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# Uncertainty of downscaling method in quantifying the impact of climate change on hydrology

Jie Chen *, François P. Brissette, Robert Leconte

*Department of Construction Engineering, École de Technologie Supérieure, Université du Québec, 1100 Notre-Dame Street West, Montreal, QC, Canada H3C 1K3*

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SUMMARY

Uncertainty estimation of climate change impacts has been given a lot of attention in the recent literature. It is generally assumed that the major sources of uncertainty are linked to General Circulation Models (GCMs) and Greenhouse Gases Emissions Scenarios (GGES). However, other sources of uncertainty such as the choice of a downscaling method have been given less attention. This paper focuses on this issue by comparing six downscaling methods to investigate the uncertainties in quantifying the impacts of climate change on the hydrology of a Canadian (Quebec province) river basin. The downscaling methods regroup dynamical and statistical approaches, including the change factor method and a weather generator-based approach. Future (2070–2099, 2085 horizon) hydrological regimes simulated with a hydrological model are compared to the reference period (1970–1999) using the average hydrograph, annual mean discharge, peak discharge and time to peak discharge as criteria. The results show that all downscaling methods suggest temperature increases over the basin for the 2085 horizon. The regression-based statistical methods predict a larger increase in autumn and winter temperatures. Predicted changes in precipitation are not as unequivocal as those of temperatures, they vary depending on the downscaling methods and seasons. There is a general increase in winter discharge (November–April) while decreases in summer discharge are predicted by most methods. Consistently with the large predicted increases in autumn and winter temperature, regression-based statistical methods show severe increases in winter flows and considerable reductions in peak discharge. Across all variables, a large uncertainty envelope was found to be associated with the choice of a downscaling method. This envelope was compared to the envelope originating from the choice of 28 climate change projections from a combination of seven GCMs and three GGES. Both uncertainty envelopes were similar, although the latter was slightly larger. The regression-based statistical downscaling methods contributed significantly to the uncertainty envelope. Overall, results indicate that climate change impact studies based on only one downscaling method should be interpreted with caution.



## 1. Introduction

The Intergovernmental Panel on Climate Change (IPCC, 2007) stated that there is high confidence that recent climate changes have had discernible impacts on physical and biological systems. Many General Circulation Models (GCMs) consistently predict increases in frequency and magnitudes of extreme climate event and variability of precipitation (IPCC, 2007). This will affect terrestrial water resource in the future, perhaps severely (Srikanthan and McMahon, 2001; Xu and Singh, 2004). For continental water resources, hydrological models are frequently used to quantify the hydrological impacts of climate change using GCM data as inputs (Salathe, 2003; Diaz-Nieto and Wilby, 2005; Minville et al., 2008, 2009). However, the spatial resolution mismatch between GCMs outputs and the data requirements of hydrological models is a major obstacle (Leavesley, 1994; Hostetler, 1994; Xu, 1999). It is therefore necessary to perform some post-processing to improve upon these global-scale models for impact studies. Consequently, dynamical downscaling (regional climate models, RCMs) and statistical downscaling (SD) methods have been developed to meet this requirement. RCMs are developed based on dynamic formulations using initial and time-dependent lateral boundary conditions of GCMs to achieve a higher spatial resolution at the expense of limited area modeling (Caya and Laprise, 1999). The main problem of RCMs is the computational cost (Solman and Nunez, 1999). Thus, it is only available for limited regions. Moreover, despite improvements, outputs of RCMs are still too coarse for some practical applications, like small watershed hydrological and field agricultural impact studies, which may need local and site-specific climate scenarios. SD techniques have been developed to overcome these challenges. They involve linking the state of some variables representing a large scale (GCM or RCM grid scale, the predictors) and the state of other variables representing a much smaller scale

* Corresponding author. Tel.: +1 514 396 8800.
*E-mail address:* chj092413@yahoo.com.cn (J. Chen).

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(catchment or site scale, the predictands). These techniques are computationally cheap and relatively easy to implement.

These SD techniques fall into three categories: transfer function (Wilby et al., 1998, 2002), weather typing (von Stoch et al., 1993; Schoof and Pryor, 2001) and weather generator (WG) (Wilks, 1999; Zhang, 2005). Transfer function approaches involve establishing statistical linear or nonlinear relationships between observed local climatic variables (predictands) and large-scale GCM outputs (predictors) (Wilby et al., 2002). They are relatively easy to apply, but their main drawback is the probable lack of a stable relationship between predictors and predictands (Wilby and Wigley, 1997). Weather typing scheme involves grouping local meteorological variables in relation to different classes of atmospheric circulation (Bardossy and Plate, 1992; von Stoch et al., 1993). The main advantage is that local variables are closely linked to global circulation. However, its reliability depends on a stationary relationship between large-scale circulation and local climate. Especially for precipitation, there is frequently no strong correlation between daily precipitation and large-scale circulation. The WG method is based on the perturbation of its parameters according to the changes projected by climate models (Zhang, 2005; Kilsby et al., 2007; Qian et al., 2005, 2010; Wilks, 2010). The appealing property is its ability to rapidly produce sets of climate scenarios for studying the impacts of rare climate events and investigating natural variability.

Another relatively straightforward and popular downscaling method for rapid impact assessment of climate change is the change factor (CF) method (Minville et al., 2008; Diaz-Nieto and Wilby, 2005; Hay et al., 2000). It involves adjusting the observed time series by adding the difference (for temperatures) or multiplying the ratio (for precipitation) between future and present climates as simulated by the RCMs or GCMs. The most significant drawbacks are that the temporal sequencing of wet and dry days, and that the variances of temperatures are unchanged.

The unique advantages and drawbacks of each downscaling method result in different future climate projections. In particular, some downscaling methods are unable to capture the extremes of climate events that are often of particular concern in hydrology. Differences in future climate projections imply that downscaling methods add uncertainties in quantifying the impacts of climate change on hydrology. Many studies have focused on uncertainties linked to GCMs (Graham et al., 2007a,b; Maurer and Hidalgo, 2008; Minville et al., 2008; Christensen and Lettenmaier, 2007; Hamlet and Lettenmaier, 1999). Rowell (2006) compared the effect of different sources of uncertainty including emissions scenario, GCM, RCM and initial condition ensembles on changes in seasonal precipitation and temperature for the UK. The uncertainty from a GCM was found to be the largest. Prudhomme and Davies (2009) used three GCMs, two greenhouse gas emission scenarios (GGES) and two downscaling techniques (statistical downscaling model (SDSM) and HadRM3) to investigate their uncertainty in propagating river flow, and demonstrated that uncertainties from GCMs are larger than those from downscaling methods and GGES. Kay et al. (2009) also investigated different sources of uncertainties including GGES, GCM's structure (five GCMs), downscaling method (CF and RCM), hydrological model structure (two models), hydrological model parameters (jack-knifed calibrated parameter sets) and the internal variability of the climate system on the impact of climate change on flood frequency in England. With this research, each different source of uncertainty was done individually rather than in combination with each other. The results showed that the uncertainty related to GCM structure is the largest, but that other sources of uncertainty are significant if the GCM structure's influence was not taken into account. Wilby and Harris (2006) presented a probabilistic framework for quantifying different sources of uncertainties on future low flow. They used four GCMs, two GGES, two downscaling techniques (SDSM and CF), two hydrological model structures and two sets of hydrological model parameters. The results indicated that GCMs revealed the greatest uncertainty, followed by downscaling methods. Uncertainties due to hydrological model parameters and GGES were less important.

Generally, GCMs are considered to be the largest source of uncertainty for quantifying the impacts of climate change. However, the uncertainty related to the downscaling and bias-correction methods must be taken into account for better estimation of the impact of climate change (Quintana Segui et al, 2010). Moreover, although some studies attempted to investigate the uncertainty related to downscaling techniques, only two methods were involved. A better method may use multi-downscaling techniques (more than two) for quantifying their uncertainty propagation in hydrology.

The objective of this study is to quantify the impacts of climate change on a Canadian river basin (Quebec province), while investigating the uncertainties related to downscaling techniques, using six downscaling methods. The downscaling methods include both dynamical and statistical approaches, including the CF method and a WG-based approach.

## 2. Study area and data

### 2.1. Study area

This study was conducted for the Manicouagan 5 river basin located in central Quebec, Canada. It covers 24,610 $km^2$ of mostly forested areas (Fig. 1). It has a rolling to moderately hilly topography with a maximum elevation of 952 m above sea level. The reservoir at the basin outlet has a mean level of 350 m above sea level. 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 $km^2$ 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 capacity of the dam is 2.6GW. The annual mean discharge of the Manicouagan 5 River is 529 $m^3/s$. Snowmelt peak discharge usually occurs in May and averages 2200 $m^3/s$.

### 2.2. Data

The different datasets used in this work are summarized in Table 1. Observed data consisted of precipitation, maximum temperature (Tmax) and minimum temperature (Tmin) interpolated on a 10 km grid by the National Land and Water Information Service (www.agr.gc.ca/nlwis-snite). The interpolation is performed using a thin plate smoothing spline surface fitting method (Hutchinson et al., 2009). Discharge data at the basin outlet was obtained from mass balance calculations at the dam and were provided by Hydro-Québec. Climate data consisted of reanalysis, GCM and RCM data. Data from the Canadian GCM (v3.1) (CGCM) and the Canadian RCM (v.4.2.0) (CRCM) was used. Average grid resolution was about 300 km for the CGCM and 45 km for the CRCM. The National Center for Environmental Prediction (NCEP) reanalysis data was used as a proxy to GCM data, to calibrate some of the downscaling used in this paper. This data uses a T62 ($\sim$209 km) global spectral model to consistently collect observational data from a wide variety of observed sources (Kalnay et al., 1996; DAI CGCM3 Predictors, 2008). It includes information from both models and observations. SD techniques were calibrated using NCEP predictors interpolated at the CGCM scale. In climate change mode, predictors from the CGCM were used directly. The CRCM data driven by NCEP was also used for calibration purposes, while in climate change mode it was driven by the CGCM at its boundary and initial conditions. This work covers the 1970–1999 period (reference period)

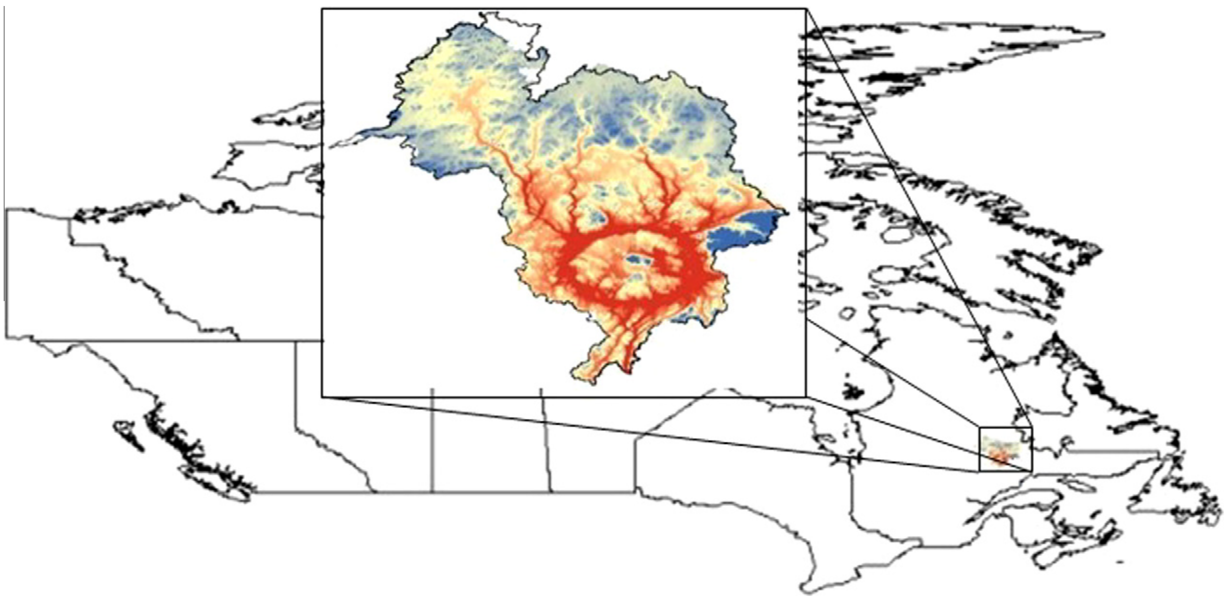

**Fig. 1.** Location map of Manicouagan 5 river basin.

**Table 1**
The datasets used in this research.

| No. | Dataset | Purpose | Time period |
|---|---|---|---|
| 1 | Observed P, Tmax and Tmin (interpolated at a 10 km scale – NLWIS dataset), measured discharge | Baseline, calibration of Hydrological model and WG | 1970–1999 |
| 2 | CGCM P, Tmax and Tmin | Downscaling of CF and WG methods | 1970–1999, 2070–2099 |
| 3 | CRCM P, Tmax and Tmin | Downscaling of CF and WG, and CRCM with and without BC methods | 1970–1999, 2070–2099 |
| 4 | NCEP predictors interpolated to CGCM grid | Calibration of SDSM and DASR | 1970–1999 |
| 5 | CGCM predictors | Downscaling of SDSM and DASR | 2070–2099 |
| 6 | CRCM P, Tmax and Tmin driven by NCEP | Calibration of HM for the method of CRCM without BC | 1970–1999 |

Note: P = precipitation; Tmax = maximum temperature; Tmin = minimum temperature; BC = bias correction; WG = weather generator; SDSM = statistical downscaling model, and DASR = discriminant analysis coupled with stepwise linear regression downscaling method.

**Table 2**
NCEP and CGCM predictor variables used to select precipitation predictors for downscaling.

| Predictor variable | Abbreviation | Predictor variable | Abbreviation |
|---|---|---|---|
| Mean sea level pressure | ncepmslp | 500 hPa Divergence | ncepp5zh |
| 1000 hPa Wind Speed | ncepp_f | 850 hPa Wind Speed | ncepp8_f |
| 1000 hPa U-component | ncepp__u | 850 hPa U-component | ncepp8_u |
| 1000 hPa V-component | ncepp__v | 850 hPa V-component | ncepp8_v |
| 1000 hPa Vorticity | ncepp__z | 850 hPa Vorticity | ncepp8_z |
| 1000 hPa Wind Direction | ncepp_th | 850 hPa Geopotential | ncepp850 |
| 1000 hPa Divergence | ncepp_zh | 850 hPa Wind Direction | ncepp8th |
| 500 hPa Wind Speed | ncepp5_f | 850 hPa Divergence | ncepp8zh |
| 500 hPa U-component | ncepp5_u | 500 hPa Specific Humidity | ncep s500 |
| 500 hPa V-component | ncepp5_v | 850 hPa Specific Humidity | nceps850 |
| 500 hPa Vorticity | ncepp5_z | 1000 hPa Specific Humidity | ncepshum |
| 500 hPa Geopotential | ncepp500 | Temperature at 2 m | nceptemp |
| 500 hPa Wind Direction | ncepp5th | | |

for calibration and the 2070–2099 period (2085 horizon) in climate change mode. The atmospheric predictors considered (NCEP and CGCM) are listed in Table 2.

## 3. Methodology

### 3.1. Downscaling methods

Six downscaling methods will be compared in this work. They consist of using CRCM data with (1) and without (2) bias correction, CF (3) and WG (4) methods at both CGCM and CRCM scales and two statistical downscaling methods: SDSM (5) and discriminant analysis coupled with step-wise regression method (6) at CGCM scale. Table 3 briefly describes all of the methods. Details follow below.

#### 3.1.1. Canadian RCM without bias correction

With the improved resolution of RCMs and the relatively small biases of RCM output data (compared to GCM data), it is now possible to envision direct use of RCM data as proxies to observed

**Table 3**
Downscaling methods used in this work.

| Method | Brief description | Acronym used in the paper |
|---|---|---|
| 1 | Direct use of CRCM precipitation and temperature data without any bias correction, but with a specific hydrology model calibration | CRCM-NONBC |
| 2 | Direct use of CRCM precipitation and temperature data with bias correction | CRCM-BC |
| 3 | Change factor method, based on CRCM and CGCM data | CRCM-CF<br>CGCM-CF |
| 4 | Weather generator method based on CRCM and CGCM data | CRCM-WG<br>CGCM-WG |
| 5 | Statistical approach using the SDSM package with variance inflation and bias correction. GCM scale predictors are used (NCEP/CGCM) | CGCM-SDSM |
| 6 | Statistical approach using discriminant analysis for precipitation occurrence and stepwise linear regression for precipitation and temperature data. GCM scale predictors are used (NCEP/CGCM) | CGCM-DASR |

data. This is especially appealing in the cases where basins are much larger than the grid resolution. In this method, no bias correction is made, but the hydrology model is specifically calibrated to this data against observed discharge. The assumption behind this method is that biases are sufficiently small to be overcome by the hydrology model through the calibration process. While many take the accuracy of observed precipitation and temperature data for granted, it is known that such data can also be biased. For example, rain gauges are known to underestimate real precipitation and weather station density is often low, especially in remote areas or at higher altitude, thus introducing spatial biases. If the specifically calibrated hydrology model is able to adequately reproduce observed discharge with realistic internal parameters, it can be argued that RCM data is no more biased than observed data. It is just biased differently, and thus the need for a specific calibration.

### 3.1.2. Canadian RCM with bias correction

While RCM data has been shown to be much more precise than their GCM counterparts, simulated monthly mean precipitation and temperatures are nevertheless biased when compared to observed data (Minville et al., 2009). These biases are large enough to induce significant errors if introduced directly into models such as hydrology models. In this method, bias correction is applied to both temperature and precipitation data. For precipitation, a correction is made to both monthly mean frequency and quantity, using the Local Intensity Scaling Method developed by Schmidli et al. (2006). This method involves three steps: (1) A wet-day threshold is determined from the daily RCM precipitation series of each month such that the threshold exceedence matches the wet-day frequency of the observed time series; (2) A scaling factor is calculated to insure that the mean of the observed precipitation is equal to that of RCM precipitation at the reference period for each month; and (3) The monthly thresholds and factors determined in the reference climate are used to adjust monthly precipitation for the 2085 horizon.

A three-step bias correction is also carried out for both the mean and variance of monthly temperatures (including Tmax and Tmin) of RCM data.

(1) Daily RCM temperatures are corrected on a monthly basis using the following equation:

$$T_{cor,2085} = T_{\mathrm{RCM},2085} + (\overline{T}_{obs} - \overline{T}_{\mathrm{RCM},ref}) \tag{1}$$

where $T_{cor,2085}$ is the daily corrected temperature at the horizon 2085 obtained by adding the difference in mean monthly temperatures between observed data and RCM reference period $(\overline{T}_{obs} - \overline{T}_{\mathrm{RCM},ref})$ to the RCM temperature data for the 2085 horizon $(T_{\mathrm{RCM},2085})$.

(2) In a subsequent step, the standard deviation of monthly temperatures 'S' at the 2085 horizon is corrected using the following equation:

$$S_{cor,2085} = S_{\mathrm{RCM},2085} \times (S_{obs}/S_{\mathrm{RCM},ref}) \tag{2}$$

Eq. (2) effectively corrects the standard deviation of RCM temperatures based on the standard deviation ratio between observed and RCM temperatures over the reference period (subscripts are the same as defined for Eq. (1).

(3) In a last step, downscaled temperatures at the daily scale for the 2085 horizon are obtained by adjusting temperatures obtained in step 1 to the standard deviation calculated in step 2. This is done by normalizing the step 1 temperatures to a zero mean and standard deviation of one, and transforming back to the step 2 standard deviation. This technique assumes that biases are time-invariant and ensures that the temperatures of the RCM over the reference period have the same monthly mean and standard deviation as those of the observed data.

### 3.1.3. Change factor (CF) method

The CF method involves adjusting the observed daily temperature $(T_{obs,d})$ by adding the difference in monthly temperature predicted by the climate model (GCM or RCM) between the 2085 horizon and the reference period $(\overline{T}_{\mathrm{CM},2085,m} - \overline{T}_{\mathrm{CM},ref,m})$ to obtain daily temperature at the 2085 horizon $(T_{adj,2085,d})$ (Eq. (3)). The adjusted daily precipitation for the 2085 horizon $(P_{adj,2085,d})$ is obtained by multiplying the precipitation ratio $(\overline{P}_{\mathrm{CM},2085,m}/\overline{P}_{\mathrm{CM},ref,m})$ with the observed daily precipitation $(P_{obs,d})$ (Eq. (4)).

$$T_{adj,2085,d} = T_{obs,d} + (\overline{T}_{\mathrm{CM},2085,m} - \overline{T}_{\mathrm{CM},ref,m}) \tag{3}$$

$$P_{adj,2085,d} = P_{obs,d} \times (\overline{P}_{\mathrm{CM},2085,m}/\overline{P}_{\mathrm{CM},ref,m}) \tag{4}$$

### 3.1.4. Weather generator (WG)-based method

The WG used in this research is CLImate GENerator (CLIGEN, Nicks and Lane, 1989). In this study, only the functions to generate precipitation occurrence and quantity, Tmax and Tmin were used. Other weather generators 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 two transition probabilities: wet day following a dry day (P01) and a wet day following a wet day (P11). For a predicted wet day, a three-parameter skewed normal Pearson III distribution was used to generate daily precipitation intensity for each month (Nicks and Lane, 1989).

A normal distribution was used to simulate Tmax and Tmin. The temperature with the smaller standard deviation between Tmax and Tmin is computed first, followed by the other temperature (Chen et al., 2008). The mean and standard deviation of Tmax and Tmin were calculated monthly and smoothed with Fourier interpolation at a daily scale.

Overall, CLIGEN requires a total of nine monthly parameters to generate precipitation, Tmax and Tmin. They include p01, and p11 for generating precipitation occurrence, mean, standard deviation and skewness for generating daily precipitation intensity and means and standard deviations of Tmax and Tmin. The skewness of precipitation is supposed to be unchanged in the future for this study. Thus, there are eight parameters that require modification for every future climate change scenario.

The parameters of CLIGEN are modified to take into account the variations predicted by a climate model (GCM or RCM). This variation is based on a delta change approach. For example, take the probability of precipitation occurrence P01. For various reasons, the P01 from GCM or RCM data will not match the P01 measured at a particular station. Thus, similarly to the CF method, the difference obtained from the GCM (or RCM) between the future and the reference periods will be applied to the observed data. This is a hybrid method combining attributes of both statistical and CF methods. The huge advantage over the CF method is that differences in precipitation occurrence and variance of all variables can be taken into account. Time series of any length can be generated, which is another advantage for the studies of extremes.

Details of this approach are as follows:

(1) Similarly to the CF method, the adjusted monthly mean Tmax and Tmin for the 2085 horizon ($\bar{T}_{adj,2085}$) are estimated as:

$$\bar{T}_{adj,2085} = \bar{T}_{obs} + (\overline{T}_{\mathrm{CM},2085} - \overline{T}_{\mathrm{CM},ref}) \tag{5}$$

The adjusted values are obtained by adding the differences predicted by a climate model (GCM or RCM) between the 2085 horizon and the reference period ($\overline{T}_{\mathrm{CM},2085} - \overline{T}_{\mathrm{CM},ref}$) to the observed mean monthly observed temperatures ($\overline{T}_{obs}$).

(2) Monthly means and variances of precipitation, monthly variances of Tmax and Tmin and transition probabilities of precipitation occurrence p01 and p11 for the 2085 horizon are adjusted by:

$$X_{adj,2085} = X_{obs} \times (X_{\mathrm{CM},2085}/X_{\mathrm{CM},ref}) \tag{6}$$

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

(3) The p01 and p11 values are expressed in terms of an unconditional probability of daily precipitation occurrence ($\pi$) and the lag-1 autocorrelation of daily precipitation ($r$) for further adjustments.

$$\pi = \frac{P_{01}}{1 + P_{01} - P_{11}} \tag{7}$$

$$r = P_{11} - P_{01} \tag{8}$$

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

$$\mu_d = \frac{\mu_m}{N_d \pi} \tag{9}$$

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 $u_m$ is the step (2)-adjusted monthly precipitation.

(5) The adjusted daily variance ($\sigma_d^2$) was approximated using Eq. (10), based on the step (2)-adjusted variance of the monthly precipitation ($\sigma_m^2$) (Wilks, 1999).

$$\sigma_d^2 = \frac{\sigma_m^2}{N_d \pi} - \frac{(1-\pi)(1+r)}{1-r}\mu_d^2 \tag{10}$$

All of the adjusted precipitation, Tmax and Tmin parameter values were input to CLIGEN to generate 900 years of daily time series (Thirty 30-year realizations). An ensemble of realizations was used to insure that the method converges toward its true mean response. Due to the stochastic nature of the WG, a single realization of 30 years could have resulted in a biased estimate.

*3.1.5. Statistical downscaling model (SDSM)*

The SDSM is a downscaling tool developed by Wilby et al. (2002) that can be used to develop climate change scenarios. The SDSM uses a conditional process to downscale precipitation. Local precipitation amounts depend on wet-/dry-day occurrences, which in turn depend on regional-scale predictors such as mean sea level pressure, specific humidity and geopotential height (Wilby et al., 1999; Wilby and Dawson, 2007). Specifically, downscaling of precipitation occurrence is achieved by linking daily probabilities of non-zero precipitation with large-scale predictors selected from the variables listed in Table 2.

The main procedures of the SDSM for downscaling wet day precipitation intensity, Tmax and Tmin (predictands) are the following: (1) Identification of the screen variable: a partial correlation analysis was used to identify the relationship between NCEP variables and predictands. Variables that significantly correlated to predictands were then selected as predictors; (2) Model calibration: multiple linear regressive equations were established between predictands and step (1)-identified predictors for each season. Since the distribution of the daily precipitation is highly skewed, a fourth root transformation was applied to the original precipitation before fitting the transfer function (Wilby and Dawson, 2007); and (3) Application of transfer functions: established transfer functions were further used to downscale precipitation amounts, Tmax and Tmin for the 2085 horizon.

The SDSM bias correction was applied to insure that observed and downscaled precipitation totals were equal for the simulation period. The variance inflation scheme was also used, to increase the variance of precipitation and temperatures to agree better with observations. When using bias correction and variance inflation, SDSM essentially becomes a weather generator, where a stochastic component is superimposed on top of the downscaled variable. This is especially true for precipitation, where the explained variance is generally less than 30% (Wilby et al., 1999).

*3.1.6. Discriminant analysis coupled with step-wise regression method (DASR)*

This approach is similar to that of the SDSM, but with no stochastic component added on top via bias correction and variance inflation. The main difference is that precipitation occurrence is downscaled using a discriminant analysis and the daily precipitation intensity of wet days is downscaled using a stepwise linear regression approach.

With discriminant analysis for the downscaling of precipitation occurrence, it is necessary to have an available "training sample" in which it is known that each of the vectors is classified correctly (Wilks, 1995). In this research, the NCEP variables interpolated to the CGCM grid and their lag-1 variables were used as the training sample. The precipitation series were first divided into two groups, a wet-day group (daily precipitation amount $\geqslant$1 mm) and a dry-day group (daily precipitation amount <1 mm). The future precipitation occurrence was similarly classified according to rules constructed based on a training sample and corresponding groups.

The SD method selected here uses a stepwise linear regression for the precipitation quantity of wet days, Tmax and Tmin (predictands). Twenty-five NCEP variables and the lag-1 variables for the reference period were used to select predictors using the stepwise regressive method. Multiple linear regressive equations were then fitted between predictands and selected predictors for each season. A fourth root transformation was also applied to the original precipitation before fitting the transfer function. The established transfer functions were then used to downscale daily precipitation for the 2085 horizon using CGCM predictors.

### 3.2. Hydrological simulation

The impacts of climate change on hydrology at the catchment were quantified based on discharges simulated with the hydrological model HSAMI, developed by Hydro-Québec, and which has been used to forecast natural inflows for over 20 years (Fortin, 2000). HSAMI is used by Hydro-Québec for hourly and daily forecasting of natural inflows on 84 watersheds with surface areas ranging from 160 km$^2$ to 69,195 km$^2$. Hydro-Québec's total installed hydropower capacity on these basins exceeds 40GW. HSAMI is a 23-parameter, lumped, conceptual, rainfall–runoff model. Two parameters account for evapotranspiration, six for snowmelt, 10 for vertical water movement, and five for horizontal water movement. Vertical flows are simulated with four interconnected linear reservoirs (snow on the ground, surface water, unsaturated and saturated zones). Horizontal flows are filtered through two hydrograms and one 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: Tmax, Tmin, liquid and solid precipitations. 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, thirty years (1970–1999) of daily discharge data were used for model calibration/validation. The optimal combination of parameters was chosen based on Nash-Sutcliffe criteria. The chosen set of parameters yielded Nash-Sutcliffe criteria values of 0.89 for both validation and calibration periods. This high value of the Nash-Sutcliffe criteria is representative of the good quality of weather inputs and observed discharge.

## 4. Results

### 4.1. Validation of downscaling methods

The validation of each downscaling method was based on the quality of the simulated hydrographs at the basin outlet, when compared to the hydrograph developed from observed weather data. Mean hydrograph results are presented in Fig. 2. The mean hydrograph from observed discharge (labeled OBS) and a hydrograph simulated from observed weather data (labeled OBS-SIM) show the small biases introduced by the hydrological model. The overall fit is quite good, with a Nash-Sutcliffe coefficient of 0.89 over the length of the time series, as mentioned above. The mean hydrograph simulated from WG generated weather data (labeled OBS-WG) is also displayed to verify the possibility of using the WG method. The other curves represent the downscaling approaches presented in Table 3, with the exception of the CF method which requires no validation. Overall, all of the methods, with the exception of CGCM-DASR, result in hydrographs that are very close the one simulated using observed precipitation and temperatures time series. The best methods were found to be CRCM data with bias correction and the SDSM. In addition, the performance of CLGEN was also qualified to use in this research. The performance of the hydrological model when calibrated with raw RCM data indicates that the biases of the climate model are small enough to be accounted for by the hydrology model. However, the Nash-Sutcliffe coefficient was better when using the standard calibration and correcting the biases (0.89 for CRCM-BC versus 0.81 for CRCM-NONBC), indicating that RCM data is either more biased than the observed values or less coherent with the observed discharge.

As mentioned above, discharges simulated with the precipitation, Tmax and Tmin downscaled by DASR were underestimated. This is because DASR underestimated the precipitation (mean and standard deviation), while the SDSM reproduced it very well (Fig. 3). This indicates that the explained variance of the linear regression approach is not sufficient to properly resolve discharge. The stochastic component added by the SDSM via bias correction and variance inflation makes up for the basic flaw of the approach (a small percentage of explained variance) with respect to precipitation. Results are much better for temperatures because of the much larger percentage of explained variance. The DASR and SDSM methods are very similar and the observed differences between these approaches outline the differences in the raw predictive power of the statistical scheme and with the added stochastic component. This will be further discussed after the results in a changed climate are presented.

### 4.2. Climate change scenarios

#### 4.2.1. Monthly and daily mean precipitations

All downscaling methods show increases in total seasonal precipitation for the 2085 horizon (Fig. 4a). The ratios of increase

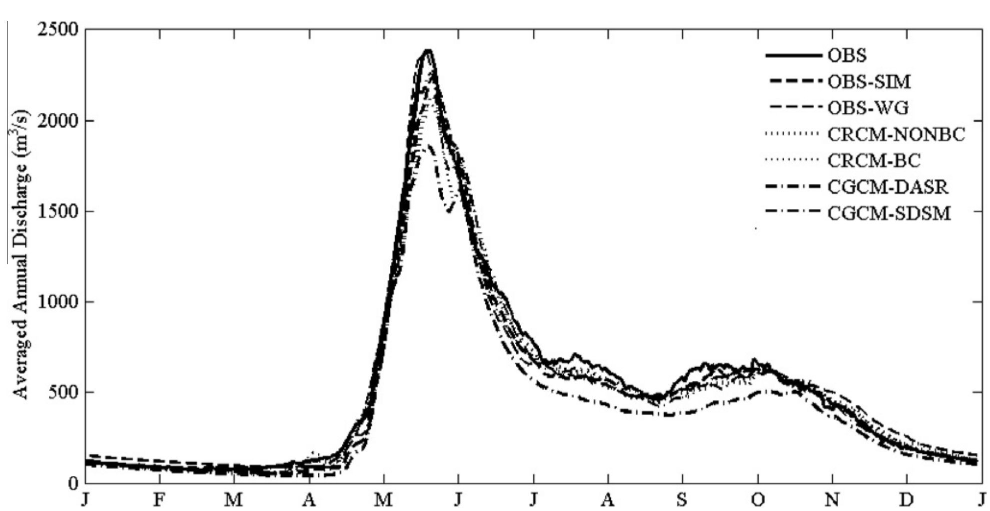


**Fig. 2.** Averaged annual hydrographs for the reference period (1970–1999) at the Manicouagan 5 river basin. Observed (OBS), observed weather data simulated (OBS-SIM), and weather generator data simulated (OBS-WG) discharges are also plotted for comparison. See Table 1 for the downscaling method acronyms.

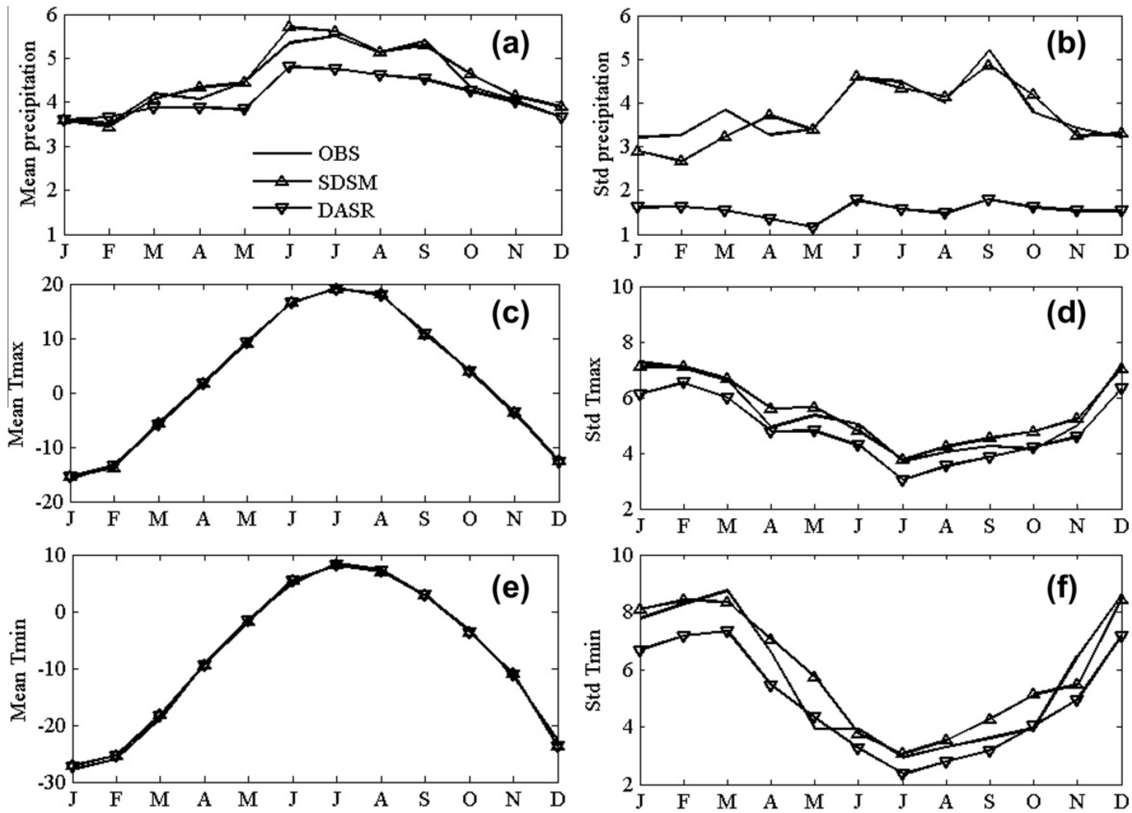


**Fig. 3.** Means and standard deviations of observed (OBS) and DASR and SDSM downscaled monthly precipitations, Tmax and Tmin at the Manicouagan 5 river basin for the reference period (1970–1999).

range from 6% to 67% for spring, 1% to 20% for summer, 3% to 21% for autumn and between 5% and 45% for winter. Although both CGCM-SDSM and CGCM-DASR are regression-based methods, the former suggests more increases in monthly precipitation than the latter. This is partly due to the underestimation of mean precipitation by the CGCM-DASR model (Fig. 3b). A bias correction is used with the SDSM to insure the downscaled mean precipitation agrees better with the observation.

The CGCM-DASR suggests 12% winter daily precipitation increase and 5% decrease for spring, 8% decrease for summer and 2% decrease for autumn (Fig. 4b). However, the other downscaling methods, with the exception of CGCM-WG, predict increases in daily precipitation for all seasons. The increased/decreased ratios range from 11% to 68% for spring, −4% (predicted by CGCM-WG) to 19% for summer, −1% (predicted by CGCM-WG) to 29% for autumn and between 12% and 40% for winter. The variation of daily precipitation in each season is not consistent with that of totally seasonal precipitation. This is because the daily precipitation quantity is affected not only by the seasonal precipitation quantity, but also by precipitation occurrence. The precipitation occurrence is different for each downscaling method (results not shown).

The CGCM-DASR predicts a 26% standard deviation increase for total winter precipitation and a decrease for all other seasons (8% for spring, 26% for summer and 19% for autumn) for the 2085 horizon (Fig. 4c). This decrease is partly due to the underestimation of the variance of precipitation as shown in Fig. 3b. As mentioned earlier, the SDSM uses a stochastic component to increase downscaled variances to better agree with observations. Other downscaling methods suggest increases in the standard deviation of seasonal precipitation for each season (20–59% for spring, 4–19% for summer and autumn and between 18% and 50% for winter). Although the CF and WG methods share similarities, the observed increases are different, because the CF method adjusts precipitation variance through a modification of the mean, while WG-based methods adjust it from changes of not only precipitation quantity but also occurrence. In addition, variances downscaled from CGCM and CRCM data are also different, although the CRCM is driven by the CGCM. Predicted changes in the standard deviation of daily precipitation are not unequivocal (Fig. 4d). The CGCM-DASR suggests reductions in the standard deviation of daily precipitation (between 50% and 63% depending on the season) while the other methods suggest increases for most of the seasons.

### 4.2.2. Average temperatures

Fig. 5 presents annual temperature (average of Tmax and Tmin) cycles for all downscaling methods for the 2085 horizon and for the observed data (reference period). All of the downscaling methods suggest increases in temperatures for the 2085 horizon. Increases range between 3.6 and 6.3 °C for spring, 0.4 and 4.1 °C for summer, 1.8 and 4.8 °C for autumn and between 5.7 and 9.1 °C for winter. Winter temperature increases are greater than for other seasons. The CRCM-NONBC method suggests lower increases in temperature than other methods. The regression-based statistical methods predict a much larger increase in autumn and winter average temperatures. Average temperature cycle graphs display the freezing dates when the average temperature climbs above and descends below zero degrees. These dates are April 27th and October 15th for the reference period. Depending on the specific downscaling method, this period could start as early as April 11th and as late as November 13th for the 2085 horizon, which implies that the freezing season could be shortened by up to 42 days. These changes would affect the snow accumulation in the winter and the spring snowmelt.

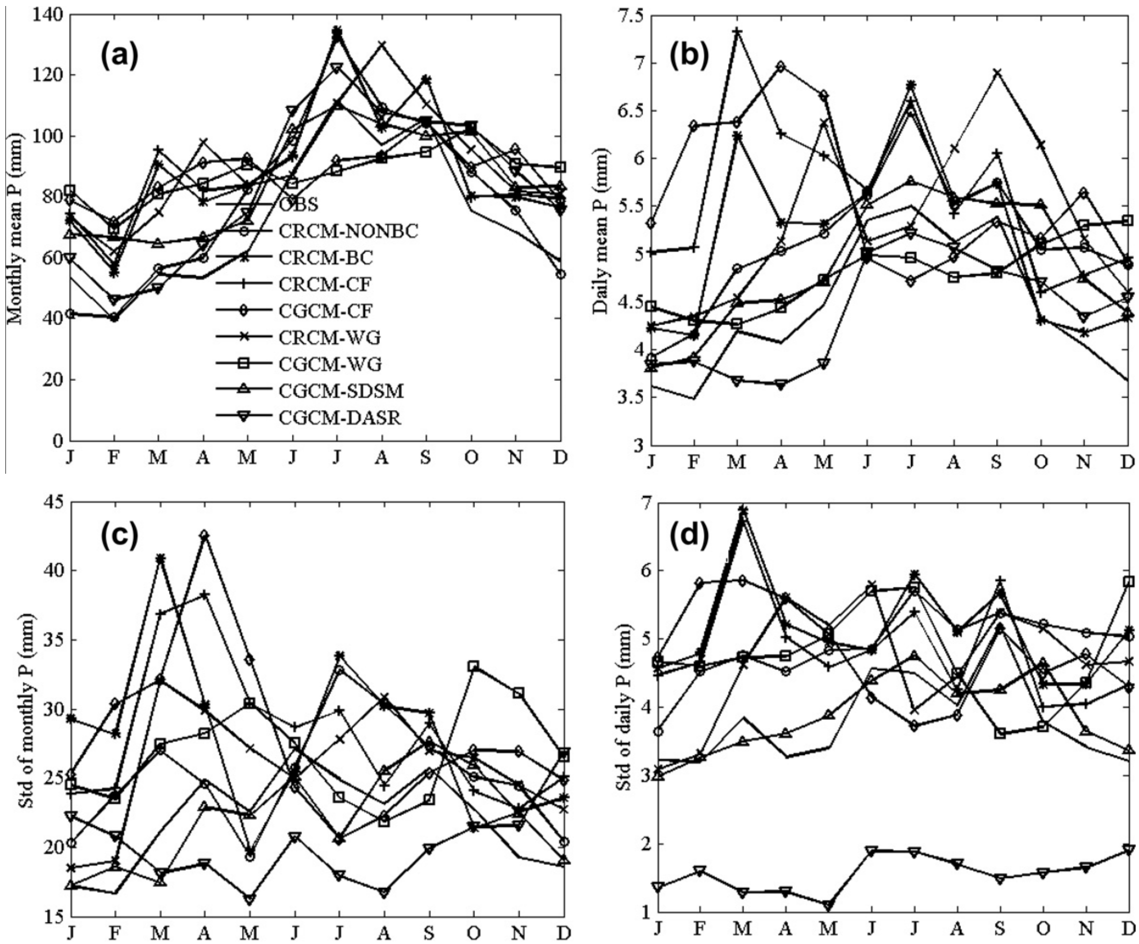


**Fig. 4.** Mean and standard deviation of the observed (1970–1999) and downscaled (2070–2099) monthly and daily precipitations at the Manicouagan 5 river basin. (a) Mean monthly precipitation; (b) mean daily precipitation; (c) standard deviation of monthly precipitation; and (d) standard deviation of daily precipitation.

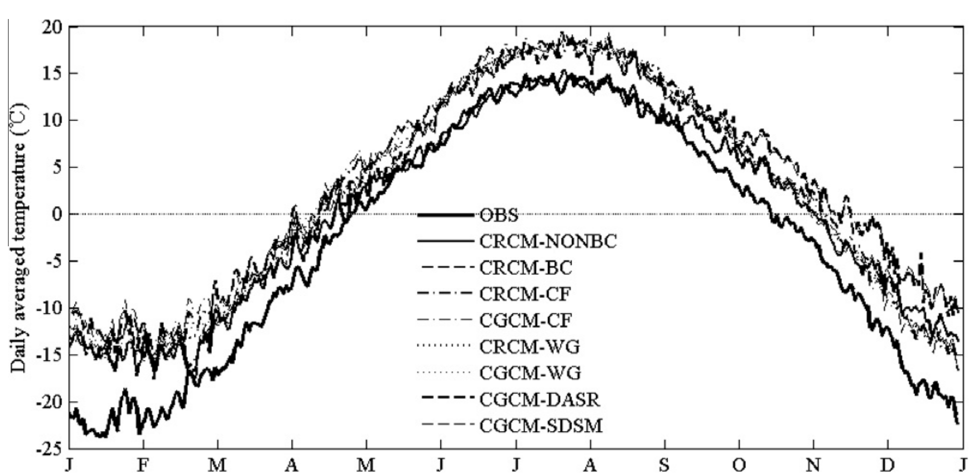


**Fig. 5.** Observed (1970–1999) and downscaled (2070–2099) average annual temperature cycle at the Manicouagan 5 river basin.

### *4.2.3. Uncertainty of annual precipitation and maximum and minimum temperatures*

Probability density functions (PDFs) of the annual precipitation, Tmax and Tmin, were built to show the uncertainties related to downscaling methods (Fig. 6). The probability of a variable (precipitation, Tmax or Tmin) falling within a given set is given by the integral of its density over the set. The total area under each PDF is equal to one. The annual precipitations for the reference period are between 557.8 mm and 1230.8 mm with a median value of 863.7 mm (there is a 50% probability of annual precipitation being greater or less than 863.7 mm) and a mode (most frequent value) of 850.1 mm. The PDFs show that all downscaling methods predict an increase in annual precipitation for the 2085 horizon; the magnitude of increase varies from one method to the other ranging

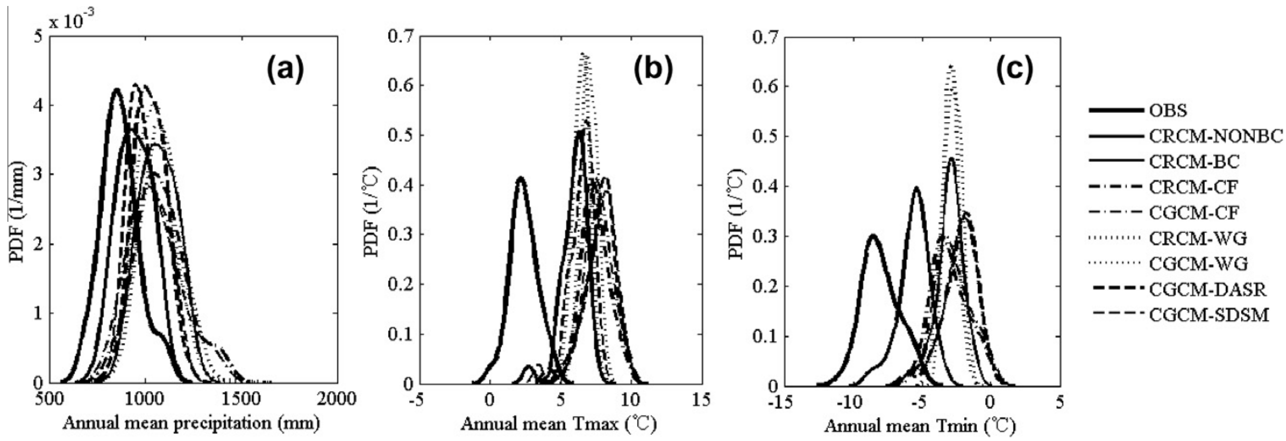


**Fig. 6.** Probability density functions (PDF) of the observed (1970–1999) and downscaled (2070–2099) annual mean precipitation and maximum and minimum temperatures at the Manicouagan 5 river basin.

between 75.0 (CRCM-NONBC) and 219.1 mm (CRCM-WG). The CRCM-WG predicts the largest increase in annual precipitation. Medians of annual precipitation would also increase by between 9% and 26% in the 2085 horizon. The CRCM-NONBC predicts the lowest increase in the median and the CRCM-WG predicts the highest. Fig. 6a shows that an average year of precipitation in the current climate would become a very dry year in the 2085 future climate.

Each downscaling method suggests increases in annual mean Tmax and Tmin for the 2085 horizon. The magnitude of the increases varies from one method to the other, ranging between 3.6 and 5.4 °C for Tmax and between 2.4 and 5.8 °C for Tmin. In addition, all downscaling methods predict increases in the medians of annual mean Tmax (3.7–5.6 °C) and Tmin (2.7–6.1 °C). The CRCM-NONBC predicts the smallest increases in temperatures, while the two regression-based methods (CGCM-SDSM and CGCM-DASR) suggest the largest increases.

### 4.3. Hydrologic impacts of climate change

#### 4.3.1. Hydrologic variables

Fig. 7 presents average hydrographs simulated with precipitation and temperature downscaled from the different methods. To avoid any bias resulting from the hydrological modeling process, discharge for the reference period is represented by modeled discharge and not by observations. The results showed that all downscaling methods suggest increases in winter discharge (November–April) and decreases in summer (June–October). The two regression-based methods predict much larger increases in winter flows than other methods, and, consequently, their snowmelt peak discharges are much lower. These two methods predict a larger increase in autumn and winter temperatures; the liquid winter precipitation rapidly contributes to runoff instead of being accumulated in the snow cover. Thus, there is not very much snowmelt in spring to contribute to peak discharge. For annual discharges, the only simulation that predicts a decrease comes from the CGCM-DASR method, largely because this method underestimates precipitation. All other downscaling methods show increases in annual discharges ranging between 3.5 (CRCM-NONBC) and 20.9% (CRCM-WG). By the 2085 horizon, the two regression-based methods and the CRCM-NONBC suggest decreases in peak discharges between 4.1% (CRCM-NONBC) and 25.1% (CGCM-DASR). The slight decrease predicted by CRCM-NONBC is due to a smaller increase in annual precipitation, relative to a larger increase in temperature. However, the CGCM-WG predicts an increase in peak discharge, as do the CRCM-WG and the CRCM-BC. For these three methods, increases in winter temperature are not sufficient to offset the precipitation increase. In addition, for all downscaling methods the peak discharges of the 2085 horizon are observed earlier than for the reference period. Lags vary from 12 days (May 12th) for the CRCM-NONBC to 27 days (April 27) for the CGCM-CF.

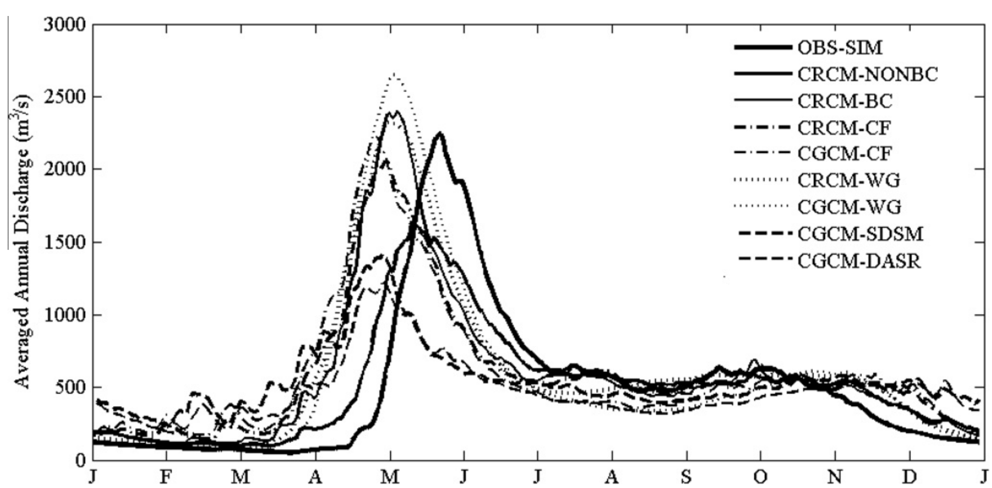


**Fig. 7.** Average annual hydrographs for the future (2070–2099) and reference (1970–1999) periods at the Manicouagan 5 river basin.

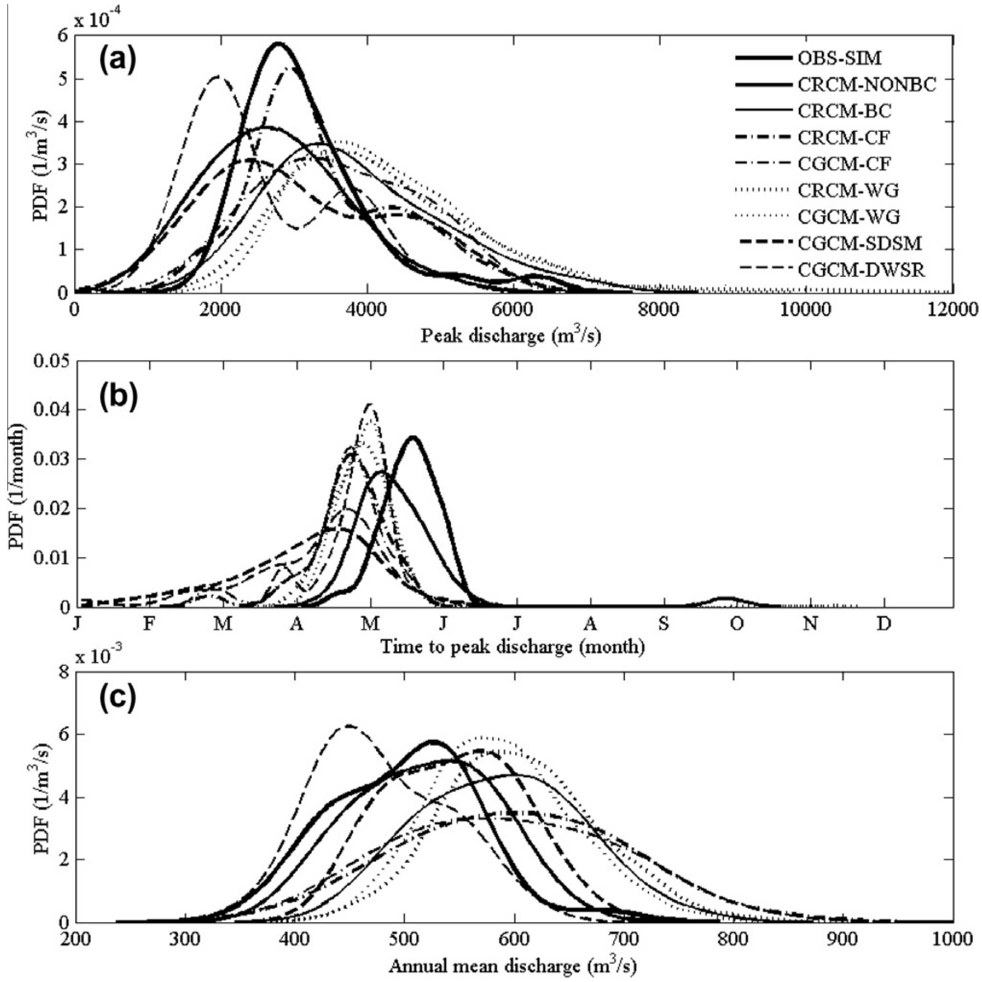


**Fig. 8.** Probability density functions (PDF) of: (a) peak discharge, (b) time to peak discharge and (c) annual mean discharge for the future (2070–2099) and reference (1970–1999) periods at the Manicouagan 5 river basin.

*4.3.2. Uncertainty of hydrologic variables*

In order to better quantify the uncertainties of hydrologic variables, PDFs were constructed for peak discharge, time to peak discharge and annual mean discharge (Fig. 8). These graphs display the global uncertainty linked to downscaling techniques. Fig. 8a shows that the two regression-based methods predict the largest decreases in peak discharges. All of the downscaling methods predict an earlier peak discharge (Fig. 8b), although there is significant inter-annual variability. Inter-annual variability is very large for the two regression-based methods as shown by their very flat PDFs. Large inter-annual variability is also shown with future annual mean discharge (Fig. 8c). As mentioned earlier, the CGCM-DASR method is the only that shows decreases in future annual mean discharge. The CF methods (CGCM-CF and CRCM-CF) display the largest future inter-annual variability of mean discharge (flattest PDFs in Fig. 8c).

## 5. Discussions and conclusions

The uncertainty of climate change impacts on hydrology has been given more and more attention in the scientific literature. By far the largest focus has been on investigating the roles of GCMs and GGES in the uncertainty cascade. Other sources of uncertainty, such as the choice of downscaling method, have been given much less attention. Six downscaling methods were compared to investigate the uncertainty of downscaling methods in quantifying the impact of climate change on the hydrology of a Canadian (Quebec province) River basin. The downscaling methods regroup dynamical and statistical approaches including the CF method and a WG-based approach. Two regression-based methods (SDSM and DASR) are also used for comparison. The downscaling methods were first validated based on the modeling of discharge. Overall, all of the methods, with the exception of CGCM-DASR, result in hydrographs that are very close to the hydrograph simulated by using observed precipitation and temperature time series. The best methods were CRCM data with bias correction and the SDSM. The DASR method underestimates the hydrograph, clearly indicating that the explained variance of the linear regression approach is not sufficient to properly resolve discharge issues. The stochastic component added by the SDSM via bias correction and variance inflation makes up for the basic flaw of the approach (only a small percentage of variance is explained) with respect to precipitation.

The analysis of climate change scenarios shows that all downscaling methods suggest increases in temperature over the basin for the 2085 horizon. The two regression-based methods show larger increases in autumn and winter temperatures than the others. Depending on the specific downscaling method, the freezing season would be shortened by 26–42 days. Predicted changes in precipitation are not as unequivocal as those for temperature. Results vary seasonally and depend on the downscaling method. The combined effects of precipitation and temperature changes influence discharge differently depending on the downscaling method. All of the methods show a general increase in winter discharge (November–April) and most show a decrease in summer discharge. Winter flows are especially large for the two regression-based methods, which also predict the largest temperature increases in autumn and winter. Liquid winter precipitation rapidly contributes to runoff instead of being temporarily stored in the snow cover. This leads to strongly attenuated snowmelt peak flows. Peak discharges appear earlier for all downscaling methods, but their timing varies according to the downscaling method.

The results indicate that climate change impact studies based only on one downscaling method should be interpreted with caution. General speaking, it is assumed that the major sources of uncertainty are linked to GCMs and GGES (Kay et al., 2009; Wilby and Harris, 2006). To make a comparison with GCM-linked uncertainty, the uncertainty envelope derived from the choice of downscaling method in this paper is compared to that originating from a combination of 28 climate projections from a combination of seven GCMs and three GGES (Fig. 9). Both uncertainty envelopes display the same characteristics. Downscaling contributes to a larger uncertainty in winter flows, but GCM-GGES projections give a much larger uncertainty over the snowmelt season. Both envelopes are very similar in the summer and fall seasons. Comparing six downscaling methods to 28 projections (from seven GCMs to three GGES) should contribute to a larger uncertainty envelope in the latter case, and overall this is what was observed. On the other hand, the two regression-based SD methods contributed proportionally more to the uncertainty envelope, because their behavior was markedly different in several instances.

The results indicated quite clearly that the choice of a downscaling method is critical for any climate change impact study on hydrology. Can the results outlined in this paper help in selecting an appropriate method? For the most part, the answer would be 'no' and that additional research is needed. However, these results do raise some important points. It can be argued that regression-based methods should be used with caution due to their distinctive behavior compared to other downscaling methods; their downscaled future temperatures are very high, especially when compared to the direct outputs from the regional climate models (which exhibit relatively small biases in the current climate). So despite the fact that a high percentage of temperature variance is explained by regression-based methods in the current climate, the anomalous downscaled future temperatures raise serious questions about the stationary nature of the regression. This was always a weak point of regression-based methods that could never be clearly disproved or confirmed. If there is doubt that regression equations are stationary for temperature, the case of the validity of the approach for precipitation is even harder to make, mostly because the percentage of explained variance is very low to begin with. The CGCM-DASR model (a regression-based model with no bias or variance correction) was included for comparison purposes only. It is clearly inadequate at reproducing adequate precipitation in the current climate. However, both this flawed method (CGCM-DASR) and the one correcting for precipitation bias and variance (CGCM-SDSM) give nearly identical future mean hydrographs (Fig. 7), further raising doubts as to the validity of transposing regression equations in changed climate predictions.

The strength and weaknesses of the CF method have been discussed in several papers. This method gives similar results whether factors are derived from the GCM or the RCM (driven by the same GCM at its boundaries). Its main weakness (that it does not modify future variance and precipitation occurrence) is probably not a major obstacle with respect to spring snowmelt. Since spring floods are the result of several months of snow accumulation followed by rapid melting, 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 a less important feature to have. On the other hand, for summer and fall events, damages often result from one major rainfall event, and droughts from long periods with little to no precipitation. In such cases, the CF method would be totally inappropriate for climate change studies and another downscaling method would be necessary. In such cases, WG based approaches may be more successful in resolving extremes series of dry days and high temperature. This would especially be the case for arid and semi-arid areas.

An interesting result from this paper is that the biases in the RCM that was used are small enough that they can be dealt with by the hydrological model, thus negating any bias correction on the outputs from the CRCM. As discussed earlier, this approach stems from the assumption that biases present in observed weather data (especially for precipitation) are of the same order as those from the RCM precipitation. As such, a specific calibration of the

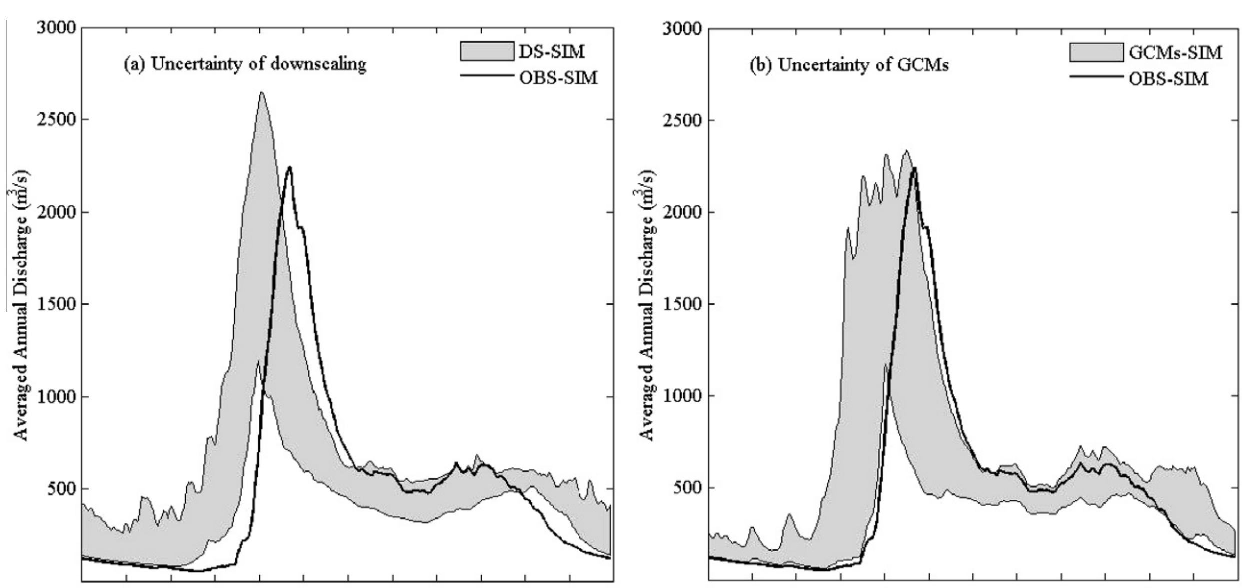


**Fig. 9.** Envelopes of simulated discharge with: (a) six downscaling methods and (b) 28 GCMs and GGES using the change factor downscaling method at the Manicouagan 5 river basin for the future period (2070–2099). The discharge simulated with observed climate data for the reference period (1970–1999) is also plotted for comparison.

hydrology model to each dataset is sufficient. While this has proved to be the case in the present climate, there are large differences in future predicted outflows between the direct inputs of RCM data (CRCM-NONBC) and the use of RCM data with bias corrections (CRCM-BC). This is partly because CRCM precipitation used to calibrate the hydrological model (1970–1999) was driven by initial and boundary conditions of NCEP, while it was driven by initial and boundary conditions of CGCM for the future period (2070–2099). However, both datasets were considerably different for the reference period (results not shown). It should be not a surprise, since NCEP data and GCM data are not entirely comparable. NCEP data aims at representing the real world, whereas GCMs operate in their own virtual world. It is difficult to say which method is the most correct from both practical and theoretical viewpoints. The fact that they give a markedly different future hydrology indicates that either the assumption of constant bias does not hold, or that the choice of different calibration parameters (in the case of CRCM-NONBC) results in significant future uncertainty. However, recent work (Poulin et al., 2011) demonstrates that the uncertainty derived from hydrology model parameters is relatively small, raising doubts toward the common assumption of constant biases over time. Even if the direct use of RCM data had proved to be the most interesting method, the problem remains that it would not be possible to sample GCM uncertainty with this approach, as it would require outputs from several RCMs, all driven by different GCMs, over the same basin.

Clearly, more research is needed before this problem is settled. In particular, it would be interesting to get results from basins in different climate zones (especially arid and semi-arid climates) as the hydrological response to a choice of a given downscaling method may be related to a given climate. It is not possible at this stage to recommend a specific downscaling method for a given application, or even to use several downscaling methods to produce an ensemble of forcings for hydrology models, such as commonly done with GCM and GGES. Cases where the downscaling uncertainty envelope is contained within other uncertainties sources should not be treated with the same attention than cases where downscaling is the main source of uncertainty. The first conclusion of this paper is that the choice of a downscaling method does matter, and that the uncertainty linked to the choice of a downscaling method should not be ignored in any climate change impact study. The second conclusion is that downscaling methods are not created equal and that the choice of one or more approach should be evaluated on a case by case basis with respect to the objectives of the climate change impact study.

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