

# Downscaling of weather generator parameters to quantify hydrological impacts of climate change

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**ABSTRACT:** A major obstacle in quantifying the hydrological impacts of climate change is the mismatch between the coarse resolution of climate model outputs (general circulation models and regional climate models) and the fine resolution requirements of hydrological models. This research presents a statistical downscaling approach combining the attributes of both the stochastic weather generator (WG) and the change factor (CF) method to overcome this problem. It is further compared against the commonly used CF method in terms of quantifying the hydrological impacts of climate change over the next century for a Canadian watershed (Quebec Province). Both downscaling methods suggested increases in winter (November–April) discharge and decreases in summer (June–October), especially for those downscaled by the WG-based method. The WG-based method predicted higher peak discharges than the CF method. The 2 downscaling methods suggested significantly different increases in annual and seasonal discharges, particularly for low flows. Hydrology results show that precipitation and temperature variability play a very important role in the runoff generating process, and that neglecting to address this variability can lead to biased results. In particular, the WG-based method has a significant advantage in simulating low flows because it takes into account the change of precipitation occurrence. The results also outline the uncertainty linked to the choice of a downscaling method.

**KEY WORDS:** Statistical downscaling · Stochastic weather generator · Change factor method · Hydrology · Climate change

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## 1. INTRODUCTION

There is substantive empirical evidence showing that the frequency of rainy days and heavy precipitation events increased during the last century for North America (Groisman et al. 2005, Pryor et al. 2009). The Intergovernmental Panel on Climate Change (IPCC 2007) stated that the average surface air temperature of Earth will likely increase between 1.8 and 4.0°C by the end of this century and that the variability of precipitation will also be on the rise. Climate change will affect the global hydrological cycle and, consequently, assessing the changes in

future precipitation (quantity and variability) is a priority. Quantifying the impacts of climate change requires a tool or an approach that is able to produce climate projections. General circulation models (GCMs) have been developed to meet this requirement. However, the spatial and temporal resolutions of current GCMs are too coarse to assess the watershed and site-specific impacts of climate change (IPCC 2007). Even though daily-scale data is available for some GCMs, it is still unsuitable for medium and small watersheds, as well as for site-specific impact studies in the current form. For example, precipitation simulated by climate models usually has

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too many small events resulting in an overestimation of the wet day frequency, as well as biases resulting in an under/overestimation of the mean annual precipitation (Rivington et al. 2008). Dynamical and statistical downscaling methods have been developed to resolve this issue. Dynamical downscaling was developed based on dynamic formulations using the initial and time-dependent lateral boundary conditions of GCMs to achieve a higher spatial resolution by nesting regional climate models (RCM) (Caya & Laprise 1999). The spatial resolution of RCMs are much higher than that of GCMs. However, the resolution remains too coarse for small and medium-sized watersheds as well as for site-specific impact studies. Moreover, RCM data is only available for limited regions, due to the large computational cost of running the models (Solman & Nunez 1999). To overcome this problem, statistical downscaling methods have been developed. These involve linking the states of some variables representing a large scale (GCM or RCM grid scale, predictors) to the states of some variables representing a much smaller scale (catchment or site scale, predictands). A range of statistical downscaling methods have been developed and can be classified into 3 categories: transfer function (Wilby et al. 1998a, 2002a), weather typing (von Storch et al. 1993, Schoof & Pryor 2001) and weather generator (WG)-based approaches (Wilks 1992, 1999, Zhang 2005, Qian et al. 2005, 2010, Kilsby et al. 2007). Each category has its advantages and drawbacks. For transfer functions and weather typing schemes, the main drawback is that they usually lack strong and stable correlations between predictors and predictands, especially when using precipitation as a predictand (Chen et al. 2012). In the case of WG approaches, the adjustment of transition probabilities, such as a wet day following a wet day ( $P_{11}$ ) and a wet day following a dry day ( $P_{01}$ ) is still a challenge. Transfer functions are the most widely used methods, with vorticity, airflow indices, wind velocity and direction, mean sea-level pressure, geopotential heights and relative humidity as the most commonly used predictors (Wilby et al. 1998b, Sailor & Li 1999, Solman & Nunez 1999, Trigo & Palutikof 2001). The challenge in selecting appropriate predictors is that they must be realistically simulated by GCMs while being strongly correlated to the predictand. In many cases, several downscaling studies used more than one of these techniques (Wilby & Wigley 1997, Schoof et al. 2010)

Over the past decade, stochastic WGs have been commonly used as downscaling tools for climate change studies (Wilks 1992, 2010, Wilby et al. 2002b,

Pruski & Nearing 2002, Zhang et al. 2004, Qian et al. 2005, 2010, Zhang 2005, Zhang & Liu 2005, Kilsby et al. 2007). Daily stochastic WGs like WGEN (Richardson 1981, Richardson & Wright 1984), CLIGEN (Nicks & Lane 1989, Nicks et al. 1995), WeaGETS (authors' unpubl. data), and LARS-WG (Semenov & Barrow 2002) can rapidly produce climate projections at a daily time scale that can be used to quantify the impacts of climate change. These weather generators are developed based on parametric and nonparametric methods, but the parametric method is the most commonly used one. Apipattanavis et al. (2007) also presented a semi-parametric multivariate and multisite weather generator that generates precipitation states with a 3-state, first-order Markov chain and multivariate variables with a k-nearest neighbor bootstrap resampler.

There are 2 main approaches for parametric adjustments of WGs (Wilks 2010). The first involves a day-by-day change to the WG parameters based on daily variations in atmospheric circulation (Wilby et al. 2002b). The other one is the most commonly used method and involves changes in WG parameters based on changes of monthly statistics projected by climate models (Qian et al. 2005, 2010, Zhang 2005, Kilsby et al. 2007, Wilks 2010). Wilby et al. (2002b) explored the use of synoptic-scale predictor variables (North Atlantic oscillation and sea surface temperature) to downscale both high- and low-frequency variability of daily precipitation at sites across Great Britain. The results showed that conditionally stochastic rainfall models displayed additive effects on monthly rainfall statistics. However, the relationship between precipitation parameters and indices was very weak for most of the tested stations. Furthermore, Schoof et al. (2010) constructed regressive models between WG parameters (precipitation parameters) and large scale predictors for developing daily precipitation projections for the United States. Again, the performance of regressive models depended on the correlations between precipitation parameters and large scale predictors.

Other work indicates that statistical downscaling using GCM precipitation directly as a predictor performed much better than using other predictors (Widmann et al. 2003, Zhang 2005). Wilks (1992) originally proposed a method modifying the daily WG parameters based on the changes of monthly averaged statistics projected by climate models. This method modified the unconditional probability of daily precipitation occurrence and a dependence parameter instead of the precipitation transition probabilities of precipitation occurrence. For the

downscaling of mean maximum and minimum temperatures ( $T_{\max}$  and  $T_{\min}$ ), changes in the mean of observations were reflected directly in the expected changes projected by GCMs. Temperatures were downscaled conditioned on wet and dry days, but the same changes were applied to the mean for wet and dry days. Zhang (2005) also presented a method for statistically downscaling GCM monthly outputs from GCM grid scale to site-specific scale using GCM-projected precipitation and temperature as predictors. GCM-projected monthly precipitation was first spatially downscaled from a grid box to a target station using transfer functions. The spatially downscaled monthly precipitation was then downscaled to daily precipitation series at the target station using CLIGEN. For the downscaling of precipitation occurrence, transition probabilities were adjusted based on spatially downscaled monthly precipitation. This method has not been tested in different climates, and the relationships between transition probabilities and monthly precipitation may depend on geographical location. A spatially downscaled monthly mean  $T_{\max}$  and  $T_{\min}$  were directly used in CLIGEN as the adjusted parameters for the changed climate. Adjusted daily temperature variances for each month were obtained by multiplying the observed daily temperature variances by the variance ratios between spatially downscaled monthly projections and observed monthly values.

The change factor (CF) method is a straightforward and widely used downscaling method (Diaz-Nieto & Wilby 2005). It establishes a baseline climatology using long-term climate data for the target site.

The changes between present and future climates derived from a GCM grid point close to the target site, usually at a monthly scale, are added to (for temperature) or multiplied by (for precipitation) each day in the baseline time series. This method is computationally straightforward and easy to apply. The most significant drawback is that the temporal sequencing of wet and dry days and the variance of temperature are unchanged. There is however a change in precipitation variance derived from the change of mean precipitation.

The objective of the present study is to present a statistical downscaling method combining the attributes of both stochastic WG and the CF methods based on the changes of monthly statistics projected by a regional climate model. This method is further compared to the CF method by quantifying the hydrological impacts of climate change for a Canadian watershed (Quebec province). The huge advantage of the developed method over the CF method is that differences in precipitation occurrence and variance of all variables can be specifically taken into account. In addition, a time series of any length can be generated: an advantage for the study of extremes.

## 2. STUDY AREA AND DATA

### 2.1. Study area

This study was conducted for the Manicouagan 5 river basin (Fig. 1) located in central Quebec, Canada. It covers 24 610 km<sup>2</sup> of mostly forested area.

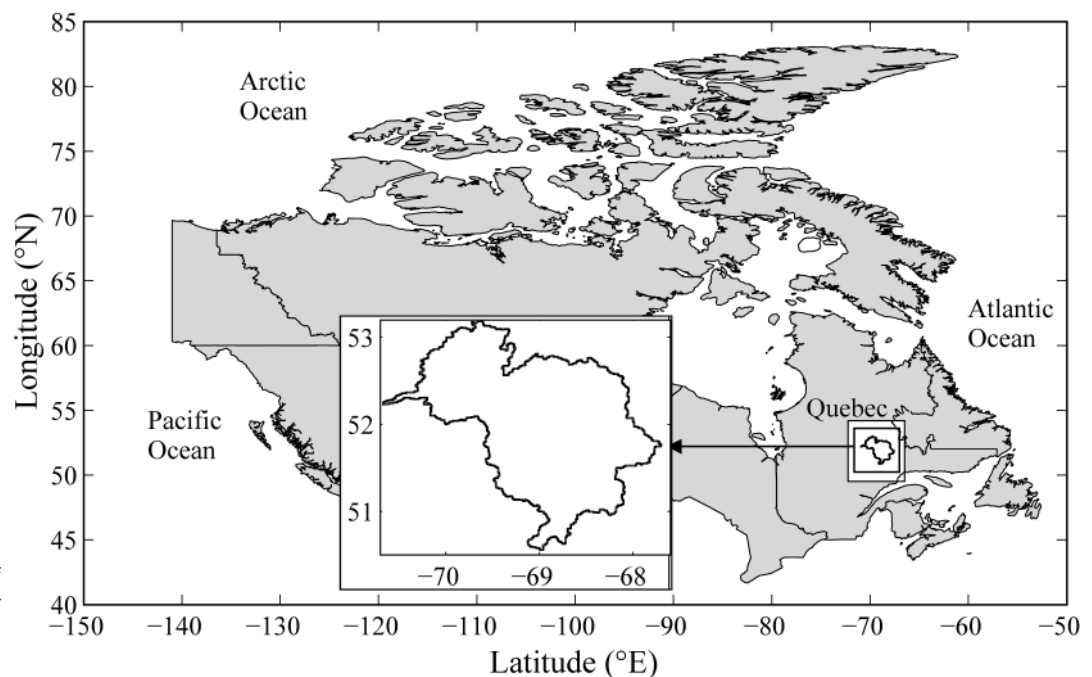


Fig. 1. Location of Manicouagan 5 river basin

It has a rolling to moderately hilly topography with a maximum elevation of 952 m above sea level (a.s.l.). The reservoir at the basin outlet has a mean level of 350 m a.s.l. Population density is extremely low and logging is the only industrial activity over the basin. The basin drains into the Manicouagan 5 reservoir, a 2000 km<sup>2</sup> annular reservoir within an ancient eroded impact crater. The basin ends at the Daniel Johnson dam, which is the largest buttressed multiple arch dam in the world. The installed hydropower capacity of the dam is 2.6 GW. The annual mean discharge of the Manicouagan 5 River is 529 m<sup>3</sup> s<sup>-1</sup>. Snowmelt peak discharge usually occurs in May and averages 2200 m<sup>3</sup> s<sup>-1</sup>.

## 2.2. Data

The observed data consisted of daily precipitation,  $T_{\max}$  and  $T_{\min}$  interpolated on a 10 km grid by the National Land and Water Information Service using 7514 weather stations over Canada ([www.agr.gc.ca/nlwis-snite](http://www.agr.gc.ca/nlwis-snite)). The interpolation is performed using a thin plate smoothing spline surface fitting method (Hutchinson et al. 2009). All grid daily precipitation,  $T_{\max}$  and  $T_{\min}$  are averaged over the river basin. Discharge data at the basin outlet was obtained from mass balance calculations at the dam and provided by Hydro-Québec. Climate data consisted of RCM-projected daily precipitation,  $T_{\max}$  and  $T_{\min}$ . Data from the Canadian RCM (CRCM v4.2.0; Music & Caya 2007, 2009) with a grid resolution of 45 km driven by the Canadian GCM (CGCM3 v3.1; DAI CGCM3 Predictors 2008) under the IPCC A2 gas emission scenario. The CRCM grid data are also averaged over the river basin to match the observed data. This work covers the 1970–1999 period (reference period) for calibration and the 2011–2099 period in climate change mode. For the 2011–2099 climate data, 30-yr moving averages were calculated, which resulted in sixty 30 yr horizons centered over 2025 to 2084.

## 3. METHODOLOGY

A downscaling method based on WG is presented below. Precipitation,  $T_{\max}$  and  $T_{\min}$  were downscaled from the CRCM scale to the site-specific scale (basin average of 10 km grid) over the 2025–2084 period (centered by 30 yr moving averages from 2011 to 2099). The precipitation threshold used to discriminate between wet and dry days is 0.5 mm. If daily

precipitation is  $\geq 0.5$  mm, this given day is defined as being wet. The choice of a different threshold has been investigated and shown not to influence the results. The results were compared against the widely-used CF method in downscaling precipitation,  $T_{\max}$  and  $T_{\min}$ , and in simulating hydrological impacts using a lumped conceptual hydrological model.

### 3.1. Downscaling of weather generator parameters

The WG used in this research is CLIGEN (Nicks & Lane 1989). In this study, only the functions to generate precipitation (occurrence and quantity),  $T_{\max}$  and  $T_{\min}$  were used. For convenience, CLIGEN was chosen in spite of generating precipitation and temperature independently, and the mean and standard deviation of each variable are explicitly used in its probability distribution function, so that the incorporation of GCM projected monthly changes in statistical moments is straightforward (Zhang 2005, Chen et al. 2009). However, other WGs could also have been used.

In CLIGEN, a first-order two-state Markov chain is used to generate the occurrence of wet or dry days. The probability of precipitation on a given day is based on the wet or dry status of the previous day, which can be defined in terms of the 2 transition probabilities:  $P_{01}$  and  $P_{11}$ . For a predicted wet day, a 3-parameter skewed normal Pearson III distribution was used to generate daily precipitation quantity for each month (Nicks & Lane 1989). A normal distribution was used to simulate  $T_{\max}$  and  $T_{\min}$ . The temperature with the smaller standard deviation between  $T_{\max}$  and  $T_{\min}$  is computed first, followed by the other temperature. This preserves the cross-correlation between  $T_{\max}$  and  $T_{\min}$  (Chen et al. 2008). To capture their autocorrelation, 2 random numbers are used to obtain the standard normal deviate; the second number for one day is reused as the first number for the next day (Zhang 2004). The mean and standard deviation of  $T_{\max}$  and  $T_{\min}$  were calculated monthly and smoothed with a Fourier interpolation scheme to the daily scale.

A total of 9 monthly parameters are needed by CLIGEN to generate precipitation,  $T_{\max}$  and  $T_{\min}$ . These include  $P_{01}$  and  $P_{11}$  for generating precipitation occurrence, the mean, standard deviation and skewness for generating daily precipitation quantity and the means and standard deviations for generating  $T_{\max}$  and  $T_{\min}$ .

A method is presented to modify the above mentioned parameters based on the changes of precipi-

tation,  $T_{\max}$  and  $T_{\min}$  projected by the CRCM. This method could also be used with GCM outputs. Based on the work of Wilks (1992), the daily WG parameters were modified according to the changes of monthly averaged statistics projected by climate models. For downscaling of precipitation occurrence, Wilks (1992) modified the unconditional probability of daily precipitation occurrence ( $\pi$ ) and a dependence parameter ( $r$ ) rather than acting directly on the transition probabilities of precipita-

tion occurrence ( $P_{11}$  and  $P_{01}$ ). However, the changes of  $P_{11}$  and  $P_{01}$  are more gradual and less noisy than those of  $\pi$  and  $r$  for both CGCM and CRCM projected daily precipitation (Fig. 2). The correlations between 30-yr moving averages of CGCM3- and CRCM-simulated seasonal  $P_{11}$  (and  $P_{01}$ ) and their linear regressions are also consistently stronger than those between  $r$  and their linear regressions for all 4 seasons (Table 1). Thus, the proposed method directly modifies the transition probabilities of pre-

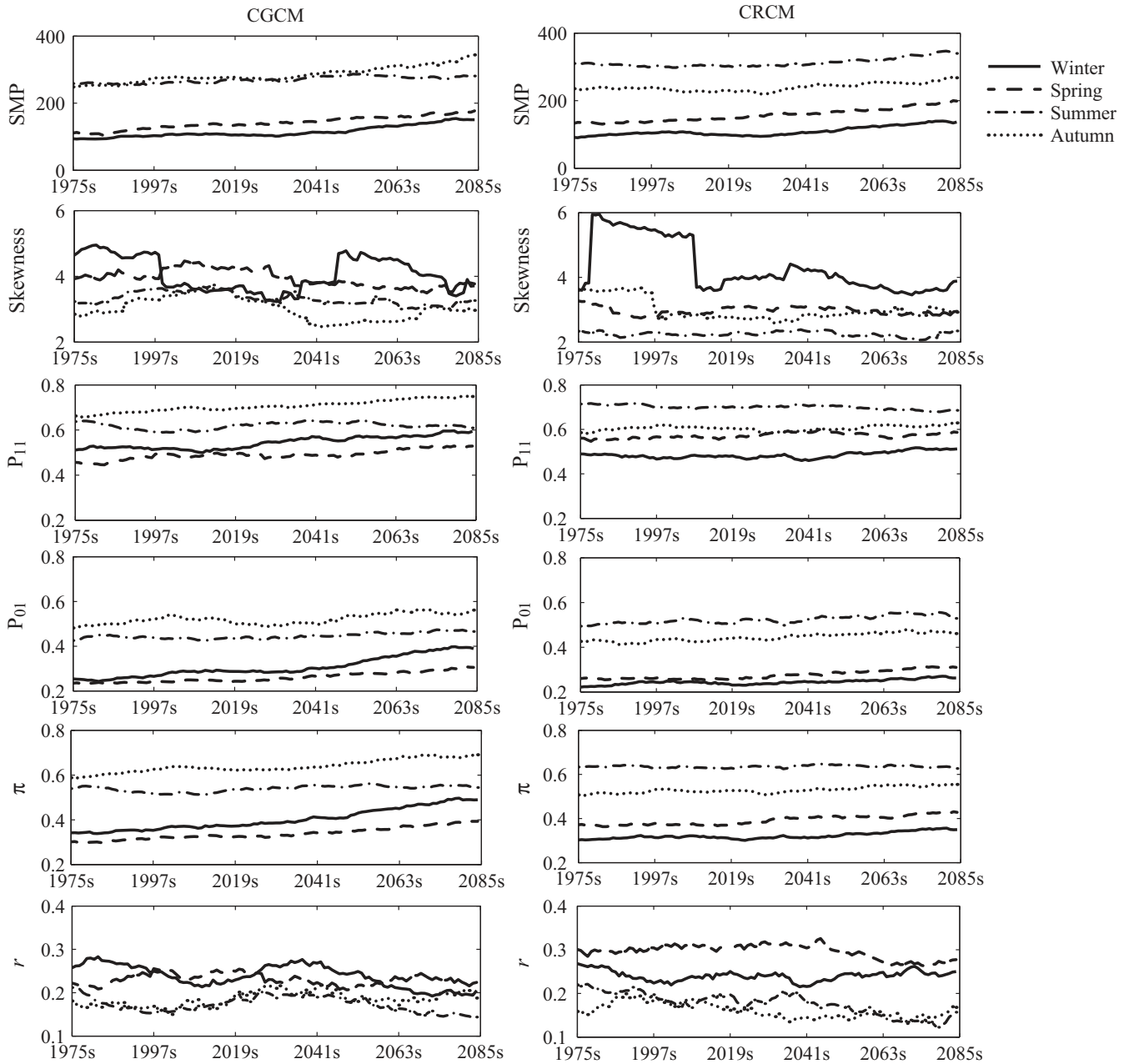


Fig. 2. The 30-yr moving averages of seasonal mean precipitation (SMP), skewness of daily precipitation distribution (Skewness), conditional ( $P_{01}$ ,  $P_{11}$ ) and unconditional ( $\pi$ ) probability of precipitation occurrence, and dependence parameter ( $r$ ) for CRCM and CGCM data over the 1961–2099 period

Table 1. Correlation coefficient ( $R^2$ ) of the linear regression for the Canadian Regional Climate (CRCM) and General Circulation (CGCM) Models statistics, including seasonal mean precipitation (SMP), skewness of daily precipitation distribution (Skewness), conditional ( $P_{01}$ ,  $P_{11}$ ) and unconditional ( $\pi$ ) probability of daily precipitation occurrence and dependence parameters ( $r$ ) for 2025–2084

	CGCM						CRCM					
	SMP	Skewness	$P_{01}$	$P_{11}$	$\pi$	$r$	SMP	Skewness	$P_{01}$	$P_{11}$	$\pi$	$r$
Winter	0.83	0.08	0.89	0.80	0.94	0.45	0.7	0.53	0.62	0.43	0.67	0.002
Spring	0.97	0.48	0.92	0.81	0.94	0.04	0.96	0.03	0.87	0.50	0.88	0.34
Summer	0.73	0.33	0.61	0.46	0.37	0.10	0.62	0.05	0.76	0.59	0.03	0.77
Autumn	0.89	0.20	0.53	0.95	0.87	0.28	0.50	0.29	0.83	0.38	0.72	0.48

precipitation occurrence ( $P_{11}$  and  $P_{01}$ ). The parameters of WG were modified to take into account variations projected by a climate model (GCM or RCM). This variation is based on a delta change approach. For example, take the probability of occurrence of  $P_{01}$ , a common parameter of WG using a two-state Markov chain for precipitation occurrence. Since the spatial resolution of GCM or RCM is of the order of 100s or 10s of km,  $P_{01}$  from GCM or RCM data will not match the  $P_{01}$  measured at a station. Thus, similarly to the CF method, the difference between  $P_{01}$  projected by GCM (or RCM) in present and future climate will be applied to the observed data. The same method was also applied to the probability of occurrence of  $P_{11}$  and the monthly mean precipitation (MMP). The skewness of daily precipitation distribution does not change gradually, but displays large fluctuations, especially for the winter precipitation (Fig. 2). This is not surprising since the skewness is largely influenced by extreme precipitations that are not well represented by climate models. Thus, a simple modification of the changes in skewness projected by climate models between future and reference periods may result in unacceptable biases. To simplify the process, the skewness of the precipitation distribution was presumed to be unchanged in the future for this study. Accordingly, 8 parameters required modification for every climate change scenario.

Details of parameter modifications follow the following steps: (1) Similarly to the CF method, the adjusted monthly mean  $T_{\max}$  and  $T_{\min}$  for the future horizon ( $\bar{T}_{adj,fut}$ ) were estimated as (Chen et al. 2011):

$$\bar{T}_{adj,fut} = \bar{T}_{obs} + (\bar{T}_{CM,fut} - \bar{T}_{CM,ref}) \quad (1)$$

The adjusted values were obtained by adding the differences predicted by a GCM or an RCM between the future (fut) horizon and the reference (ref) period ( $\bar{T}_{CM,fut} - \bar{T}_{CM,ref}$ ) to the observed mean monthly observed temperatures ( $\bar{T}_{obs}$ ).

(2) Monthly means and variances of precipitation, monthly variances of  $T_{\max}$  and  $T_{\min}$  and the transition probabilities of precipitation occurrence  $P_{01}$  and  $P_{11}$  for the future horizon were adjusted by:

$$X_{adj,fut} = X_{obs} \times (X_{CM,fut}/X_{CM,ref}) \quad (2)$$

where  $X$  represents the variable to be adjusted. The subscripts were the same as above.

(3) The  $P_{01}$  and  $P_{11}$  values are expressed in terms of  $r$  for further adjustments, as:

$$\pi = \frac{P_{01}}{1 + P_{01} - P_{11}} \quad (3)$$

$$r = P_{11} - P_{01} \quad (4)$$

(4) The adjusted mean daily precipitation per wet day ( $\mu_d$ ) was estimated (as Wilks 1992, 1999, Zhang 2005):

$$\mu_d = \frac{\mu_m}{N_d \pi} \quad (5)$$

where  $N_d$  is the number of days in a month,  $N_d \pi$  is the average number of wet days in a month, and  $\mu_m$  is the step (2)-adjusted monthly precipitation.

(5) The adjusted daily variance ( $\sigma_d^2$ ) was approximated using Eq. (6), based on the step (2)-adjusted variance of the monthly precipitation ( $\sigma_m^2$ ) (Wilks 1992, 1999).

$$\sigma_d^2 = \frac{\sigma_m^2}{N_d \pi} - \frac{(1 - \pi)(1 + r)}{1 - r} \mu_d^2 \quad (6)$$

All adjusted precipitation,  $T_{\max}$  and  $T_{\min}$  parameter values are input into CLIGEN to generate 900 yr long time series of daily meteorological data. Long time series are used to obtain the true expectancy of a WG. Short time series could result in biases due to the random nature of the stochastic process. Each 900 yr time series is representative of a 30 yr horizon as defined earlier. All in all, sixty 900 yr time series (centered over 2025 to 2084) were generated. The flow chart of WG-based downscaling is presented in Fig. 3.

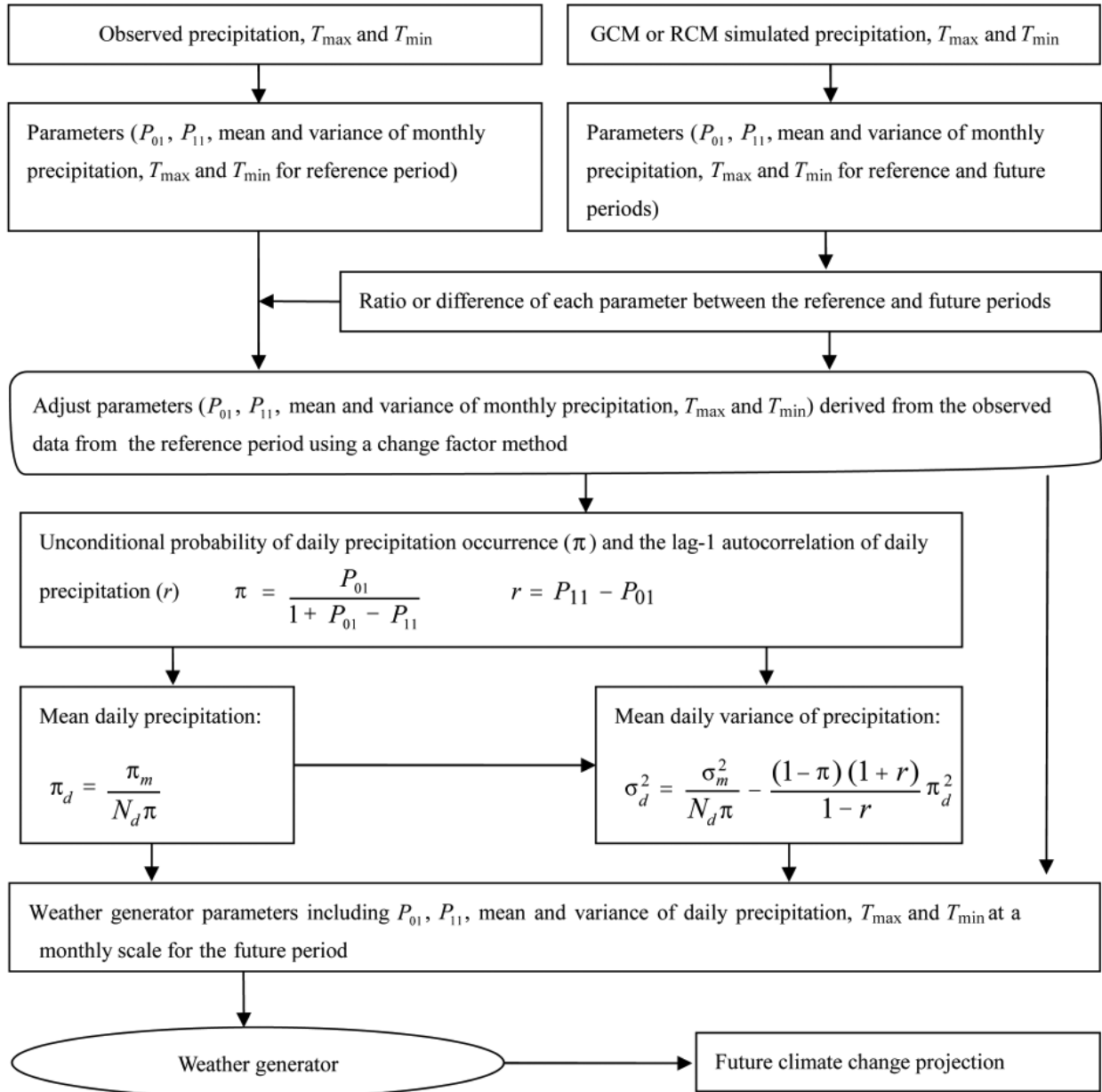


Fig. 3. Flow chart of downscaling of weather generator parameters

### 3.2. Change factor method

The CF method involves adjusting the observed daily temperature ( $T_{obs,d}$ ) by adding the difference in monthly temperature between the future horizon and the reference period predicted by the climate model (GCM or RCM) ( $\bar{T}_{CM,fut,m} - \bar{T}_{CM,ref,m}$ ) to obtain the daily temperature at the future horizon ( $T_{adj,fut,d}$ ) (Chen et al. 2011):

$$T_{adj,fut,d} = T_{obs,d} + (\bar{T}_{CM,fut,m} - \bar{T}_{CM,ref,m}) \quad (7)$$

The adjusted daily precipitation for the future horizon ( $P_{adj,fut,d}$ ) was obtained by multiplying the precipitation ratio ( $\bar{P}_{CM,fut,m}/\bar{P}_{CM,ref,m}$ ) by the observed daily precipitation ( $P_{obs,d}$ ):

$$P_{adj,fut,d} = P_{obs,d} \times (\bar{P}_{CM,fut,m}/\bar{P}_{CM,ref,m}) \quad (8)$$

### 3.3. Hydrological simulation

The hydrological simulation used the HASMI hydrological model developed by Hydro-Québec,

which has been used to forecast natural inflows for over 20 yr (Fortin 2000). HSAMI is used by Hydro-Québec for hourly and daily forecasting of natural inflows over 84 watersheds with surface areas ranging from 160 to 69 195 km<sup>2</sup>. HSAMI is a 23-parameter, lumped, conceptual, rainfall–runoff model. Two parameters account for evapotranspiration, 6 for snowmelt, 10 for vertical water movement, and 5 for horizontal water movement. Vertical flows are simulated with 4 interconnected linear reservoirs (snow on the ground, surface water, unsaturated and saturated zones). Horizontal flows are filtered through 2 hydrograms and 1 linear reservoir. Model calibration is done automatically using the shuffled complex evolution optimization algorithm (Duan 2003). The model takes snow accumulation, snowmelt, soil freezing/thawing and evapotranspiration into account.

The basin-averaged minimum required daily input data for HSAMI are  $T_{\max}$ ,  $T_{\min}$ , and liquid and solid precipitations. The liquid and solid precipitations are partitioned based on the mean temperature. If the mean temperature is  $\geq 2^{\circ}\text{C}$ , all precipitation is rainfall, if the mean temperature is  $\leq -2^{\circ}\text{C}$ , all precipitation is solid. Otherwise, precipitation is linearly partitioned between snow and rainfall. Cloud cover fraction and snow water equivalent can also be used as inputs, if available. A natural inflow or discharge time series is also needed for proper calibration/validation. For this study, 30 yr (1970 to 1999) of daily discharge data were used for model calibration/validation. The optimal combination of parameters was selected based on Nash–Sutcliffe criteria (Duan et al. 1994, Duan 2003). The set of parameters thus chosen

yielded Nash–Sutcliffe criteria values of 0.89 for both the validation (20 yr) and calibration (10 yr) periods. This high Nash–Sutcliffe criteria value is representative of the good quality of the weather inputs, observed discharge values and hydrological model.

## 4. RESULTS

### 4.1. Validation of the weather generator and the hydrological model

The validation of the hydrological model HSAMI was based on the performance of the simulated hydrographs (using the hydrology model driven by the observed meteorological data, labeled SIM) at the basin outlet compared to the observed hydrograph. The 10th, 50th and 90th percentiles of annual hydrographs are presented in Fig. 4. Annual hydrographs simulated by HSAMI using CLIGEN-generated data (labeled WG) using the observed monthly statistics for the reference period are also displayed to validate the ability of CLIGEN at generating weather data representative of its training period. Annual hydrographs from the observed discharge (labeled OBS) are also presented for comparison. The observed precipitation and temperatures resulted in hydrographs that are very close to observed ones. Additionally, precipitation and temperatures obtained from the weather generator are able to reproduce the interannual variability of streamflow. Even though slight biases were introduced by CLIGEN and HSAMI, the overall fits are quite good.

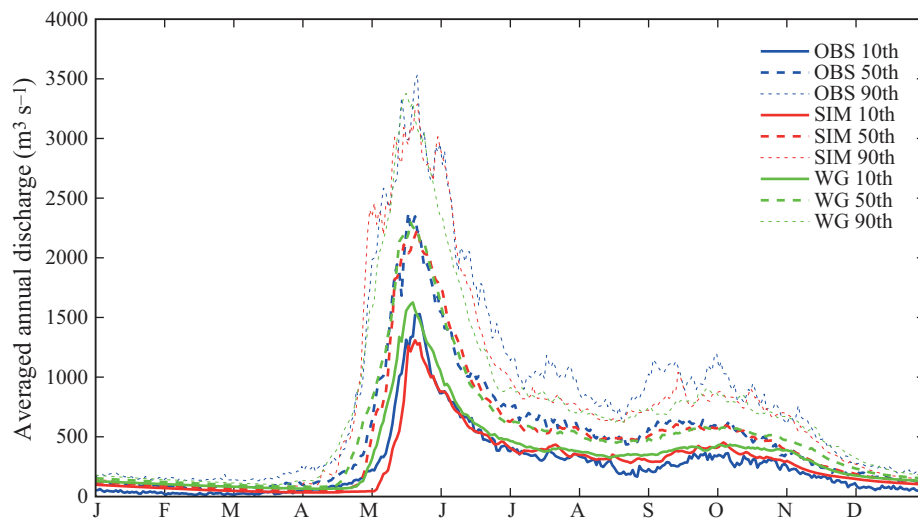


Fig. 4. Tenth, 50th and 90th percentiles of observed (OBS) and HSAMI simulated (SIM) hydrographs (mean annual discharge) for the reference period (1970–1999) at the Manicouagan 5 watershed. HSAMI-simulated hydrographs using CLIGEN-generated meteorological data at the reference period (WG) are also plotted



## 4. 2. Climate change projections

### 4.2.1. Dry and wet day spells

The CF method does not take into account the temporal sequencing of dry and wet days, which is its main drawback. The WG-based method modifies the transition probabilities of precipitation occurrence based on RCM-projected variations. Thus, the dry and wet day spells change according to the differences in RCM-projected dry and wet day spells between the future and reference periods. Fig. 5 shows the average dry and wet day spells downscaled by the CF and WG-based methods, respectively, for 12 mo over the 2025–2084 period (30 yr moving average from 2011 to 2099) for the Manicouagan 5 river basin. Changes in precipitation occurrence are not taken into account by the CF method. Thus, the average dry and wet day spells are stationary over the 2025–2084 period for all months (horizontal dashed lines in Fig. 5) and are similar to those from the reference period. The WG-based method displays clear trends throughout the century,

which is markedly different from the situation at the reference period. The WG-based method suggested shorter dry day spells for all months of the 2025–2084 period compared to those of the reference period, indicating that wet days will become more common. However, there is no uniform pattern for monthly average wet day spells, which are predicted to be longer for April and November and shorter for July and August for the 2025–2084 period. In addition, this pattern would be first shorter and then longer than that of the reference period for January, March, September, October and December throughout the 2025–2084 period. In contrast, February wet day spells would have an opposite trend to that of the reference period.

### 4.2.2. Mean and standard deviation of daily precipitation

Both the CF and WG-based methods specifically take into account the changes of monthly precipitations projected by RCM; thus, they suggest similar increases in annual and seasonal precipitations for

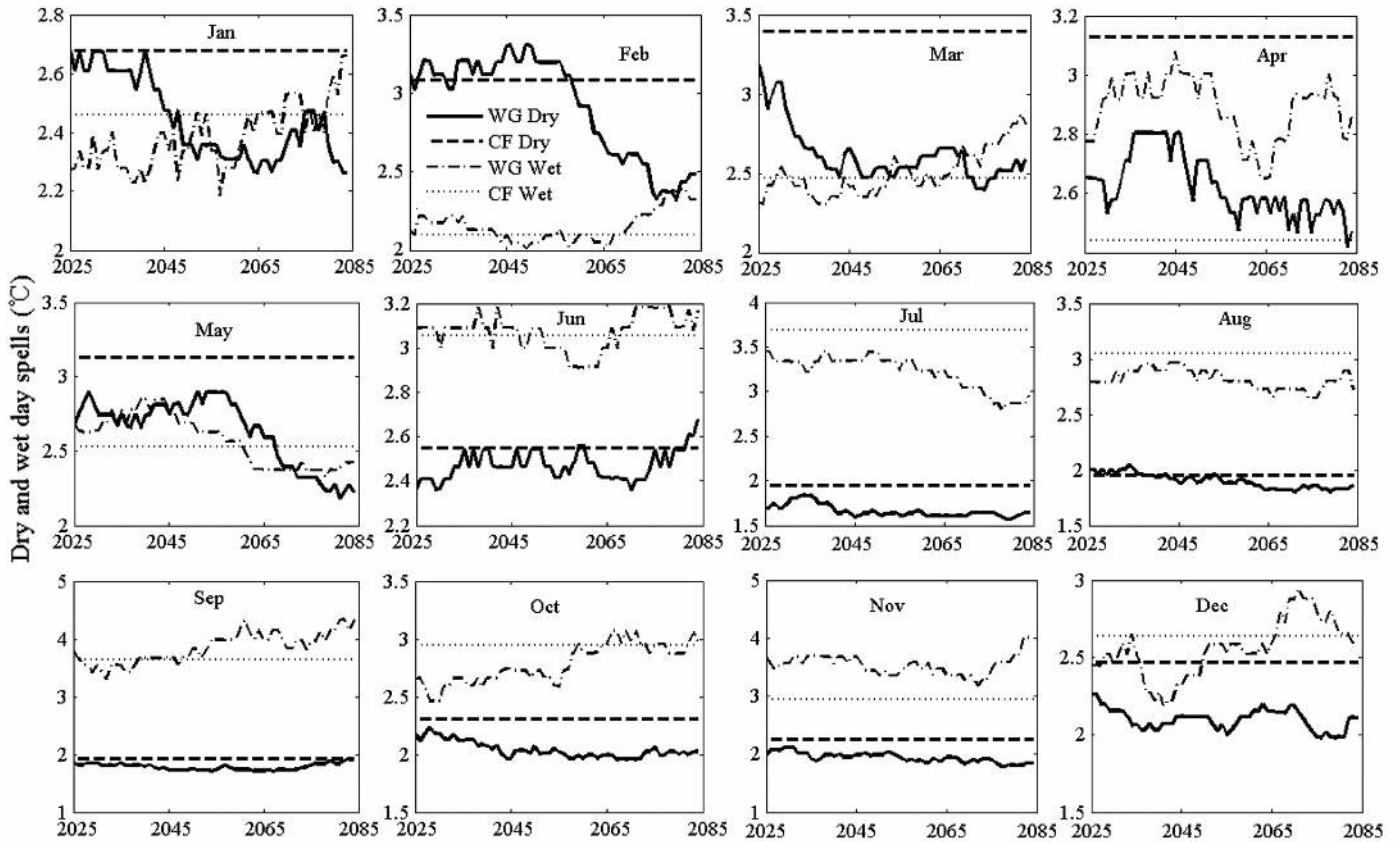


Fig. 5. Mean dry and wet day spells downscaled by change factor (CF) and weather generator-based (WG) methods for each month of 2025–2084 for the Manicouagan 5 river basin

the 2025–2084 period (results not shown). But, as mentioned earlier, the dry and wet day spells are significantly different. Specifically, mean daily precipitation changes in the opposite direction to that of the wet day frequency. Fig. 6 demonstrates the mean and standard deviation of daily precipitation downscaled by the 2 methods for 12 mo over the 2025–2084 period. Both downscaling methods show gradual increases in mean daily precipitation for all months in this period. However, the CF method suggests more increases in mean daily precipitation than the WG-based method. This is because the WG-based method predicts more wet days with similar annual and seasonal precipitations than the CF method.

Both CF and WG-based methods suggest changes in daily precipitation variance. The change of variance predicted by the CF method is based on the change of mean daily precipitation, because the CF method does not specifically modify the precipitation variance. However, the WG-based method specifically takes into account the variance of precipitation based on RCM-projected variations. Both downscaling methods suggest general in-

creases in the standard deviations of daily precipitation for all months (Fig. 6). For the CF method, the change in standard deviation of daily precipitation is consistent with the change in the mean precipitation. The WG-based method suggests more future variability, consistent with that predicted by the RCM.

#### 4.2.3. Standard deviation of daily $T_{\max}$ and $T_{\min}$

The CF method does not take into account the change of variance for  $T_{\max}$  and  $T_{\min}$ . Standard deviations of  $T_{\max}$  and  $T_{\min}$  downscaled by the CF method are constant for the 2025–2084 period, which is exactly equal to that of the reference period as presented in Fig. 7. However, similarly to the transition probabilities of precipitation occurrence, the WG-based method adjusts the variances of  $T_{\max}$  and  $T_{\min}$  based on the RCM-projected changes. Compared to the reference period (1970–1999), the WG-based method suggests decreases in the variability of winter (December, January and February)  $T_{\max}$ , while it suggests increases for all other months.

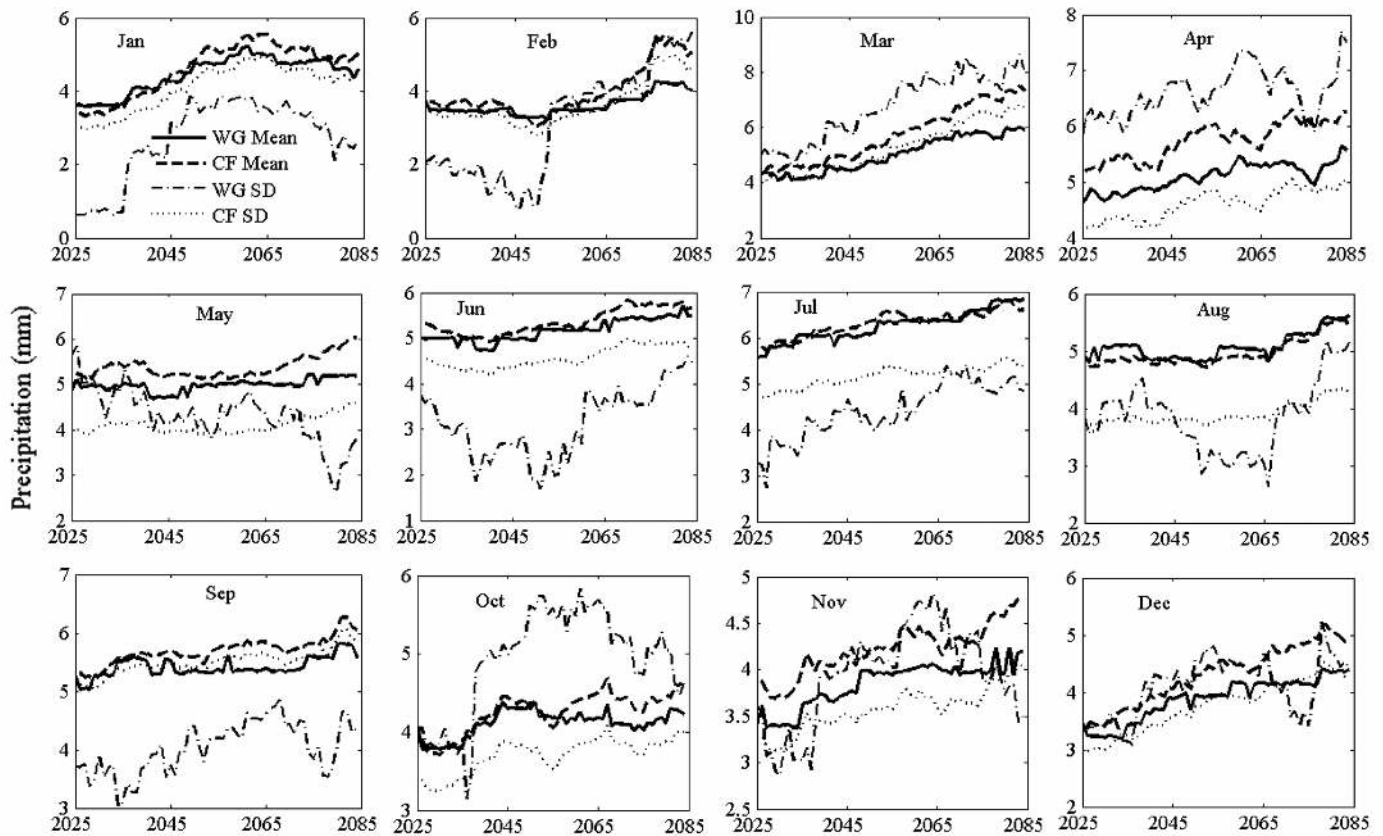


Fig. 6. Mean and standard deviation (SD) of daily precipitation downscaled by change factor (CF) and weather generator-based (WG) methods for each month of 2025–2084 for the Manicouagan 5 river basin

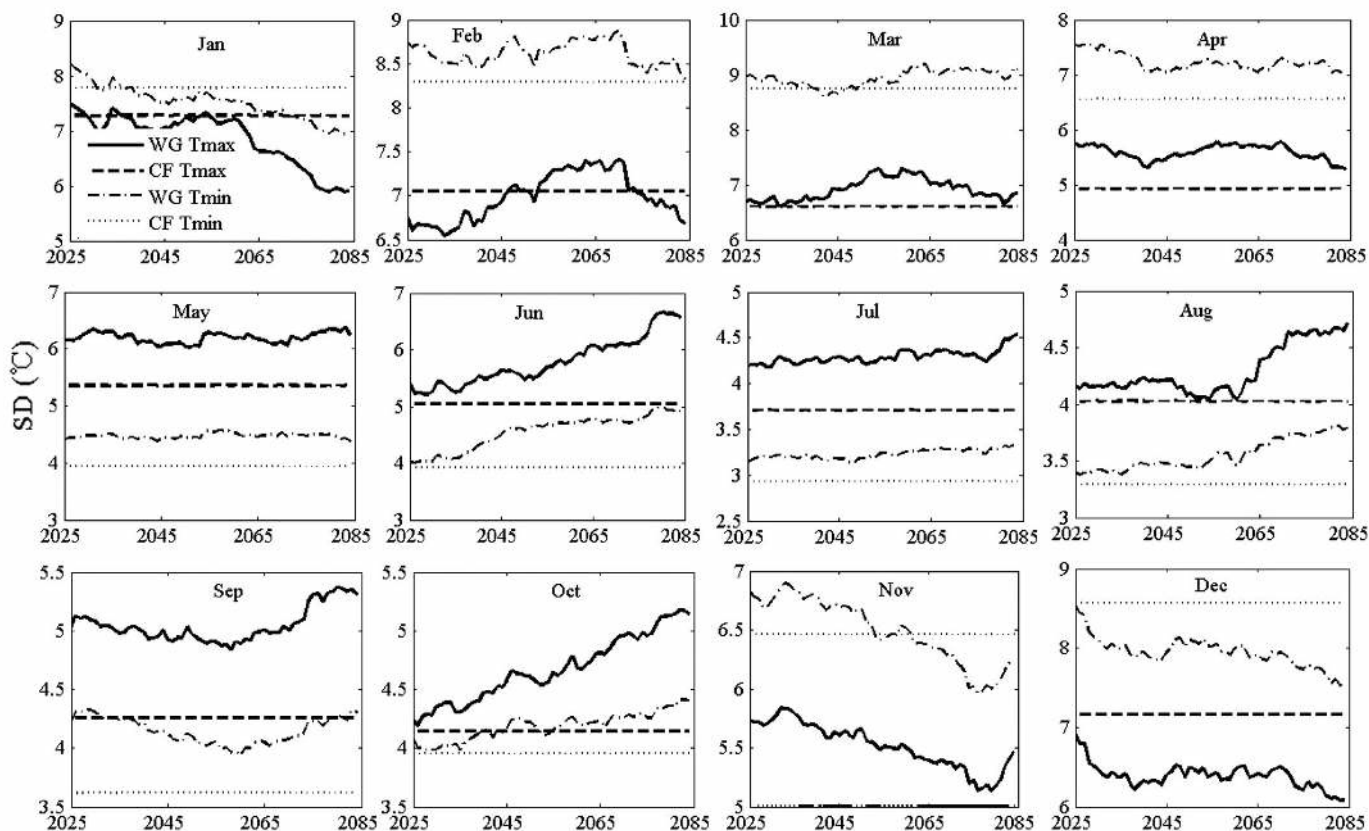


Fig. 7. Daily standard deviation (SD) of  $T_{\max}$  and  $T_{\min}$  downscaled by change factor (CF) and weather generator-based (WG) methods for each month of 2025–2084 for the Manicouagan 5 river basin

### 4.3. Hydrological impacts

#### 4.3.1. Annual hydrograph

Fig. 8 presents the envelope of the annual hydrographs simulated with the weather variables downscaled by the CF and WG-based methods. Each envelope is represented by 60 annual hydrographs (2025–2084 period). When the time period is near the reference period, the annual hydrograph of the future period is close to that of the reference period. To avoid the minor bias resulting from the hydrological model when comparing the future to the reference period, the discharge at the reference period is represented by model data and not by the observed discharge. The results showed that both downscaling methods suggest increases in winter (Nov–Apr) discharge. Decreases in summer (Jun–Oct) are predicted for most future horizons, especially for those downscaled by the WG-based method. The WG-based method suggests peak discharges higher than both those of the CF method and the simulated peak discharges at the reference period. Significantly, the peak discharges increase even

more as the future advances. Peak discharges over the 2025–2085 period are predicted to be earlier than those at the reference period by both downscaling methods. Lags vary from 12 d (May 12) to 19 d (May 5) for the WG-based method and from 6 (May 18) to 22 d (May 2) for the CF method.

#### 4.3.2. Annual and seasonal discharges

Fig. 9 presents the 30 yr moving averages of annual and seasonal discharges simulated by HSAMI using weather data downscaled by the CF and WG-based methods. Compared to the reference period discharge (straight dashed line in Fig. 9), both methods suggest increases in annual, spring and winter discharges over the 2025–2084 period. The CF method predicts decreases in summer–autumn discharge for most horizons, whereas the change is more gradual with the WG approach. Even though both downscaling methods predict similar annual and seasonal mean precipitations and temperatures, the annual and seasonal discharges are different, especially for seasonal discharge. This indicates that the annual

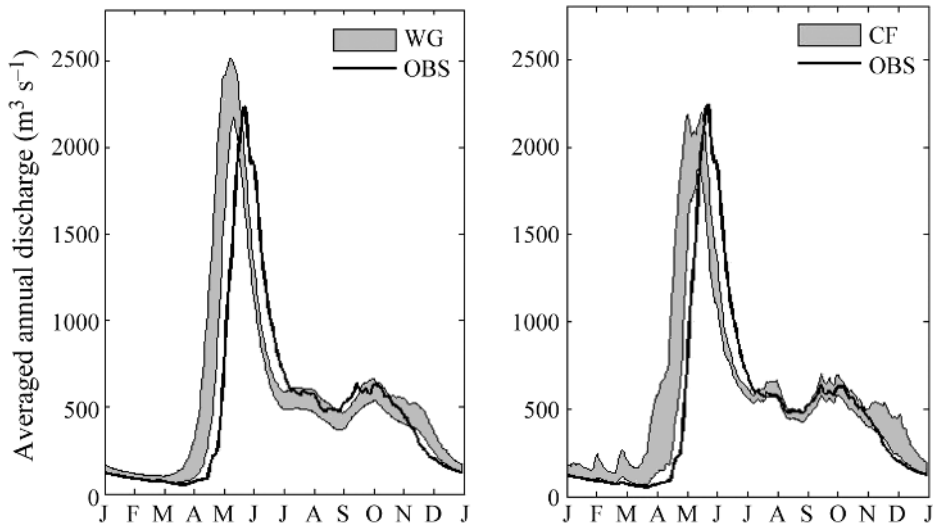


Fig. 8. Envelopes of 60 annual hydrographs simulated with precipitation,  $T_{max}$  and  $T_{min}$  values downscaled using change factor (CF) and weather generator-based (WG) methods over the 2025–2084 period at the Manicouagan 5 river basin. The observed hydrograph (OBS) for 1970–1999 is displayed for comparison

and seasonal discharges are not only affected by the means of the precipitation and temperatures, but also by their variances and precipitation occurrences. In addition, these results reflect that the process from climate projections to hydrologic variables is non-linear. Annual discharge suggested by the CF method is slightly more than that predicted by the

WG-based method over the 2025–2085 period. The discharges differ more at the seasonal scale than at the annual scale. Compared to the CF method, the WG-based method suggests larger increases in spring (Apr–Jun) discharge, and smaller increases in summer–autumn (Jul–Nov) and winter (Dec–Mar) discharges.

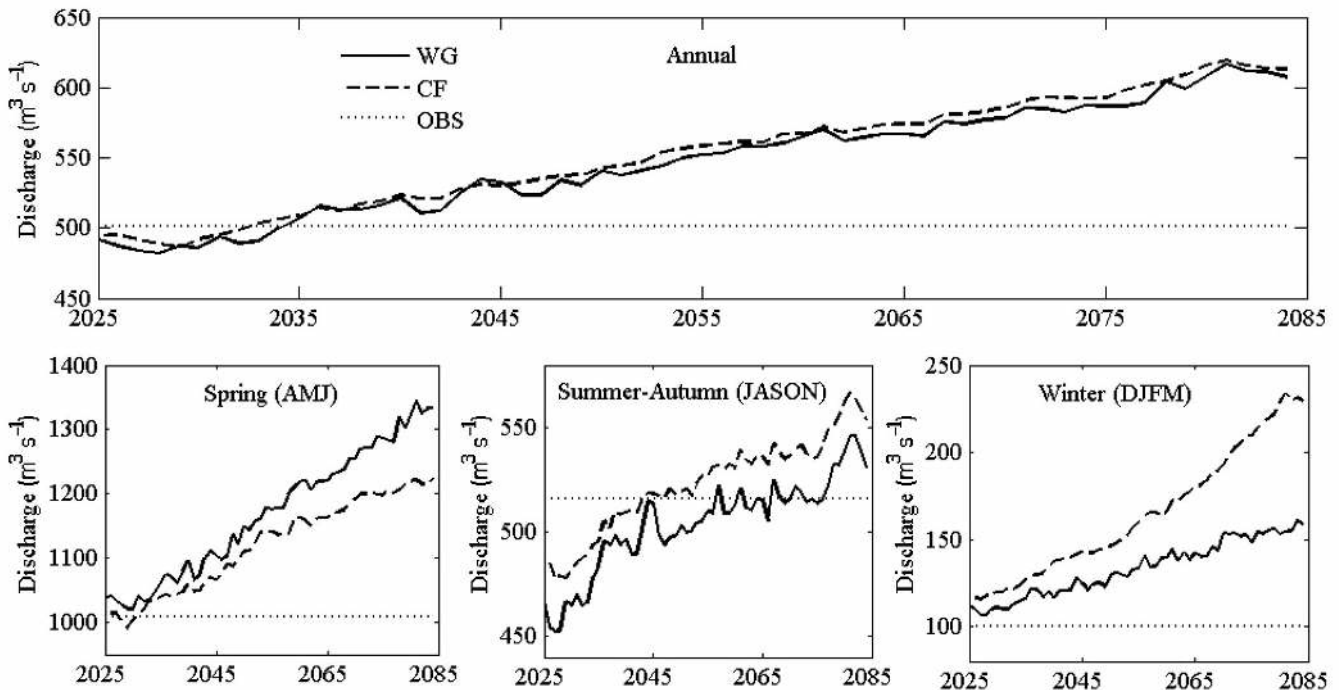


Fig. 9. Annual and seasonal mean discharge simulated with precipitation,  $T_{max}$  and  $T_{min}$  values downscaled using change factor (CF) and weather generator-based (WG) methods for 2025–2084 at the Manicouagan 5 river basin. OBS: annual and seasonal mean discharge over the reference period (1970–1999), shown for comparison

#### 4.3.3. Annual and seasonal low flows

Changes in monthly precipitation averages can conceal subtle variations in dry spells that are potentially significant for low flows (Diaz-Nieto & Wilby 2005). The 2 downscaling methods suggest similar changes in monthly precipitation, but different changes in precipitation occurrence, resulting in noticeable differences in mean low flows at the river basin. Fig. 10 presents the 30 yr moving averages of mean annual and seasonal low flows for the 2025–2084 period. Both downscaling methods suggest general increases in average annual and seasonal low flows, but there are considerable differences in their predictions. The CF method predicts larger increases in mean annual low flow than the WG-based method. These greater increases, compared to the WG-based method, occur in spring and winter low flows, resulting in the larger increases in annual low flow.

Fig. 11 presents the 30 yr moving averages of the annual and seasonal minimal low flows for the 2025–2084 and the reference periods. Similarly to the mean low flows shown in Fig. 10, both downscaling methods suggest increases in annual and seasonal minimal low flows, but those predicted by WG-based figures display more variability. The WG method has a much longer time series (900 yr compared to 30 yr)

that is better at sampling climate variability. The CF method predicts larger increases in minimal low flow, especially for the more distant future period, and larger increases in spring and winter minimal low flows than the WG-based method. The WG-based method is better able to capture long series of dry days that lead to low flows. The WG-predicted summer–autumn minimal low flows for the 2025–2084 period are considerably larger than those for the reference period. Both methods give similar results, although the WG-based method predicts low flows that are 10% smaller than those of the CF method, on average.

## 5. DISCUSSIONS AND CONCLUSIONS

A statistical downscaling method combining a stochastic WG and some aspects of the CF method was presented in this paper. The parameters of the WG were perturbed to take into account the relative variations in the means and variances of weather variables projected by a climate model. The precipitation and temperature parameters projected by climate models display gradual (significantly non-stationary) changing patterns, which form the basis for the parameter perturbation of the WG. This downscaling method is relatively simple to use and negates the

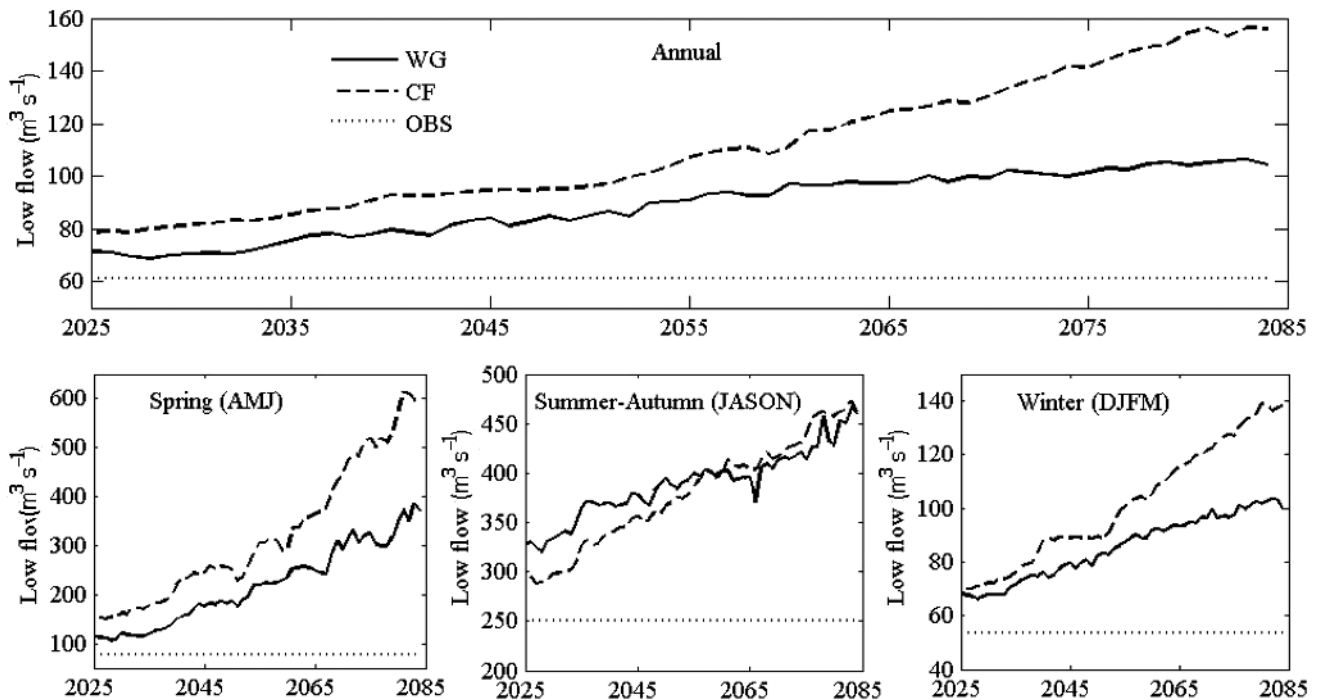


Fig. 10. Annual and seasonal mean low flow simulated with precipitation values downscaled using change factor (CF) and weather generator-based (WG) methods,  $T_{\max}$  and  $T_{\min}$  for 2025–2084 at the Manicouagan 5 river basin. OBS: annual and seasonal low flow for the reference period (1970–1999; OBS)

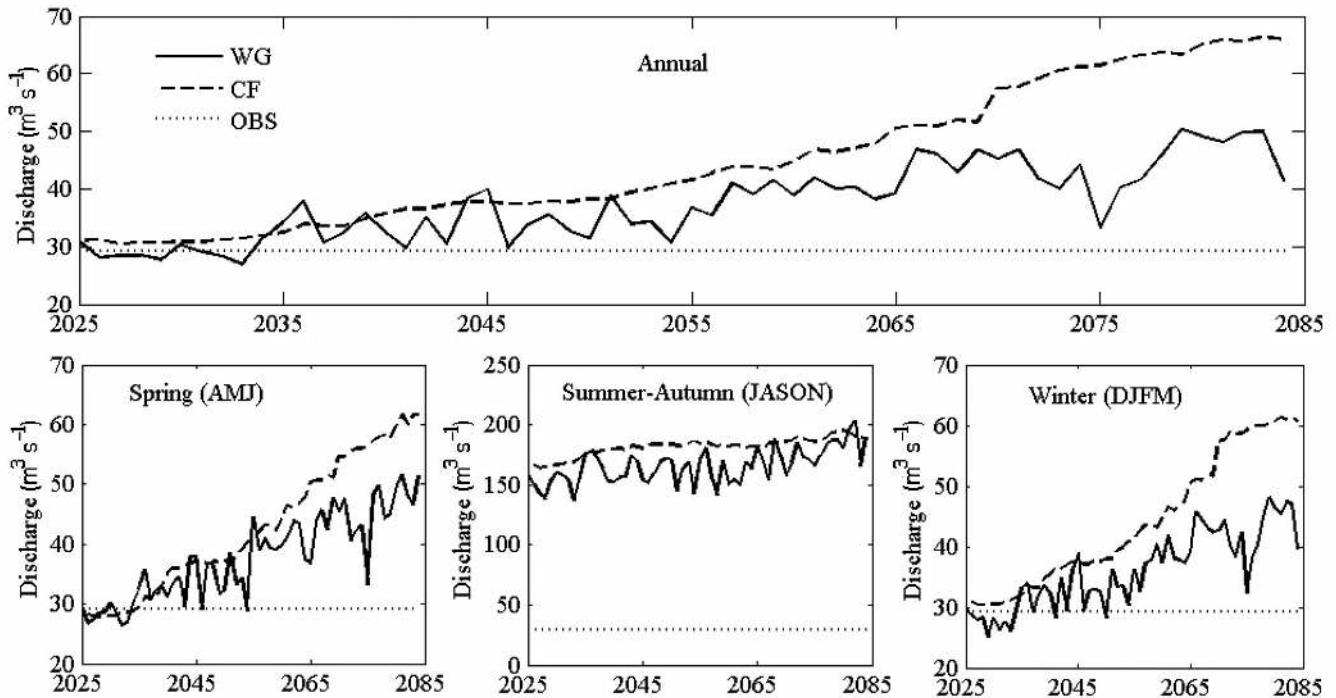


Fig. 11. Minimal annual and seasonal low flow ( $Q_5$ ) simulated with the change factor (CF) and weather generator-based (WG) downscaling methods for 2025–2084 at the Manicouagan 5 river basin. OBS: data for the reference period (1970–1999)

prerequisite of a strong relationship between local-scale variables (predictants) and large scale climate model variables (predictors) common to most statistical downscaling methods.

The proposed downscaling method was compared to the CF method in downscaling precipitation,  $T_{\max}$  and  $T_{\min}$ , and further quantifying the hydrological impacts of climate change over the 2025–2084 period for the Manicouagan 5 river basin. Both downscaling methods suggest similar increases in annual and seasonal precipitations and temperatures for the 2025–2084 period (results not shown). This was as expected, since both approaches are similar with respect to their treatment of precipitation and temperature means. Analysis of climate change scenarios shows that monthly dry and wet spells for the 2025–2084 period predicted by the WG-based method would be considerably different from those of the reference period. The CF method does not consider any change in precipitation occurrence over the reference period, a clear weakness of the approach. Compared to the reference period, the WG-based method predicted shorter dry day spells for the 2025–2084 period, thus indicating an increasing wet day frequency. Different dry and wet day spells and similar seasonal precipitation result in different mean daily precipitations between the 2 downscaling approaches. The standard deviation of daily precipi-

tation,  $T_{\max}$  and  $T_{\min}$  differs markedly depending on the downscaling method. This should not be a surprise, since the WG-based method specifically takes the variance change of precipitation and temperatures into account, while the CF method does not. To evaluate how those changes translated into hydrological variables, weather variables derived from both downscaling methods were fed into the lumped semi-conceptual hydrology model HSAMI.

Both downscaling methods suggest general increases in winter (Nov–Apr) discharge and decreases in summer (Jun–Oct), the increases being larger when downscaled by the WG-based method. The WG-based method suggest higher peak discharges than those predicted by the CF method and those of the reference period. Peak discharges over the 2025–2084 period would be observed earlier than those at the reference period according to both downscaling methods. The differences between the weather variables downscaled from the 2 methods are amplified when transferred to hydrologic variables. Even though both downscaling methods suggest similar increases in annual and seasonal precipitations and temperatures, the annual and seasonal discharges are markedly different, especially for seasonal discharge. This indicates that precipitation and temperature variability play an important role in the processes leading to runoff.

The comparison of the 2 downscaling methods reveals the main weakness of the CF method: that it keeps the precipitation occurrence and variability of all weather variables constant. This fallibility is probably not a major obstacle with respect to spring snowmelt, as shown in Fig 9, because spring floods are the result of several months of snow accumulation followed by rapid melting. As such, the most important feature to have in a climate change study is the correct total quantity of solid precipitation. The variability of solid precipitation during the winter months is likely a less important feature, unless variability adds the frequent mid-winter thaws that cannot be captured by the CF method. For summer and fall events, climatic disasters often result from one major rainfall event, or from droughts that occur after long periods with little to no precipitation. In such cases, the CF method would be totally inappropriate for climate change studies. This situation is clearly delineated by the low flow results, where the 2 downscaling approaches display very different trends. The proposed WG-based method takes into account the change of precipitation occurrence and the variance of all variables, so it should arguably result in better climate projections for impact studies. Time series of any length can be generated with this method: another advantage for the study of rare events.

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