and improve the forecasting process. Results show that flood volume biases are significantly improved using this method.

4.6 Conclusion

This paper introduced a simple method to consider the non-stationarity of climatic variables in producing long-term ensemble streamflow forecasts. The approach can account for the combined impact of anthropogenic forcing and internal variability. It conditions the parameters of a stochastic weather generator by putting more weight on recent years, while using the entire historical time series to estimate variability. The last 5-year period was found to be the optimal time window when it came to estimating the mean monthly values of climatic variables, for the studied watershed. The proposed method was found to outperform the traditional approach of resampling historical time series or using a stochastic weather generator calibrated on the full length of the historical dataset. It was also shown to significantly improve flood volume forecasts.

In addition, there are some suggestions for future works. The proposed time window method is performed without having any pre knowledge information. The optimal time window is found by evaluating the 30 time-window. For the future projects, checking the autocorrelation plots of precipitation, maximum and minimum temperatures for estimating the optimal time window is highly recommended. This study used the annual scale for defining the time windows, while there is a high potential for more improvement by using the seasonal scale time window.

CHAPITRE 5

COUPLING LARGE-SCALE CLIMATE INDICES WITH A STOCHASTIC WEATHER GENERATOR TO IMPROVE LONG-TERM STREAMFLOW FORECAST IN CANADIAN WATERSHED

Samaneh Sohrabi [a] and François P. Brissette [b] and Richard Arsenault [c]

[a,b,c] Department of Construction Engineering, École de Technologie Supérieure,
1100 rue Notre-Dame West, Montreal, Québec, H3C 1K3, Canada

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Abstract

This paper aims at improving long-term streamflow forecasts by conditioning the parameters of a stochastic weather generator on large-scale climate indices. The most important climate indices are identified by looking at yearly correlations between a set of 40 indices and meteorological data (precipitation and temperature) at the watershed scale. A linear model is then constructed to identify precipitation and temperature anomalies to induce perturbations in the stochastic weather generator. Time windows of 5, 10, 15, 20 and 30 years are used in determining the optimal linear model. The performance of the proposed approach is assessed against that of a resampling of past climatology and using the same stochastic weather generator unconditioned on climate indices. Each ensemble weather forecast is then used as input to a hydrological model to create Ensemble Streamflow Forecasts with up to a one-year ahead lead times. The three approaches are tested in hindcast mode over a 30-year period at 12 forecast dates. Results show that temperatures are significantly correlated with large-scale climate indices, whereas precipitation is only weakly related to the same indices. The length of the time window has a considerable impact on the prediction ability of the linear models. The precipitation models based on short duration time windows performed better than those

based on longer windows, while the reverse was found for the temperature models. A comparison between all three Ensemble Streamflow Forecast approaches is assessed using the CRPS metric. Results show that the proposed method improves long-term streamflow forecasting, particularly around the spring flood.

5.1 Introduction

Sustainable water resource management is a fundamental requirement across the globe , and streamflow forecasting is an integral component of an efficient water management strategy (Wood et al. 2019).

The main issue in making and improving long-term streamflow forecasts is dealing with complex uncertainties rooted in the stochasticity, non-linearity and non-stationarity characteristics of streamflow time series (Narsimlu et al. 2015). To better manage the different sources of forecast uncertainty, probabilistic forecasts have come to replace more traditional deterministic approaches. In a probabilistic approach, a collection of deterministic forecasts is generated to simulate the same event and provide representative samples of the future. The first use of probabilistic approaches in inflow forecasting dates back to 1980, and was called 'Ensemble Streamflow Prediction' (Day 1985). The ESP forecast offers a way to communicate uncertainties, and its advantages over deterministic forecasts has been explored in many studies (Arnal et al. 2018).

The two main approaches for making long-term ESPs consist of a resampling of past climatology and a process using weather generators. Resampling past climatology is by far the most common long-term forecasting method. It was first used in the 90s in order to tackle the problems parametric models faced in forecasting hydrological time series (King et al. 2014). The main problem with these methods was their assumption of normality and the requirement that data be transformed into a normal distribution prior to the models being fitted. Data distribution transformation represents one of the main sources of bias in parametric methods. Moreover, these methods cannot fully capture the non-linearity of hydrological data (Prairie et al. 2007; Sharma et al. 1997). To overcome this problem, resampling methods such as the index sequential method, K-NN bootstrapping methods, and kernel-based approaches have been developed (Keller et al. 2017; Khaki et al. 2018; Sharifazari and Araghinejad 2015). Resampling methods are widely used due to their relative ease of implementation. However, most of these methods suffer from the same potential drawbacks: 1- any deficiency in the historical records will be transferred to the forecast, 2- the number of forecast members in an ensemble is generally limited to the length of existing records, and 3- resampling methods typically assume stationarity of the data over the historical record. Forecasts can therefore be unreliable in non-stationarity conditions such as that induced by anthropogenic climate change (Li et al. 2017; Ndzabandzaba 2020). Various methods and techniques have been proposed through the years to improve resampling methods, but additional research is still needed to address the issues mentioned (Lee et al. 2010; Sharifazari and Araghinejad 2015; Sivakumar 2017).

Stochastic weather generators were first developed in the 80s (Semenov 2008; Wilks and Wilby 1999). The initial purpose of weather generators was to generate long time series of weather variables with statistical properties identical to those of observed series. The weather time series thus generated could be used in hydrological modeling and risk assessment studies, where access to long time series is an important issue. The ability of stochastic weather generators to provide long time series without any missing values has been assessed and demonstrated in many studies (Caron et al. 2008; Dabhi et al. 2018; Goldman 2017). These weather generators' performance has improved in many aspects over the years. For example, several methods have been developed to improve their low-frequency variability underestimation (Chen et al. 2010; Hansen and Mavromatis 2001). Multisite stochastic weather generators have been developed to consider the spatial variability of hydroclimatologic time series (Breinl et al. 2015; Khalili et al. 2011). In addition, various approaches have been implemented to improve the representation of intervariable correlations (Chen and Brissette 2015; Chen et al. 2018). Climate change impact studies represent one of the main areas in which stochastic weather generators have been used in the past decade. They have been used to downscale the resolution of coarse climate data to finer and local scales (Caron et al. 2008;

Goldman 2017; Wilks 1999b). This approach was first proposed by Wilks (1992), and is based on conditioning the parameters of the stochastic weather generator according to climate projections based on greenhouse gas emission scenarios. Results have shown that stochastic weather generators can be used as a reliable downscaling tool in climate change impact assessment studies (Maraun and Widmann 2018). Stochastic weather generators have also been used as a downscaling tool in many other more generic studies (Chen et al. 2012b; Chen et al. 2018). Despite the widespread use of these generators in climate change impact studies, comparatively little attention has been paid to their advantages in hydrological modeling and streamflow forecasting. The ability to condition the parameters of a weather generator to account for a dynamic climate can be leveraged in streamflow forecasting, and in particular, used to take into account the anthropogenic component of climate change.

There is a scientific consensus on climate change and its impact on regional ecosystems (IPCC 2007). However, many hydrometeorological models have been developed under the assumption of stationarity for both climate and hydrological time series. Under this assumption, internal variability is assumed as the main cause of interannual variability. With the anthropogenic signal now being dominant for temperature variability over many parts of the world (Martel et al. 2018), it is therefore fundamental to take into account trends in hydrometeorological time series. Failure to consider non-stationarity in hydrological modeling can result in the underestimation or overestimation of forecast streamflows, and may consequently impact the management of water resources system (Blöschl et al. 2019; Liu et al. 2019b).

In non-stationarity conditions, the probability distribution of hydrological time series changes over time. Distribution statistics, such as the mean and variance, therefore change through time as well (Gagniuc 2017). In recent decades, various approaches have been proposed to consider non-stationarity in hydrological modeling, with one of the main ones consisting in the use of large-scale climate indices as covariates. Large-scale climate indices represent non-stationary patterns of variability that are linked to hydrometeorological time series distributions (Ouarda and Charron 2018; Ouarda and Charron 2019). In general, the first methods developed for incorporating large-scale climate indices in hydrological forecast can be classified in under pre- and post-processing schemes. In pre-processing schemes, meteorological inputs to the hydrological model are based on large-scale climate index information. Here, historical records are selected based on past similarity to current oceanic and atmospheric states as represented by climate indices (Hamlet and Lettenmaier 1999; Werner et al. 2004; Wood et al. 2002). In post-processing schemes, forecasting is performed as usual, but each forecast is weighted based on past similarity to current climate indices (Najafi et al. 2012; Werner et al. 2004). The most common approach used to define a relationship between large-scale climate indices and hydro meteorological variables uses the former as a main predictor to predict a hydro meteorological variable. Methods such as simple and multiple regressions, principal component analysis, singular value decomposition (SVD), canonical correlation analysis and combined principal correlation have been used to define a relationship between the different spatial and temporal scales of large-scale oscillations and local observations (Bhandari et al. 2018; Bhandari et al. 2019; Kalra et al. 2013; Tootle and Piechota 2006). Notwithstanding all the recent work that has been done in this area, efforts are still ongoing to determine how to properly link current atmospheric and oceanic states to improve streamflow forecasts (Liu et al. 2019a; O'Brien et al. 2019).

The main objective of this study is therefore to propose an approach to capture non-stationarity in long-term streamflow forecasting by incorporating large-scale climate indices in the streamflow forecasting process. The approach is based on constructing precipitation and temperature models that depend on a subset of relevant large-scale climate indices. These models will be used to modify the parameters of a stochastic weather generator, in order to produce times series of precipitation and temperature that are more representative of climate variability at the time the streamflow forecast is issued.

The remainder of this paper is divided into four sections. The watershed and data are first described in section 5.2, followed by the methodology in section 5.3. Results are then presented and discussed in sections 5.4 and 5.5, respectively.

5.2 Watershed and data description

This study was conducted on the Lake Saint-Jean watershed, located in the province of Quebec, Canada (Figure 5.1). The Lake Saint-Jean basin has a surface area of 45,261 km^2. Four main rivers flow into the Lake Saint-Jean, which for its part measures 1000 km^2. Rio Tinto, one of the world's largest aluminum producers, operates six power plants on this watershed, with an average capacity of 2000 megawatts. The development of the aluminum industry and its impact on the regional economy are closely linked to the hydropower potential of the Lake Saint-Jean watershed (Dibike and Coulibaly 2005). During summer and fall months, rainfall is usually sufficient to ensure the high efficiency use of the reservoir. During winter, streamflows to the reservoir decrease sharply, and water must be drawn from the reservoir to maintain production. Finally, during spring, the freshet brings enough water to fill the reservoir several times over, leading to regular unproductive spills during that period. Therefore, it is critical that planning be done to ensure that long-term winter and spring melt reservoir levels will provide maximum energy production during winter, but avoid water shortages before the freshet (Arsenault and Côté 2018; Arsenault et al. 2016b; Côté and Arsenault 2019). The Lake Saint-Jean is sparsely inhabited and consists of a mostly homogeneous boreal forest cover. The mean annual precipitation over the watersheds is 970 mm, while the mean annual minimum and maximum temperatures are -5.4 °C and 5.7 °C, respectively. The mean annual streamflow for its part is 861 m^3/s. The watershed outlet is on the Saguenay River, which flows into the St-Lawrence River. Figure 5.1 shows the Lake Saint-Jean watershed.

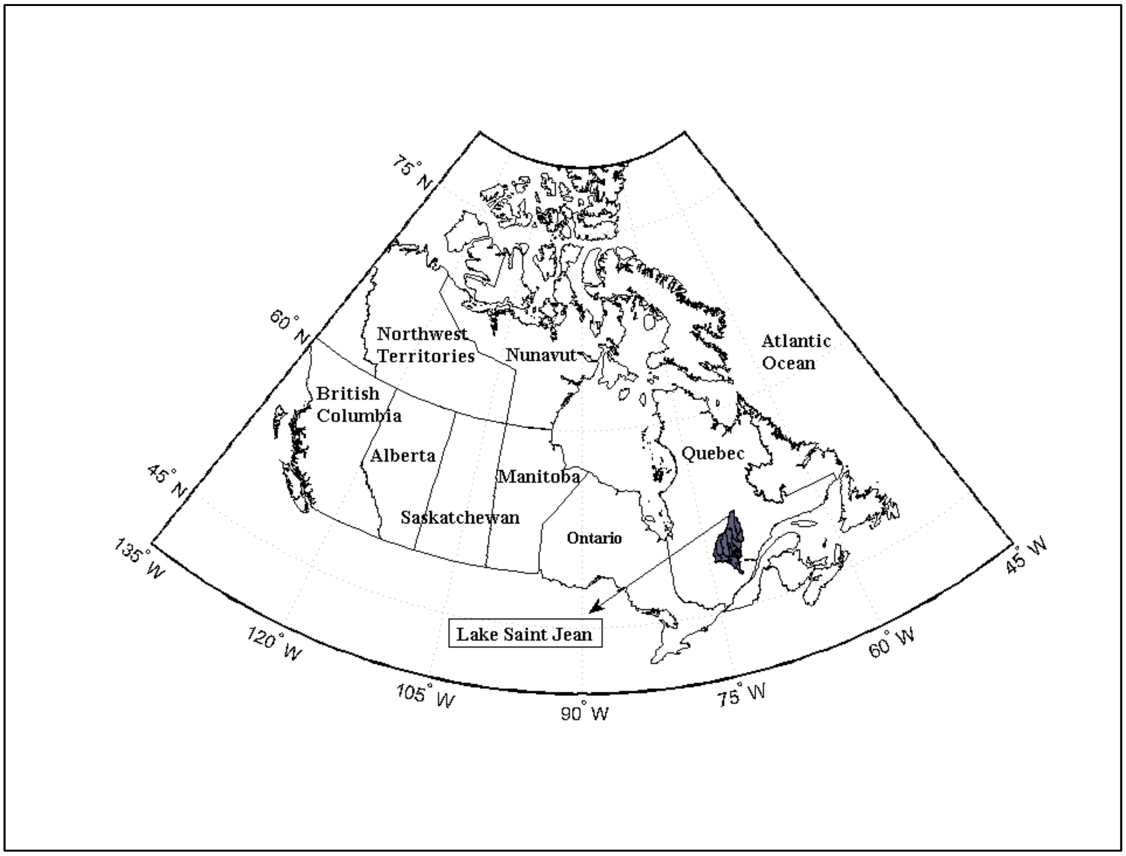

Figure 5.1 Location of Lac-Saint-Jean watershed

Precipitation and temperature data used in this study come from the Natural Resources Canada (NRCan) dataset. The NRCan dataset is a 10-km resolution Canada-wide gridded daily precipitation and temperature dataset (Hutchinson et al. 2009). The mean annual precipitation, maximum and minimum temperatures over the watershed for the 1950-2010 period are plotted in Figure 5.2. The 10-year precipitation, maximum and minimum temperatures moving average is plotted as well. There is an increasing temperature trend over the past 40 years (1.5 degrees), which matches the expected anthropogenic climate change at high latitudes. A sharp decrease in precipitation over the past 15 years can also be observed, and is most likely the result of natural variability since a large majority of climate models predict precipitation increases by the end of the century.

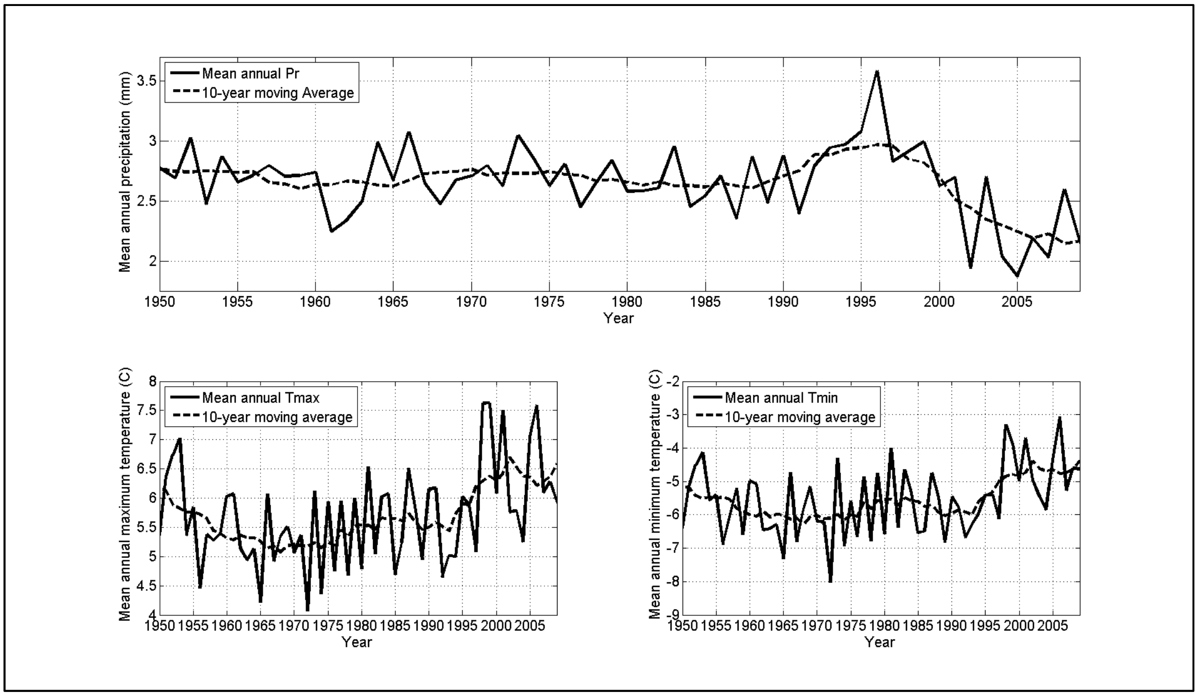

Figure 5.2 Mean annual precipitation, maximum and minimum temperatures for the Lake Saint-Jean watershed from 1950 to 2010

For this study, a set of 40 large-scale climate indices at the monthly scale was obtained from NOAA's Climate Diagnostics Center. By using an uncertain pre-screening process, this large selection of indices ensures that no potentially relevant indices are left out. Table (1) presents the list of all climate indices considered.

Table 5.1 List of large-scale climate indices used in this study

Climate Index	Name	Climate Index	Name
AAO	Antarctic Oscillation.	NINO3.4	East Central Tropical Pacific SST
AMM	Atlantic Meridional Mode	NINO4	Central Tropical Pacific SST
AMO_Nsmoothed	Atlantic multidecadal Oscillation-unsmoothed	NOI	Northern Oscillation Index
AMO_smoothed	Atlantic multidecadal Oscillation-smoothed	NP	North Pacific pattern
AO	Antarctic Oscillation	NTA	North Tropical Atlantic Index
BEST	Bivariate ENSO Timeseries	ONI	Oceanic Nino Index
CAR	Caribbean Index	PNA	Pacific North American Index
EA_WR	Eastern Asia/Western Russia	PDO	Pacific Decadal Oscillation
ENSO	ENSO precipitation index	PSD	Western Pacific Index
ATSST	Atlantic Tripole SST EOF	PW	Pacific Warmpool
EP_NP	East Pacific/North Pacific Oscillation	QBO	Quasi-Biennial Oscillation
GLAAM	Globally Integrated Angular Momentum	SF	Solar Flux
GMLOT	Global Mean Lan Ocean	SOI	Southern Oscillation Index
HA	Monthly totals Atlantic hurricanes	SR	Sahel Standardized Rainfall
MEI	Multivariate ENSO Index	SWMRR	SW Monsoon Region rainfall
NAO	North Atlantic Oscillation	TNA	Tropical Northern Atlantic Index
NAO_J	North Atlantic Oscillation	TNI	Indices of El Niño evolution
NBRA	Northeast Brazil Rainfall Anomaly	TPSST	Tropical Pacific SST EOF
NINO1+2	Extreme Eastern Tropical Pacific SST	TSA	Tropical Southern Atlantic Index
NINO3	Eastern Tropical Pacific SST	WHWP	Western Hemisphere warm pool

5.3 Methodology

In this section, the resampling and weather generator ESP methods are described, following which, the proposed method for this study is introduced and detailed. The experimental setup and evaluation framework are presented at the end of the section.

5.3.1 Resampling method

In this study, past observed climatology resampling is used as the benchmark method. This approach is the most commonly used non-parametric method for generating long-term ensemble weather forecasts. This work uses equiprobable resampling, with no reshuffling between precipitation and temperature years. The number of members in each of the ensembles is therefore equal to the number of years in the historical period up to the forecast year.

5.3.2 Stochastic weather generator

The stochastic weather generator used in this study is WeaGETS, which is a MATLAB-based daily scale weather generator (Chen et al. 2012a). WeaGETS starts by generating precipitation in two steps. The probability of a wet day is evaluated using a Markov Chain. On wet days, precipitation amounts are modeled using either an exponential or a gamma distribution. Minimum and maximum temperatures are then computed based on the wet or dry day status. A first-order auto-regressive process ensures the proper autocorrelation and cross-correlation of all three weather time-series. WeaGETS is based on the work of Richardson and Wright (1984). We use a first-order Markov Chain is used for precipitation occurrence. This implies that the probability of precipitation on any day only depends on the dry/wet status of the previous day. The exponential distribution is used to generate precipitation quantity as per equation (5.1).

$$f(x,\lambda) = \lambda e^{-\lambda x} \tag{5.1}$$

where $f(x,\lambda)$ is the probability density function with λ as parameters and x as variable, λ is the inverse of the mean daily precipitation, and x is the daily precipitation value.

5.3.3 Coupling large-scale climate indices with a stochastic weather generator

This approach consists of four main steps, as shown in Figure 5.3. First, for each forecast year, a regression model between a subset of large-scale climate indices and each weather variable (precipitation, maximum and minimum temperatures) is established based on common available years between the weather variables historical records and large-scale climate indices. In a second step, for each forecast during a year, the regression model is used to calculate predicted precipitation and temperature anomalies over the forecast horizon. These predicted anomalies are then used as perturbations to the stochastic weather generations previously calibrated using the entire historical record. In essence, the climate indices are used as predictors of climate anomalies in tuning the weather generator parameters. Next, a 500-year ensemble weather forecast (EWF) is generated using the weather generator. Finally, the hydrological response to the EWF is simulated using the hydrological model to create the ensemble streamflow forecast. These steps are explained in greater detail in the following sections.

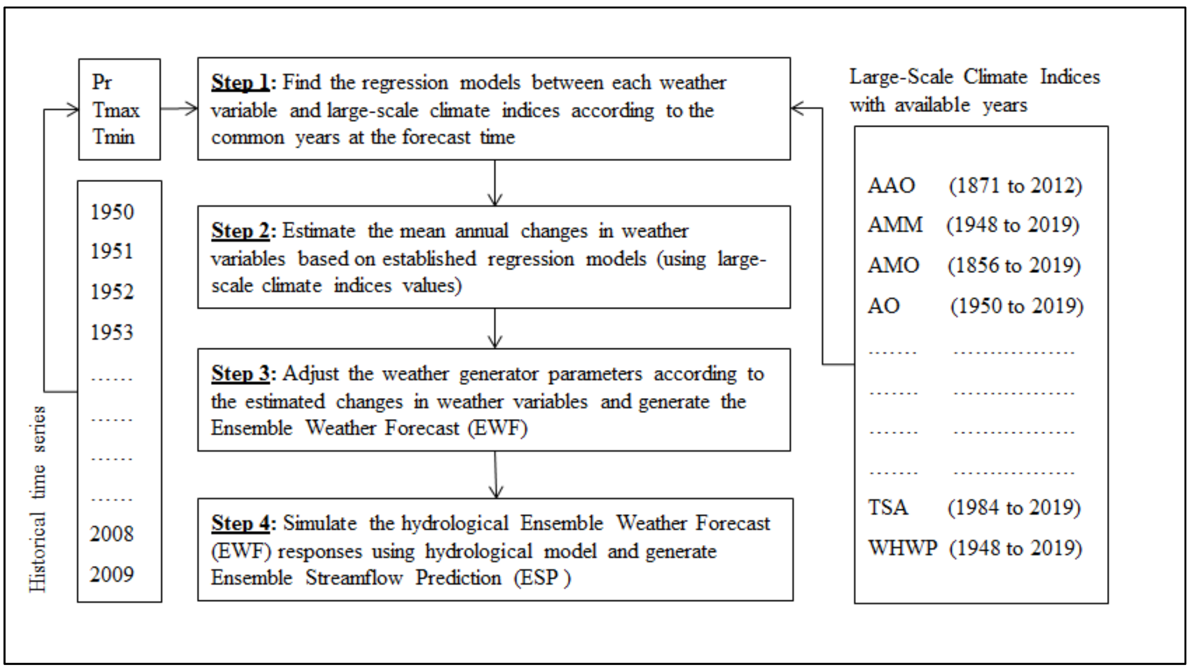

Figure 5.3 Procedure for coupling large-scale climate indices with a stochastic weather generator in long-term streamflow forecasting

5.3.3.1 Step 1- Weather variables' regression models based on large-scale climate indices

In the first step, a climate index best selection is made for each weather variable, at the annual scale. A simple stepwise linear regression is chosen for selecting the best subset of large-scale climate indices, as is shown in equation (5.2).

$$y_w = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i + \varepsilon \qquad (5.2)$$

Where y_w is the predicted weather variable (predictand), and w is either the mean annual precipitation, or the maximum or minimum temperature; x_i are the climate indices i (i=1, 2... 40) which are used as predictors, and β and ε are respectively the regression coefficients and residual.

The phase of climate indices varies in the inter-annual, multi-annual, decadal and multi-decadal timescales due to complex interactions between the atmosphere and sea-surface temperature anomalies. Consequently, the correlations between large-scale climate indices and weather variables are expected to vary in time due to non-linear interactions within the climate system. It is therefore also necessary to find the optimal time window to define these correlations. Accordingly, this study defines 5 time periods (last 5, 10, 15, 20 and 30 years) in its strategy to find the optimal time period for defining the regression between the climate indices and weather variables.

5.3.3.2 Step 2- Calculating expected precipitation and temperature anomalies at the forecast date

The regression models (previous step) are used to compute the expected mean annual precipitation and temperature anomalies over the forecast period. The anomalies represent the deviation from the historical climatology using the Change Factor method (Diaz-Nieto and Wilby 2005) as presented in equations (5.3) and (5.4).

$$\hat{P}_{(Anomaly)} = (\bar{P}_{(CI)} / \bar{P}_{(Ref)}) \qquad (5.3)$$

$$\hat{T}_{(Anomaly)} = (\bar{T}_{(CI)} - \bar{T}_{(Ref)}) \qquad (5.4)$$

The precipitation $\hat{P}_{(Anomaly)}$ and temperature $\hat{T}_{(Anomaly)}$ anomalies are expressed as the ratio (precipitation) and difference (temperature) between their projected values over the forecast period ($\bar{P}_{(CI)}$ and $\bar{T}_{(CI)}$) and historical mean values $\bar{P}_{(Ref)}$ and $\bar{T}_{(Ref)}$.

5.3.3.3 Step 3- Modification of the weather generator parameters

The parameters of the stochastic weather generator defining the monthly means are modified according to the calculated precipitation and temperature anomalies, using equations (5.5) and (5.6).

$$\bar{P}_{(WG)} = \bar{P}_{(ref)} \times \hat{P}_{(Anomaly)} \tag{5.5}$$

$$\bar{T}_{(WG)} = \bar{T}_{(ref)} + \hat{T}_{(Anomaly)} \tag{5.6}$$

where $\bar{P}_{(WG)}$ and $\bar{T}_{(WG)}$ become the main driving values as opposed to $\bar{P}_{(Ref)}$ and $\bar{T}_{(Ref)}$. The ensemble weather forecast (EWF) is then generated by the stochastic weather generator. The perturbation scheme only modifies the mean values, and variability remains based on the entire historical record.

5.3.3.4 Step 4-Hydrological simulation

In the final step, the hydrological response to the ensemble weather forecast (EWF) is simulated with a hydrological model. The HSAMI hydrological model was used in this study (Bisson and Roberge 1983; Fortin 2000). HSAMI is a lumped, conceptual, rainfall-runoff hydrological model with 23 adjustable parameters that was developed by Hydro-Québec. It is used for operational forecasting at the daily and hourly time scales over 100 catchments. It has also been used for many research applications across North America with good results (Arsenault et al. 2016a; Arsenault et al. 2013; Castaneda-Gonzalez et al. 2018). Two parameters are used for scaling potential evapotranspiration; six used for snowmelt, five for simulating horizontal flows, and ten for vertical flows. Water movement in the vertical axis is simulated by four interconnected linear reservoirs consisting of surface water, snow on the ground, and saturated and unsaturated zones. Water movement in the horizontal axis is filtered by one linear reservoir and two unit hydrographs. HSAMI requires daily precipitation and maximum and minimum temperatures as inputs. While the cloud cover fraction and snow water equivalent can also be used, these data are, however, not measured at the study site.

The calibration of HSAMI in this study was performed with the CMAES Covariance Matrix Adaptation Evolution Strategy (Igel et al. 2007) algorithm with the objective of finding the maximum value of the Nash-Sutcliffe Efficiency criteria. This algorithm choice was made following the work of Arsenault et al. (2013). In order to avoid injecting additional unnecessary biases due to the hydrological modeling, HSAMI was calibrated with all observed discharge data for 1950 to 2009, to include as much information as possible in the parameter set (Arsenault et al. 2018), and the simulated discharge was used in this work instead of observed discharge. This resulted in a 'perfect' hydrological modeling, therefore removing any uncertainty due to initial conditions as well as the need to implement a data assimilation system.

5.3.4 Evaluation Framework

To investigate the merits of using this method in long-term streamflow forecasting, the 1980-2009 time horizon is used as the hindcasting period, with the 1950-1979 period representing the original historical record. For each year of the hindcast period, the best regression model is chosen and applied to compute precipitation and temperature anomalies, using all of the preceding years as the historical record. Twelve forecasts are generated every year (on the first day of each month) to assess the sensitivity of the proposed method to the issue date. The method's performance is compared with the resampling method and the unmodified stochastic weather generator. Figure 5.4 shows the evaluation framework implemented in this study.

The Bias and Pearson correlation coefficient (R) are employed to evaluate the ensemble weather forecasts (EWFs). The Continuous Ranked Probability Score (CRPS) is used to evaluate the performance of the proposed ESP method.

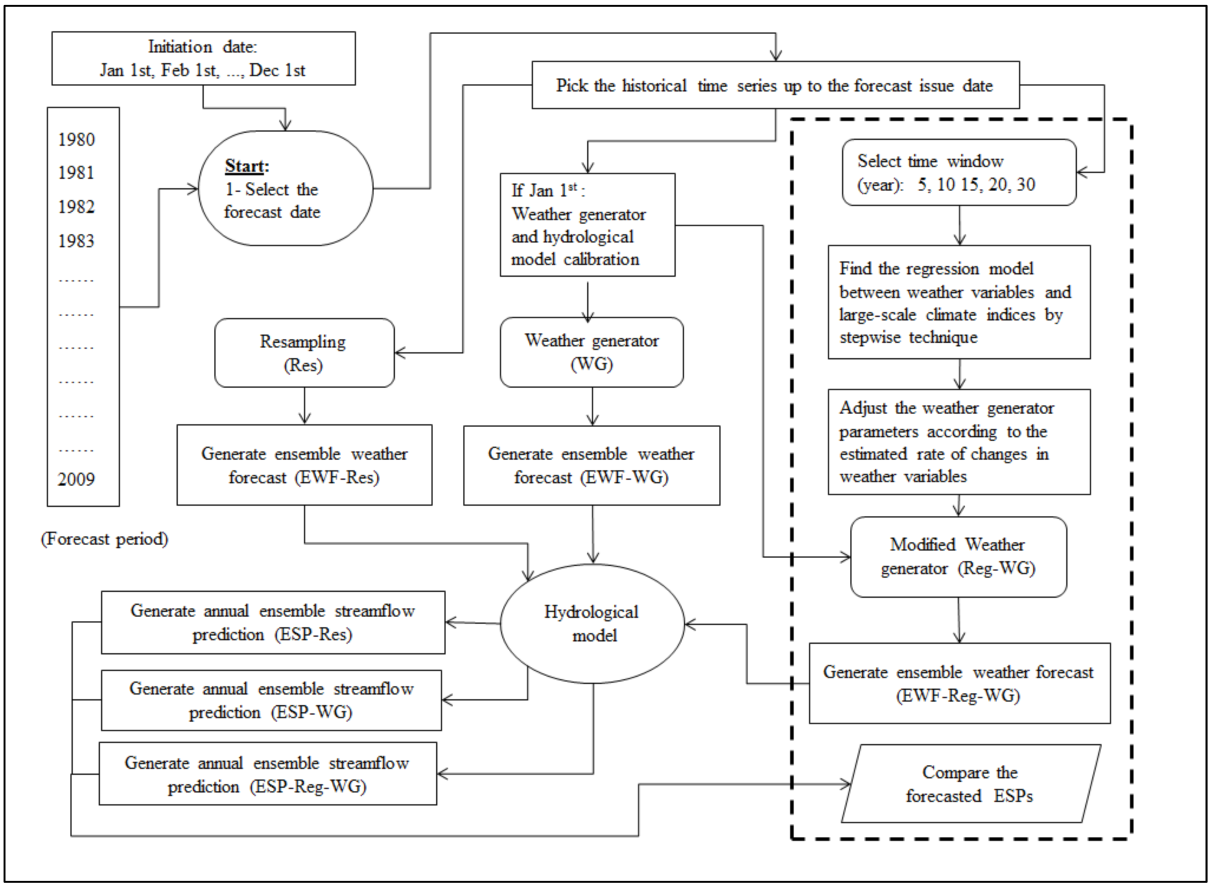

Figure 5.4 Study framework; the procedure for coupling climate indices with the stochastic weather generator is indicated within the dashed line area

5.4 Results

Figure 5.5 presents the correlation coefficient between the observed mean annual precipitation, the maximum and minimum temperatures and the mean annual value of each of the 40 selected climate indices. The correlations were all calculated using all common available years between the records of each climate index and weather variable.

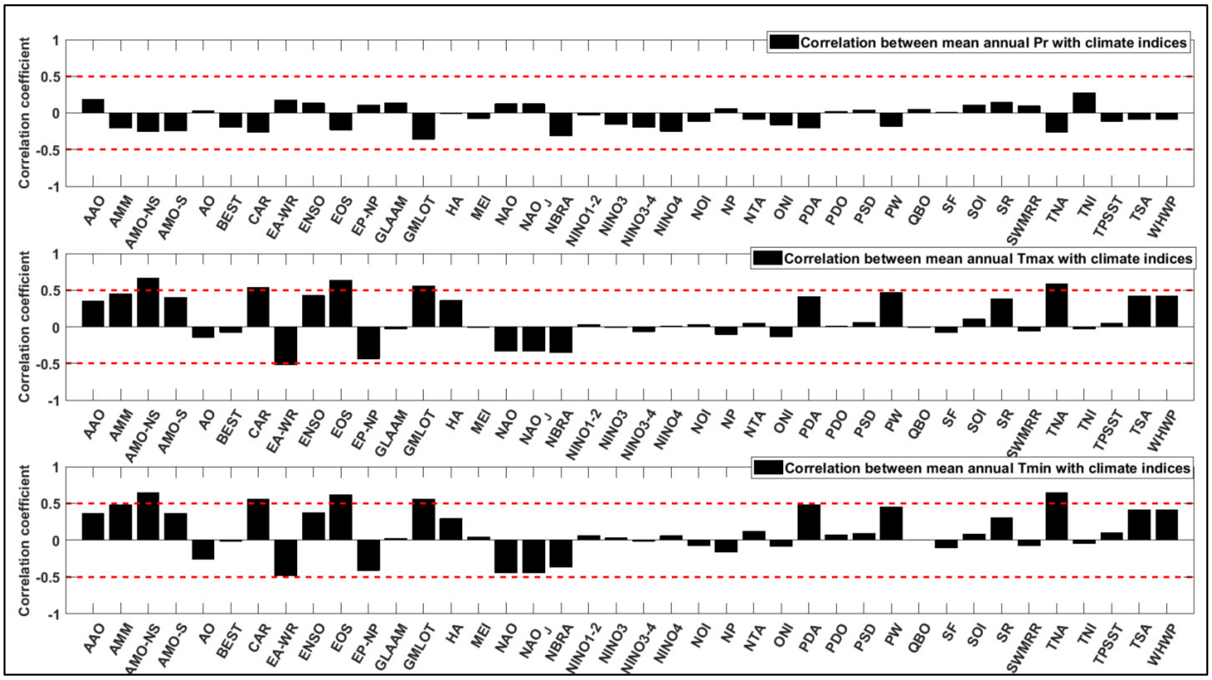

Figure 5.5 Correlation coefficient between mean annual climate index values and observed mean annual precipitation, maximum and minimum temperatures

Figure 5.5 shows that temperatures correlate more with large-scale climate indices than with precipitation. The number of large-scale climate indices which have a correlation with temperatures is also larger than for precipitation. However, because of the dynamical interactions between the various indices, correlations with surface variables may not be constant in time, and using a large time window to establish correlations may in fact hide stronger correlations in the shorter term, To illustrate this, Figure 5.6 shows the annual correlation between Nino-3 and a 10-year moving average for precipitation and maximum and minimum temperatures.

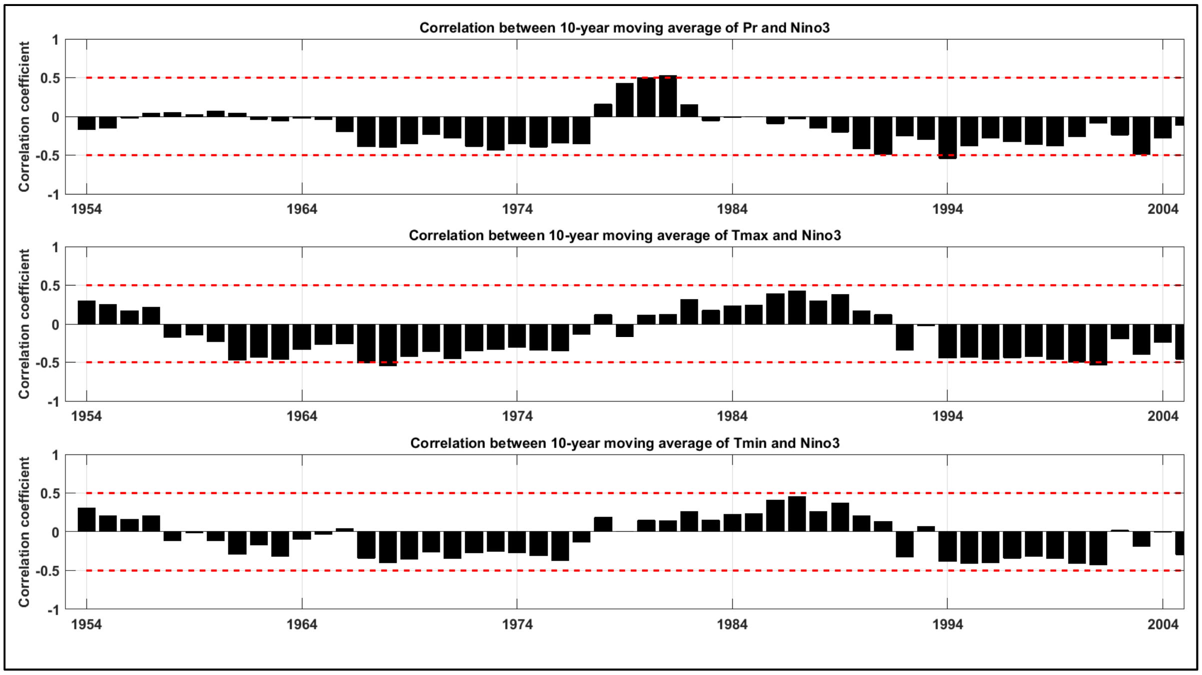

Figure 5.6 The correlation coefficient of Nino-3 with 10-year average of weather variables over long term from 1954 to 2004

Figure 5.6 clearly shows the cyclical nature of the correlation between NINO3 and climate variables on the Lake Saint-Jean watershed. As shown in Figure 5.5, there is no correlation with NINO3 when looking at the entire duration of the time series. To address this issue in identifying the relationship between large-scale climate indices and weather variables, 5 time windows (5,10,15,20 and 30 years) were considered for defining the regression models. The regressions between each weather variable and large-scale climate indices are dynamically constructed based on each new forecast year. The regression models are then used to assess precipitation and temperature anomalies to modify the weather generator. Figure 5.7 shows 1-year ahead predicted mean annual temperature and precipitation based on the regression models for every monthly forecast made over the 1980-2009 period. Each graph therefore contains 360 points.

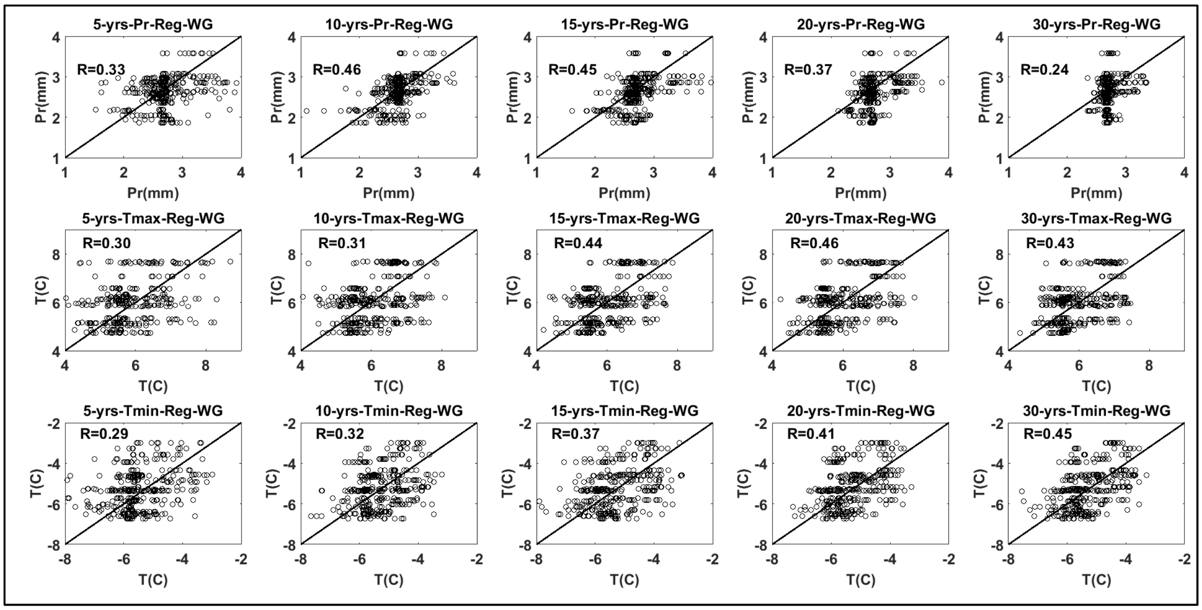

Figure 5.7 Correlation coefficients between forecast mean annual precipitations, maximum and minimum temperature and observed values for 360 year-long forecasts over the 1980-2009 period

Figure 5.7 shows a clear impact of the length of the time window used to build the regression models. The precipitation model favors a shorter time window of 10 to 15 years, whereas temperatures can make a better use of longer time series, up to their full length, and certainly longer than 15 years. Based on these results, 10-, 20- and 30-year time windows were selected to construct the optimum regression model for precipitation, maximum and minimum temperatures, respectively.

The number of times each climate index is used in a regression model is counted over every monthly forecast over the 30-year calibration period. Results are sorted and plotted in Figure 5.8.

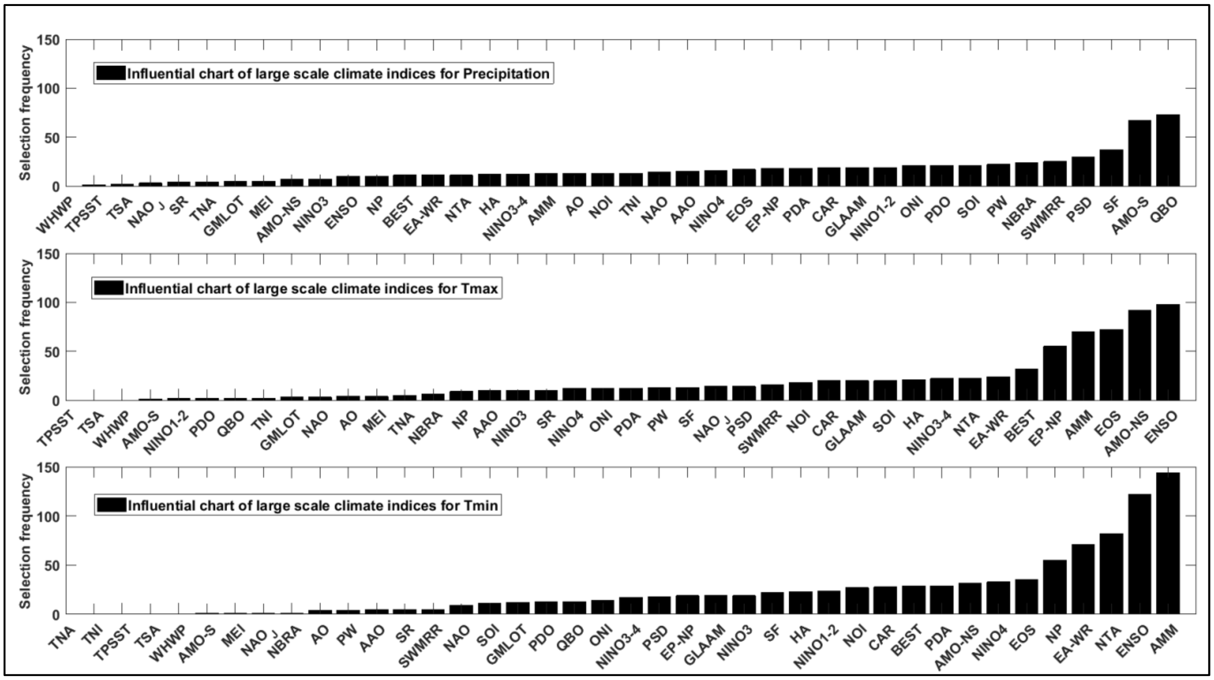

Figure 5.8 Selection frequency of large-scale climate indices for precipitation, maximum and minimum temperatures on Lake Saint-Jean watershed

As can be seen in Figure 5.8, a small subset of climate indices is systematically preferred. For temperature, a subset of 5 indices emerges, ENSO and AMM among the five most influential elements for both minimum and maximum temperatures. The others are AMO_NS, EOS and EP_NP, for maximum temperature, and NTA, EA_WR and NP, for minimum temperature. For precipitation, the selection frequency is more uniform, but two indices emerge nonetheless: QBO (Quasi-Biennial Oscillation) and AMO (Atlantic Multidecadal Oscillation).

To evaluate the performance of the proposed method in forecasting the mean annual precipitation, maximum and minimum temperatures, Figure 5.9 shows the biases between forecast and observed values. The Figure also presents the biases of the three chosen ESP methods, namely, resampling, weather generator and conditioned weather generator with regression time windows varying between 5 and 30 years.

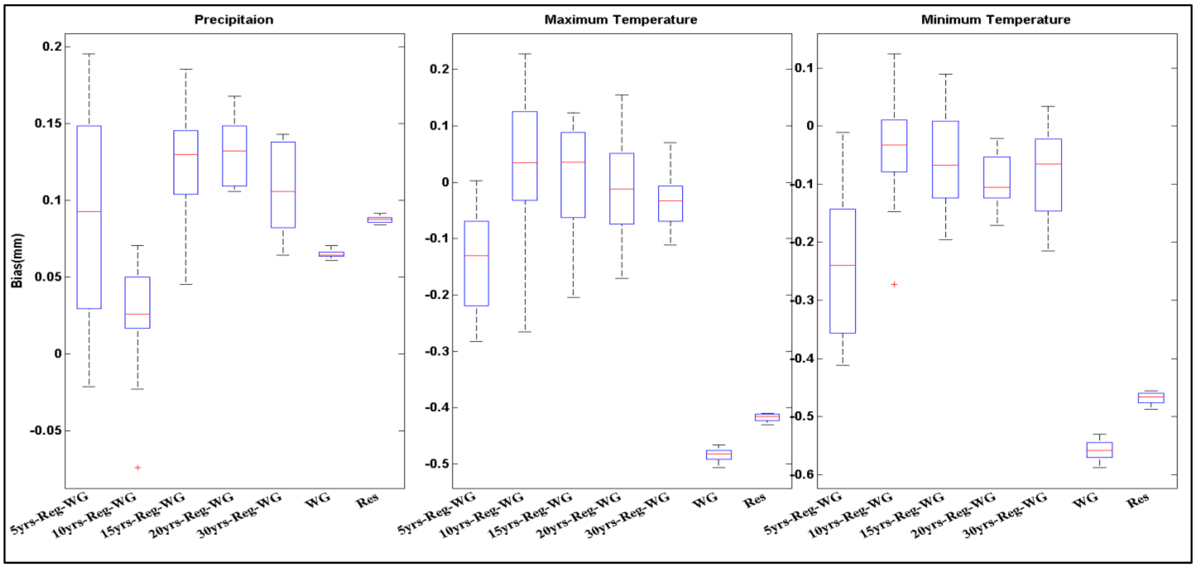

Figure 5.9 Distribution of mean annual biases between forecast and observed precipitation, minimal and maximum temperatures for all three ESP methods. Boxplots are comprised of 360 values corresponding to the 1-year forecasts made on the first of each month over the 1980-2009 period

As was the case for Figure 5.7, the performance of the proposed method in forecasting mean annual precipitation is strongly linked to the length of the time window used to build the regression model. The last 10 years is the best window length to use for the studied catchment. The mean biases are always smaller than for the other time windows and the resampling and basic weather generator benchmark methods. The proposed method also clearly decreases the mean bias of the forecast maximum and minimum temperature in comparison with the other two methods. This applies to all time windows. Using a longer time window gives slightly better results, especially for maximum temperature. The impacts of using the 5- to 30-year regression models on streamflow forecasts are presented in Figure 5.10 , which shows the mean annual forecast hydrographs over the 30-year hindcast period for the January 1st issue date.

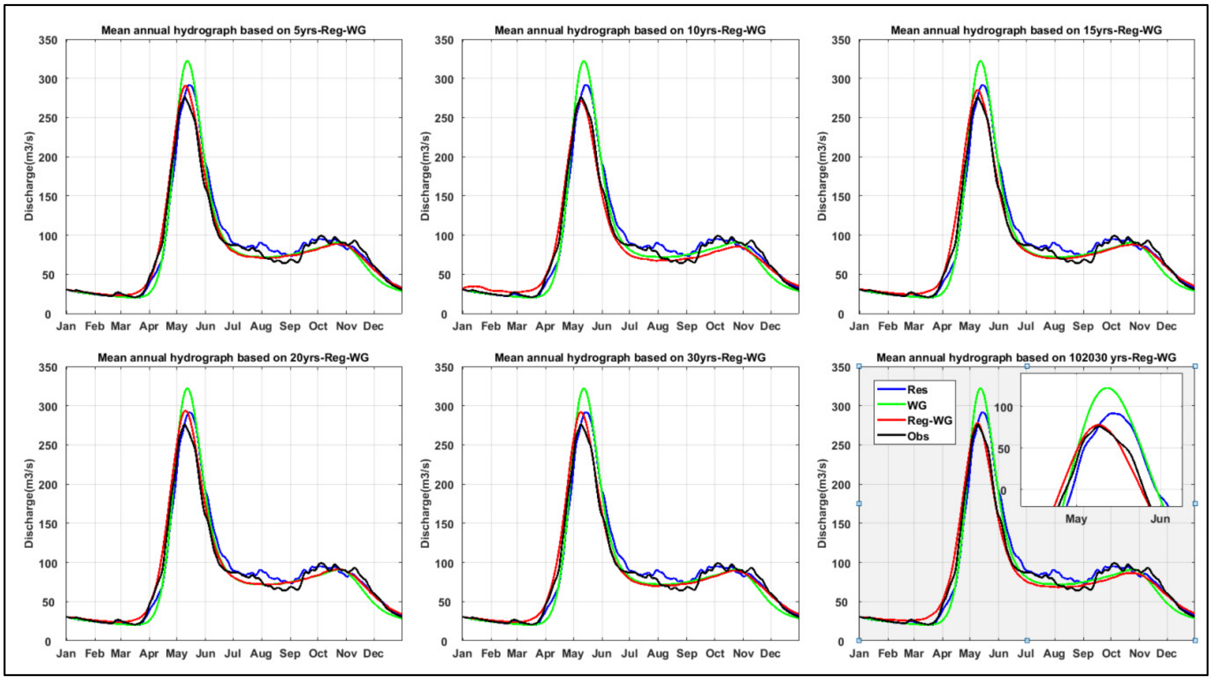

Figure 5.10 Mean annual hydrographs over the 30-year hindcast period for the proposed ESP method with window lengths of 5, 10, 15, 20 and 30 years. The bottom right graph shows the results with the optimal window length for each of the three variables. Results obtained for the two benchmark ESP methods are also shown in each graph

Figure 5.10 shows the impact of the window length on the performance of the proposed ESP. Using 10- or 15-year windows yields the best results, with noteworthy improvements around the spring flood. The best performance is obtained using 10-, 20- and 30-year time windows for precipitation, maximum and minimum temperatures, respectively (bottom right Figure). Historical resampling results in a late flood onset, along with an overestimation of flood peak. The performance of the basic weather generator is close to that of the resampling method, albeit slightly worse for the mean hydrograph peak flow. Figure 5.11 presents mean CRPS values for each method.

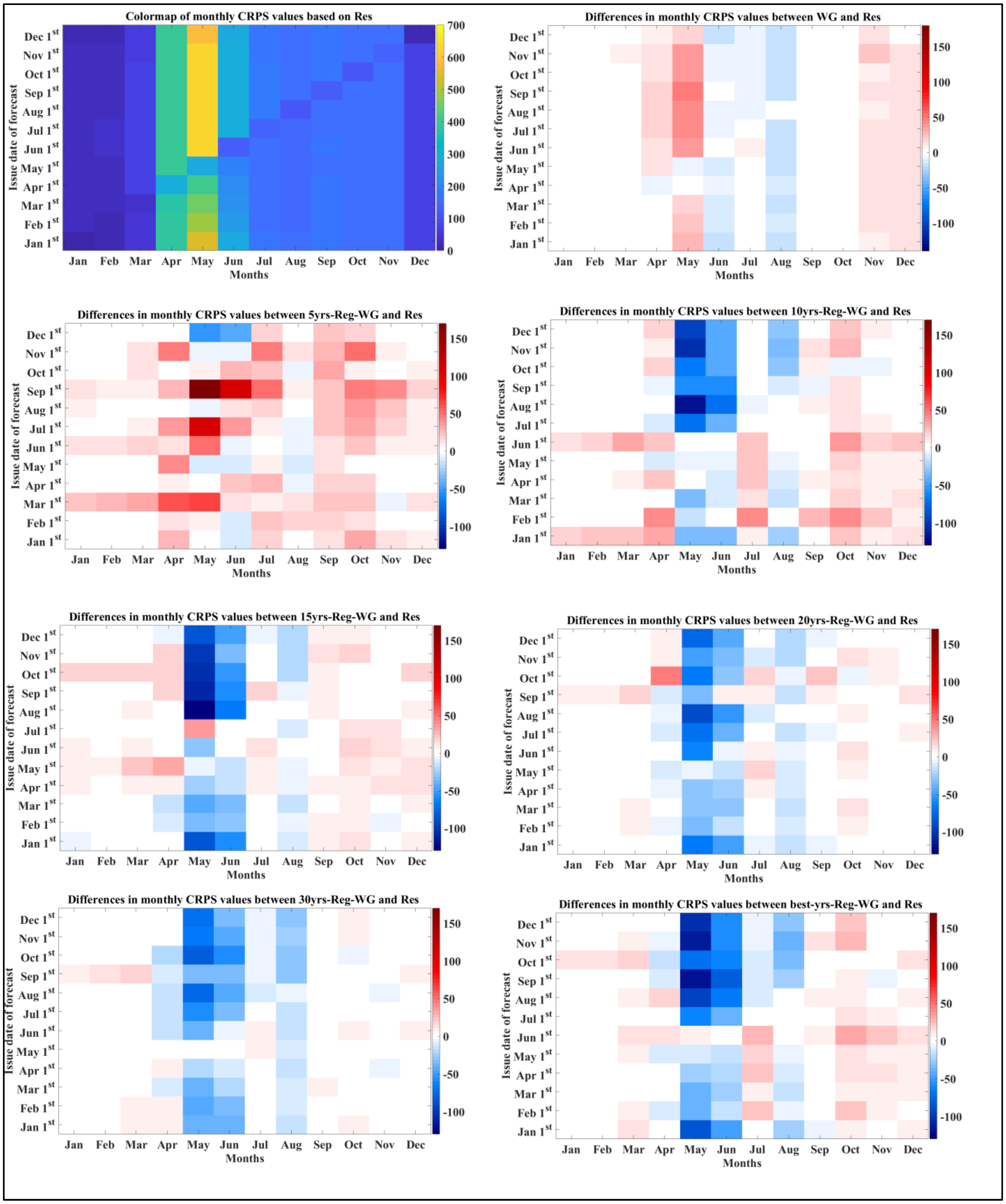

Figure 5.11 Upper left: Mean CRPS values for monthly 1-year ahead forecasts over the 1980-2009 hindcast period, for historical resampling. All other graphs: difference between Weather generator and perturbed weather generator using various time windows with resampling method

Values in blue indicate a lower CRPS, and therefore, an improvement over historical resampling. Values in red indicate a performance decrease. The Y-axis shows the issue date of forecast and the X-axis shows the extracted mean monthly CRPS values over 30 years of forecasts (from 1980 to 2009). The differences in mean monthly CRPS indicate that the performance of the calibrated weather generator is very close to that of the resampling method, with the exception of a slight overestimation around flood time, which is consistent with the results of Figure 5.10. The proposed perturbation method reduces CRPS values during the flooding period, but its performance depends on the chosen window length. Figure 5.11 shows that making ESP forecasts using regressions based on the past 5 years decreases forecast performance, whereas all other time windows produce better forecasts. The main improvements are observed for the spring flood, which is a critical period for water management. There are only minor differences between using 10- to 30-year windows, but using 15 years for all three variables nonetheless results in slightly better-performing forecasts for the flood period. Outside the flooding period, using a longer window yields slightly better results. Using optimal windows for all three variables (lower right Figure) provides results largely similar to that of using a fixed 15-year window.

5.5 Discussion

In this study, large-scale atmospheric and oceanic indices were used to describe patterns of natural climate variability. According to many studies, the control of large-scale climate indices on the climate is not constant through time, and this non-stationarity is expressed at different time scales (Hertig et al. 2015). It is therefore not surprising that the relationship between regional weather variables and large-scale climate indices is dynamic and non-stationary, as discussed in other studies (Nalley et al. 2019). Figures 5.5 and 5.6 demonstrate the extent to which correlations can be found to be absent or statistically significant, depending on the chosen time period. Finding the best time scale for investigating the relationship between weather variables and large-scale climate indices is one of the major challenges in this area (O'Brien et al. 2019). This study therefore considered 5 different time windows in building the best-performing regression model.

As was shown in the results of Figure 5.7, the precipitation regression models which are established based on shorter windows provide better precipitation estimates. In contrast, the temperature regression models benefit from longer windows. A possible explanation may be related to the concept of historical memory. Any climate state can be decomposed into two parts: "the memory part" and "the weather-scale dynamical excitation part" (Hasselmann 1976). The predictability of weather variables is limited by those two terms. Since measuring the dynamical forcing is challenging, attention is mostly concentrated on modeling the internal variability using the existing memory part (Doblas-Reyes et al. 2013; Meehl et al. 2014). It has been shown that climate memory has a non-negligible impact on most climate variables, with the exception of precipitation (Xie et al. 2019). According to earlier studies, the long-term memory contribution to the modeling and characterization of precipitation is weak, and, in some cases, long-term precipitation correlation behaves as white noise in precipitation modeling (Jiang et al. 2017). Therefore, the precipitation models rely less on the memory part than does the temperature model. This can explain why the best temperature models are built based on longer time windows. Another way of looking at this is simply to realize that at the spatial and temporal scales considered in this study, and for the chosen watershed, internal climate variability is much more important for precipitation than temperature, when compared to the synoptic control of sea surface temperature anomalies.

The influence of each climate index on weather variables was presented in Figure 5.8. These results indicate that many climate indices have a simultaneous influence on the local climate. While most of the work in this domain has tended to focus on the main indices (e.g., ENSO, AMO, NAO, PDO), the results from this study indicate that other indices also have a significant influence, a fact that is often neglected in other studies. In this work, AMO and QBO are identified as the two most significant climate indices in precipitation modeling. The impact of AMO over Eastern Canada has been relatively widely studied (Assani et al. 2010), but that of QBO, which influences convection and precipitation (Gray et al. 2018), has largely been neglected. Recent studies also suggest that there is a need to improve our understanding of other climate indices in order to increase North American climate predictability (Hartmann 2015; Kug et al. 2015; Wang et al. 2014). The results for the studied watershed indicate that a comparatively larger number of indices are correlated with temperature, as compared to precipitation. The same findings are obtained in other studies that have attempted to assess the complex interaction between multiple large-scale climate indices and weather variables (de Beurs et al. 2018; Leathers et al. 1991; Tomingas 2002). Climate studies have shown that temperature variability is largely related to synoptic scale variability, while precipitation is significantly more affected by the local scale, and is hence driven by large-scale circulation to a much lesser extent than is temperature. Climate change impact studies have also clearly demonstrated the importance of the spatial scale when looking at precipitation variability (Fischer and Knutti 2014; Martel et al. 2018). Variability becomes less important as we go from the local to the regional scale. Accordingly, looking for relations between precipitation and large-scale circulation poses a much bigger challenge at the catchment scale than it would be at the regional scale, with the exception of the largest continental size catchments.

The performance of the proposed method in forecasting mean annual precipitation and temperatures was evaluated and compared to that of historical resampling, and using the basic calibrated weather generator. Results showed that the proposed method reduced both precipitation and the temperature mean annual biases in comparison with the two other methods. It improved temperature forecasting for all the time windows considered. Improvements in precipitation forecasting were more dependent on the time window considered to build the regression model. These results were largely transferred to streamflow forecasts after a hydrological model was used. The ensemble streamflow forecasts were assessed by looking at the forecast mean annual hydrographs and monthly CRPS values. The results presented in Figures 5.10 and 5.11 suggest that spring flood can be better estimated when a 10-year or longer time window is used to build the regression models. The proposed method performed well at estimating the flood onset. This improvement is related to a better temperature estimation as shown in Figure 5.9. Temperature is the main driver of snowmelt initiation, and therefore plays a key role in the physical processes leading to the onset of the spring flood. It has been shown that the flood onset and recession are mainly determined by temperature (Barnett et al. 2005). An under- or overestimation of forecast temperatures will affect all streamflow characteristics during the snowmelt period. The benchmark methods of resampling and unconditioned weather generator lead to a forecast flood beginning too late, on average. This results when forecast temperatures are too cold, as has also been reported in other studies (Hongbo et al. 2015; Liu et al. 2019b; Meng et al. 2019). The increasing temperature trend in Figure 5.2 cannot be captured by both benchmark methods. The incorporation of large-scale climate indices in the forecasting process leads to a better representation of temperature anomalies during the snowmelt period, thus leading to better flood forecasts.

The methodological framework chosen for this study comes with limitations. An important one is that the hindcast approach used in this project assumes perfect a priori knowledge of climate indices over the forecasting period. In real life, these values will not be perfectly known as climate indices would also have to be forecast. This is not necessarily a problem for decadal indices, but it is definitely a challenge for interannual indices such as ENSO, which have been shown to be difficult to accurately forecast (Ham et al. 2019). The proposed methodology could be improved in many ways. While this work only considered stepwise regression, more complex non-linear approaches (e.g., neural networks) could be used to link climate indices to local climatology. Since it is known that local-scale induced variability is largest in the summer, it would likely be beneficial to perform the analysis on a seasonal basis. This should result in better performance over the winter season than the performances presented at the annual scale. As well, this would lessen the problem of having to forecast the climate indices over the longer yearly horizon. Finally, the results presented cannot be generalized to other watersheds since the links between sea surface temperature anomalies and the local climate are region-dependent. The approach should therefore be tested on other watersheds.

5.6 Conclusion

This paper presented a long-term ensemble streamflow forecasting method in which a stochastic weather generator is conditioned on large-scale climate indices to take into account internal climate variability. Stepwise linear regression models between a subset of 40 climate indices and local climate anomalies are built to represent climate non-stationarity for an

Eastern Canadian catchment. The stochastic weather generator uses the predicted climate anomalies to produce an ensemble weather forecast. This forecast is then fed to a hydrological model to generate long-term ensemble streamflow forecasts. Results show that the proposed method improves long-term streamflow forecasts over the studied catchment, and especially around the flood peak. Results also show a strong dependence on the time window duration used in defining the regression models. Shorter durations are preferable for precipitation, whereas longer time windows result in better performance for minimum and maximum temperatures. These results are consistent with the larger internal climate variability of precipitation at the catchment scale.

CHAPITRE 6

DISCUSSION

Uncertainty about current and future water supply makes water management a challenging task. Streamflow forecasts play an important role in water resources management. Many sources of uncertainty affect streamflow forecasts, and most of these grow with the forecast lead time (Zhang et al. 2019) which makes long-term forecasts particularly challenging. In addition to the traditional challenges of long-term streamflow forecasting, climate non-stationarity related to global warming brings additional uncertainties to the forecasting process (Solomon et al. 2007). Non-stationarity causes trends and other inhomogeneities in hydrological time-series. Ignoring trends in climate variables and assuming stationarity can result in biased sub-optimal streamflow forecasts (Blöschl et al. 2019; Liu et al. 2019b). Reliable long-term streamflow forecasts should therefore consider all sources of uncertainties into account including climate uncertainty.

Significant trends for many climate variables have been observed in most parts of the world including Canada (Vincent et al. 2018). These trends are particularly large for winter temperature and can impact long-term streamflow forecasting. Bush and Lemmen (2019) showed that resampling past climatology (directly, or with a stochastic weather generator) without accounting for climate non-stationarity may result in biased forecasts which fail to accurately predict the onset and magnitude of the spring flood. This issue is particularly relevant for snow-dominated catchments such as Lac Saint-Jean where increasing temperatures directly affect snowmelt and streamflows (Mote 2006).

One of the major challenges in a non-stationary climate is to find applicable approaches to transfer climate variability patterns into the hydrological modeling chain for streamflow forecasting. Non-stationarity can manifest itself as a monotonous change, as a sudden shift in mean or variability, or a combination thereof. One possible approach to take these into account is to allow the distribution/model parameters to evolve with time (Richards 2012). In this way, the parameters of distribution/ hydrological models are updated as a function of time or according to another measure of climatic variability. In this work a stochastic weather generator was chosen for modeling non-stationarity. The parameters of the stochastic weather generator are initially calibrated using the entire historical record to capture internal variability and mean climate. This study looked at two different approaches to model mean climate anomalies as perturbations to the weather generator.

The first step in this work was to evaluate the ability of a stochastic weather generator at generating ensemble weather forecasts suitable for streamflow forecasting. The benchmark for this first step was the widely used method of resampling past historical data. Results showed that a stochastic weather generator can indeed be used for long-term forecasting with a performance similar to that of historical resampling. With these positive results, it was then possible to look at different approaches to induce parameter perturbation to account for climate variability.

The first approach presented was specifically designed to take into account gradual changes in mean climatic values, such as induced by anthropogenic forcing. Using shorter time windows to calculate mean monthly values specifically recognizes that recent years should be weighted more heavily than earlier years. This approach can take into account monotonous trends as well as inter-annual up to decadal internal variability, with the former being characterized by the autocorrelation of hydrometeorological time series. In both cases, using a time-window shorter than the historical record simply recognizes that the past ‘n’ year are more likely to be good predictors of climate anomalies for the upcoming year than older years (Giles and Flocas 1984; Mirza et al. 1998; Yue et al. 2002). According to Sharma et al (2019), annual precipitation time series in particular have been shown to exhibit autocorrelation patterns in a majority of the world’s regions. Di Cecco et al (Di Cecco and Gouhier 2018) also showed that there is a high temporal autocorrelation for temperature time series and that climate change is expected to increase temporal autocorrelation at the global scale. There is therefore scientific justification to support this overall simple perturbation method to improve long-term streamflow forecasts.

The second method specifically looked at using atmospheric and oceanic large scale anomalies as predictors of precipitation and temperature anomalies resulting from internal climatic variability. While the previous method can potentially take into account both monotonous trends and internal variability, method two is resolutely oriented towards internal variability.

Both methods rely on the perturbation of monthly mean anomalies used by the weather generator. In both cases, the entire historical record is kept to compute the other statistics and, in particular monthly temperature variability and cross-correlation between temperature and precipitation. While it is very likely that variability will be affected by anthropogenic forcing (as shown by climate models simulations), such changes are typically small compared to mean temperature changes and unlikely to be easily detected and modeled only using a partial historical record. Using a too short time window brings the risk of under-estimating variability and it was therefore decided not to try modeling climate variability anomalies as part of this project. It should however be noted that this work uses the exponential distribution to model precipitation amounts. For this distribution, the standard deviation is related to the mean value. Correcting for mean precipitation anomalies therefore also affect precipitation variability. Such is not the case for temperature.

Results showed that both methods successfully improve the long term streamflow forecasting skill. The largest improvement was seen during the spring flood, where both benchmark methods predicted a late flood onset due to the increase in temperature linked to global warming.

Many questions arise from the findings of this work with respect to the two developed methods to improve long-term streamflow forecasting. These questions are introduced and discussed below.

Are both methods transferable to other watersheds and other climate regions?

Both methods can definitely be applied to other climatic region and therefore any watershed. However the ability of each method to improve long-term streamflow forecasts will depend on the region's hydroclimatic characteristics. The first method relies on gradual trends in observed climate variables, or at least on a somewhat strong autocorrelation of the same variables. The second method relies on existing relationship between climatic variables and large scale climate indices. Therefore, the first method should work better in regions with low internal variability or in regions with a stronger climate change trend (like high-latitude regions), whereas the second one should perform better in regions where internal variability dominates the anthropogenic climate change. In regions of large inter-annual variability with only weak correlations to climate indices, it is likely that the performance of both proposed methods will not be much better than that of traditional resampling.

What are the limitations for using both methods in the real world?

The efficiency of the first method is highly dependent on the existence of a statistically significant autocorrelation in hydrological time series. The optimal length of the time-window for extracting the climate information is determined by the number of positive autocorrelation lags in precipitation and temperature time series**.** In a case of weak autocorrelation or rapid changes in precipitation and temperature time series, the first proposed method may not show quantifiable improvements of long-term streamflow forecasts. Finding the optimal time-window for extracting the suitable climate information is the most challenging aspect of this method. The applicability of the second method is mainly limited to the existence of relevant large scale climate indices. Therefore, finding a relevant subset of climate indices and relevant time-scales are the main challenges to the applicability of the second method. A limitation of the second method as used of this study is the perfect a-priori knowledge of the value of large scale indices over the forecast horizon. In real world, we would have to either rely on the current value of indices, or rely on forecasted values of the indices which is not a trivial task.

Which method should be preferred?

The first method in definitely more simple and straight forward in its applicability. There is no need for external covariates as the approach simple relies on existing climate time series. The determination of the optimal time-window remains the most complex step but can be determined to a large extent by looking at autocorrelation of relevant climatic variables. As mentioned above, this method is likely to provide best results in regions with low climatic internal variability and/or in regions with a stronger climate change trend.

The second method is more complex since it involves external covariates. Using covariates in the forecasting process brings new sources of uncertainties and increases the complexity of the forecasting process. There are however some advantages in using the second method, and notably in regions where climate variables display a higher level of internal climate variability, such as observed in tropical zones for examples. This method can quickly react to changes in climate indices which can be quite sudden, whereas the first method will display a strong inertia to rapid changes. For example, the second method could deal with a rapid ENSO shift (e.g. from El Niño to La Niña), whereas the first method would be totally transparent to this change.

In essence, both approaches have advantages and disadvantages and their relative performance will depend on the nature of the non-stationarity observed in climate variables. It is therefore not possible to put one method ahead ot the other.

Does using either method result in real-world measurable improvements in water resources management?

The main application of both proposed methods is in long-term water resources management and in particular for hydropower generation. Both methods have shown improvements in long-term streamflow forecasts, which should, in principle improve decision-making for water resources management. However, the observed improvements are relatively small and uncertainties remain large for longer lead-time, as is the case for all long-term streamflow forecasting methods. To definitely answer this question, one would need to simulate all past operation rules in hindcasting mode using the new ensemble forecasts from both methods, and use metrics to estimate whether or not an operational efficiency can be measured. For hydropower, such a metric could be total produced energy, or unproductive spills for example In any event, this is not a trivial task.

6.1 Future work

There are many recommendations for future work to build and improve the work presented in this Thesis. As mentioned immediately above, evaluating the impact of the method on real-world management would be important. The economic benefit of the proposed methods can be assessed by using the improved streamflow forecasts in a reservoir operation plan. Hydropower generation is affected by reservoir inflow forecasting. In a study by Hamlet (Hamlet et al. 2002) the annual revenue of hydropower generation using long-term streamflow forecasts has seen increases up to 45%. Therefore, a logical next step of this project would be to focus on assessing the economic benefit of both methods on hydropower generation.

The performance of both methods should be compared and further assessed in other watersheds in different climate zones. As discussed earlier, the first method should work better in regions with low internal variability or in regions with a stronger climate change trend (like high-latitude regions), whereas the second one should perform better in regions where internal variability dominates the anthropogenic climate change.

A single-site stochastic weather generator was used in this study and a lumped modelling approach was used for the chosen watershed. Using a distributed approach with a multi-site weather generator could improve hydrological modeling (Caron et al. 2008) by better representing hydroclimatic spatial variability. The lumped approach was chosen for this work in order to limit the complexity of this exploratory work.

Skillful seasonal forecasts are valuable to sectors and provide valuable information to management authorities as well (Arnal et al. 2018; Coughlan de Perez et al. 2017). This thesis focused on the annual scale. It is however known that anthropogenic climate change and internal variability present seasonal patterns. Winter temperature has increased more than in the summer. The impact of most climate indices is also easier to detect in the fall and winter. It is therefore possible that additional performance gains could be made by applying the proposed methods at the seasonal scale. Climate variable anomalies and relationship to climate indices would have to be defined at the seasonal scale instead of annual, as done in this work. The performance of the proposed methods at the seasonal scale could then be compared against seasonal weather forecasts which are becoming more widely available.

6.2 Contribution to science

This study provides a detailed assessment on the use of a stochastic weather generator for long-term streamflow forecasting. Stochastic weather generators have been widely assessed as to their ability to generate time series with statistical properties similar to that of the target series. The complex non-linear interactions between generated time series of precipitation and temperature have also been evaluated, albeit to a much smaller extent, through the use of hydrological models to generate streamflow series. This work goes one step further with the evaluation of weather generator outputs for long-term streamflow forecasting. The evaluation framework allows investigating the performance of a stochastic weather generator according to various aspects. The 30-year hindcast period is long enough to evaluate the joint impacts of anthropogenic forcing and internal variability. The sensitivity to the date of forecast was investigated by using 12 issue dates within a year. This work therefore presents a comprehensive study of the ability of a stochastic weather generator at providing long-term ensemble streamflow forecasts. The results of this study can be confidently used as a reference for other studies.

This study is one of the first using a stochastic weather generator to generate long-term weather and streamflow forecasts. More importantly, it is very likely a first study using a weather generator perturbation scheme to take into account climate variability in the recent past. Perturbation schemes have previously been applied to weather generators for climate change impact studies in a few studies, but this is a relatively straightforward application since you are comparing two highly contrasted well-defined periods. Using a perturbation scheme with a weather generator opens up interesting research avenues to generate ensemble weather forecasts more in-tune with the current state of climate anomaly at the time of making a long-term forecast.

Two original methods to do so were presented in this study. The first one is relatively simple and is based on the concept that recent years are more representative of the current climate than older years. We proposed a framework to find the optimal time-window length to define the mean climate state at the forecast issue date. Keeping the entire historical record to define variability while only keeping the 'n' previous years to define the mean current climate is also an original contribution that exploits the non-stationarity characteristics of both components. The second method is more complex and proposes to use large-scale oceanic and atmospheric circulation indices as co-variates to define the state of the mean climate at the moment of generating a streamflow forecast. While our implementation of a stepwise regression is a relatively simple one, we believe this is a first study using large-scale indices to drive a weather generator. Overall, both proposed methods have been shown to improve the quality of long term streamflow forecasts and this opens up other research opportunities to improve the methods presented in this Thesis.

CONCLUSION

The purpose of this project was to improve long term streamflow forecasts for water resources management using a stochastic weather generator. The project was conducted into three steps and applied to the Lake St-Jean watershed in central Quebec. In the first step, the performance of a stochastic weather generator at generating long-term streamflow forecasts was compared to that of resampling past historical time series. In steps 2 and 3, two methods were introduced to condition the parameters of a stochastic weather generator, in order to take climate non-stationarity into account. The first approach was designed to take into account gradual changes in mean climatic values, such as induced by anthropogenic forcing. Using shorter time windows to calculate mean monthly values specifically recognized that recent years should be weighted more heavily than earlier years. The second method specifically looked at using atmospheric and oceanic large scale anomalies as predictors of precipitation and temperature anomalies resulting from internal climatic variability. Approach 1 can potentially take into account both monotonous trends and decadal internal variability, whereas method two was oriented towards taking internal variability at the interannual scale into account.

Step 1 results showed that weather generators can be used as substitutes to resampling the historical past to produce long-term streamflow forecasts. Results from the second paper (step 2) showed that the approach improves long-term streamflow forecasts accuracy, but that results are dependent on the time window used to estimate current mean climatic estimates. Finally, the third paper (step 3) showed that temperatures are significantly correlated with large-scale climate indices, whereas precipitation is only weakly related to the same indices. The length of the time window has a considerable impact on the prediction ability of the linear models. The precipitation models based on short-duration time windows performed better than those based on longer windows, while the reverse was found for the temperature models. The proposed method also improved long-term streamflow forecasts, particularly around the spring flood.

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