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Hydrological impacts of warmer and wetter climate in Troutlake and Sturgeon River basins in central Canada

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Running title: Hydrological impacts in central Canada

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Abstract

The impact of climate change on water availability in two river basins located in central Canada is investigated. Several statistical downscaling methods are used to generate temperature and precipitation scenarios from the third-generation Canadian Coupled General Circulation Model, forced with different emission scenarios. The hydrological model SLURP is used to simulate runoff. All downscaling methods agree that temperature will increase with time and that precipitation will also increase, although there is considerably more uncertainty in the magnitude of precipitation change. The study concludes that the change in total annual precipitation does not necessarily translate into similar changes in runoff. The seasonal distribution of precipitation changes is important for runoff, as is the increase in evapotranspiration. The choice of downscaling method appears to have a greater impact on runoff projections than the choice of emission scenario. Therefore, it is important to consider several downscaling methods when evaluating the impact of climate change on runoff.

Keywords: climate change; statistical downscaling; runoff; uncertainty; Canada

1 Introduction

The impact of climate change on water resources is an important issue in Canada, including in the province of Manitoba which has a considerable amount of surface water and an important hydropower industry. However, relatively few studies have addressed climate change impacts on the hydrology of Manitoba. Choi *et al* (2009) found that mean runoff in two basins in central Manitoba is projected to increase as a result of climate change. Shrestha *et al* (2011) studied climate-induced hydrological changes in the Lake Winnipeg basin, with focus on two river basins in southeastern Saskatchewan and southern Manitoba, and also found that total runoff is likely to increase and the spring freshet likely to occur earlier in the future. Other studies (e.g. Burn *et al* 2008; St. George 2007; Sushama *et al* 2006; Yulianti and Burn 1998) have examined the hydrology or hydrological impacts of climate change for the Canadian Prairie region in general. Except for the global-scale study by Hamududu and Killingtveit (2012) and continental-scale study by Sushama *et al* (2006), there is limited research relevant to mid-sized basins contributing to Lake Winnipeg.

The present study focuses on the impact of climate change on the runoff regime of two mid-sized catchments within the Winnipeg River basin. The Winnipeg River, located primarily in southeastern Manitoba and northwestern Ontario, is a major source of inflow to Lake Winnipeg. The general methodology employed here involves running a hydrological model with future climate scenarios simulated by a global climate model (GCM). Due to their global nature, GCMs have coarse spatial resolutions, typically in the order of several hundred kilometers, and most GCMs have significant biases, especially in precipitation output. It is therefore necessary to perform some post-processing of simulated precipitation and temperature in order to use these variables as input to hydrologic models (Mareuil *et al* 2007). Methods for downscaling GCM output are commonly classified as dynamic or statistical. Dynamic downscaling methods involve the use of high-resolution regional climate models set up for the domain of interest, with the GCM providing the necessary boundary conditions. Statistical downscaling methods use relatively simple statistical models to relate large-scale atmospheric variables, presumably well simulated by the GCM, to temperature and precipitation at the location of interest. Statistical downscaling is computationally cheaper and easier to implement than dynamic downscaling, and can often be designed to produce unbiased simulations for specific locations which is not always possible with dynamic downscaling models. A general review of downscaling methods, including their relative advantages and disadvantages, is provided by Fowler *et al* (2007). Statistical downscaling methods are commonly divided into three classes (Wilby and Wigley 1997): transfer function models, weather generators, and weather-typing models. Some downscaling methods are hybrids of these classes. In the present study, three statistical downscaling methods representing different classes were employed. More specifically, we used the Statistical DownScaling Model (SDSM, Wilby *et al* 2002), which falls into the category of transfer function models, the Long Ashton Research Station Weather Generator (LARS-WG, Semenov and Barrow 1997) which is a weather generator, and nearest neighbor resampling (NNR, Gangopadhyay *et al* 2005), a non-parametric method that can be viewed as a special case of weather typing.

The construction of hydrological change scenarios involves a number of steps, and each of these steps introduces uncertainty (Wilby and Harris 2006). To be of credible value, projected changes must be accompanied by at least some crude estimate of associated uncertainties or range of possibilities. The selection of GCM and emission scenario is an important source of uncertainty (Wilby and Harris 2006; Prudhomme *et al* 2003), but recent studies suggest that downscaling methods also introduce significant uncertainties (e.g. Chen *et al* 2013, Hanel *et al* 2013, Samadi *et al* 2013, Ghosh and Katkar 2012, Zhang *et al* 2011, and Quintana Sequi *et al* 2010).

The studies mentioned above provide a useful context for the research presented here. The main objective of the present study is to quantify climate change impacts and uncertainties on runoff in two watersheds within the Winnipeg River basin. We are particularly interested in determining the relative contribution of downscaling method and greenhouse gases emission scenarios to the total uncertainty. This does not cover the entire range of uncertainties, as the present study does not consider the uncertainties associated with the choice of GCM and choice of hydrologic model. Nevertheless, it is a useful exercise to isolate and study specific sources of uncertainty.

2 Methods

2.1 Study basins

The study focuses on two river basins, Sturgeon and Troutlake, located in northwestern Ontario (Figure 1). The watersheds are part of the Winnipeg River basin, which in turn is part of the greater Nelson River basin. The region is sparsely populated and the landscape is typical for the Canadian Shield, characterized by coniferous forest and numerous lakes. The drainage areas upstream of the hydrometric stations are 4450 km^2 for the Sturgeon River and 2370 km^2 for the Troutlake River.

There are two weather stations in the vicinity of the sub-basins (Red Lake and Sioux Lookout) (Figure 1). The average annual precipitation is 640 mm, and the annual mean temperature is 0.9°C at Red Lake Airport over the period 1971-2000. Sioux Lookout Airport has a similar climate, albeit slightly wetter and warmer. The average discharge at Troutlake, measured over the period 1970-2008, is 17.0 m^3s^{-1}, with spring peak flow usually occurring in late May. The Sturgeon River has a similar seasonal pattern with an average discharge of 39.3 m^3s^{-1} during the period 1961-2008. There are several control structures in the Winnipeg River basin, but the two basins selected for this study have natural flow regimes.

2.2 Hydrological modeling

The SLURP model (**S**emi-distributed **L**and **U**se-based **R**unoff **P**rocesses) Version 11.2, developed by Kite (1998), was selected for streamflow simulation. SLURP is a conceptual hydrologic model with a relatively small number of parameters. The model treats a watershed as a union of aggregated simulation areas (ASA). ASAs are delineated based on elevation using a geographic information system (GIS), and the flow contributions from upstream ASAs are routed to downstream ASAs by a user-selected routing scheme. The vertical water balance is calculated for each land cover type in each ASA. The input data for SLURP are daily time series of mean temperature, total precipitation, relative humidity, and bright sunshine hours (or shortwave radiation). More details on the SLURP model can be found in Kite (1998).

The land cover data for the study basins were obtained from the Advance Very High Resolution Radiometer via GeoGratis (http://geogratis.cgdi.gc.ca/geogratis/en/index.html) with a scale of 1:2M. The digital elevation model with a resolution of 3 arc seconds was obtained from the National Aeronautics and Space Administration Shuttle Radar Topography Mission via the U.S. Geological Survey (http://seamless.usgs.gov). Based on the GIS analysis, the Sturgeon River basin was divided into seven ASAs and the Troutlake basin into four (Figure 1).

Daily time series of temperature, precipitation, and relative humidity were obtained from Environment Canada for the two weather stations shown in Figure 1. Both weather stations are reasonably close to their respective watersheds and provide the most representative information available. Solar radiation data, extracted from the North American Regional Reanalysis (NARR; Mesinger *et al* 2006), were used in place of bright sunshine hours that are not available at the weather stations in the region.

The SLURP model was set up for each river basin and calibrated using measured streamflow data for the years 1995-1997 (Sturgeon) and 1994-1996 (Troutlake). The automatic optimization tool embedded in SLURP was used first and later some parameters were adjusted manually to improve the model performance in terms of relative errors and goodness-of-fit. Three performance statistics were considered in the calibration: deviation of volume (D_v), Nash-Sutcliffe efficiency (E), and mean absolute error (MAE). These measures were chosen based on the recommendation by Legates and McCabe (1999). Daily scale E values were 0.71 (Sturgeon) and 0.66 (Troutlake), D_v was under +/- 10%, and MAE values were 9.7 m^3s^{-1} (Sturgeon) and 3.1 m^3s^{-1} (Troutlake). The calibration periods were selected based on the availability of weather data. The E values are reasonable and typical for this type of watersheds where weather stations are limited in numbers and the watersheds are characterized by many lakes. MAE values are around 25% of the mean observed streamflow.

2.3 Downscaling methods

Three statistical downscaling methods were implemented in this study, using the daily output from the third-generation Canadian Coupled General Circulation Model (CGCM3.1). The

CGCM3.1 output was obtained for three different greenhouse gas emission scenarios from the Special Report on Emissions Scenarios (SRES; Nakicenovic and Swart 2000), B1, A1B, and A2. The scenarios represent 'low', 'medium' and 'high' emissions, respectively (Meehl *et al* 2007). It should be emphasized that there are also considerable uncertainties associated with the choice of GCM model. These uncertainties are well documented, for example in the IPCC (2007) report. The primary focus of the present research is to assess the uncertainty arising from the application of different statistical downscaling methods and different emission scenarios, and therefore only one GCM was used. The CGCM was chosen because it is a Canadian model that has been extensively validated over Canada and has been used in other Canadian studies (e.g. Sultana and Coulibaly 2011; Dibike and Coulibaly 2005).

SDSM is a statistical downscaling technique based on multiple regression models between large-scale atmospheric variables (predictors) and local-scale variables (predictands). Three predictands, daily maximum temperature, minimum temperature and precipitation, were modeled by SDSM for the baseline and future periods for this study. The general procedure to set up SDSM is described in Wilby and Dawson (2004). SDSM was calibrated for Sioux Lookout using the National Centers for Environmental Prediction-National Center for Atmospheric Research global reanalysis data (Kistler *et al* 2001). Twenty-five predictor variables were initially considered (details in Koenig 2008). The model was calibrated for the period 1961-1990 and validated for the 1991-2000-period. CGCM3.1 was used to obtain predictors for the baseline and future periods. Due to the lack of observed climate data, SDSM could not be implemented for the Red Lake station. Instead, the mean monthly differences in observed temperature and precipitation were calculated between the Sioux Lookout and Red Lake stations, and the differences were superposed on the SDSM parameters for Sioux Lookout to generate SDSM data for Red Lake.

LARS-WG is a stochastic weather generator that can produce synthetic series of daily precipitation, maximum temperature (Tmax), minimum temperature (Tmin), and solar radiation. In LARS-WG, the occurrence of daily precipitation is modeled as alternating sequences of dry and wet spells. The daily weather variables – Tmax, Tmin, solar radiation and precipitation amount – are then simulated conditional on whether precipitation occurs or not. To generate future scenarios, LARS-WG uses changes in daily weather variables determined from the GCM baseline and future periods to revise parameters to represent the future climate. LARS-WG requires observed Tmax, Tmin, and precipitation data as input. LARS-WG was implemented for the location of the Sioux Lookout weather station to generate precipitation, Tmax, Tmin, and solar radiation. As in the case of the SDSM model, the results were transferred to Red Lake. Data from 1961-1990 were used for the calibration while the period of 1991-2000 was used for validation (Koenig 2008).

NNR is a non-parametric method that produces local weather data by resampling from the record of observed weather variables, based on the similarity of the daily large-scale atmospheric patterns of a GCM and the corresponding observed patterns. The basic idea is that by comparing large-scale atmospheric variables from a GCM for a given simulation day with the same variables in the historical record, days with similar large-scale variables (nearest neighbors) can be identified in the historical record. The comparison between the simulation day and the historical record is done using a vector of variables referred to as the feature vector. The number of variables included in the vector may vary, and Buishand and Brandsma (2001) obtained the best results with 2 and 5 after trying 2, 5, 20, and 50. Using a pre-defined metric, the distance between the feature vector for a given simulation day and feature vectors in the historical record can be determined, and the group of the k most similar days can be identified. One of these is selected at random to provide the local weather data for the simulation day. A higher selection probability is given to the closer days by using a decreasing kernel density function. The NNR method requires large-scale atmospheric variables for the feature vector and corresponding historical weather data. The large-scale variables considered here are surface temperature, 500 hPa temperature, 850 hPa temperature, 500 hPa geopotential height, and 850 hPa geopotential height covering a significant area over west-central Canada.

3 Results

3.1 Comparison of statistical downscaling methods for the baseline period

The three downscaling methods produced temperature and precipitation series for the baseline period (1971-2000) both for Sioux Lookout and Red Lake. The results were evaluated by comparing downscaled temperature and precipitation statistics with those observed at the Sioux Lookout station. The results for the Red Lake station show a similar pattern between downscaling methods. As seen in Table 1, all downscaling methods result in mean annual temperatures that are higher than the observed (Station), but only SDSM annual temperature is significantly different from the station at the 5% significance level. This difference is largely due to the fact that SDSM annual temperatures were higher than Station annual temperatures in most of the 1990s, the validation period for SDSM. LARS-WG is closest to the station data in terms of mean annual temperature. The interannual variability of temperature is somewhat underestimated in the statistical downscaling results, which is common in observation-model comparisons. The 95th and 5th percentile of daily temperature values are fairly similar among the data sets. The difference between the three downscaling methods is more pronounced in the case of precipitation statistics, although none of the downscaled annual total precipitations are significantly different from Station. All downscaling methods underestimate the observed interannual variability, and the underestimation is particularly severe in SDSM. Maximum daily precipitation is different by as much as 14.7 mm (between SDSM and LARS-WG), but the 95th percentile of daily precipitation is very similar among the data sets.

The distribution of monthly total precipitation values is portrayed in Figure 2 for all months as well as for the period of May to October, which generally are the wettest months of the year. Except for outliers, the three downscaling methods have quite similar distributions, although the NNR method has a slight bias towards lower values. SDSM produced higher July precipitation than other downscaling methods, resulting in some particularly large outliers in the boxplot. The box plots for the May-October period show that the precipitation distributions are similar, which suggest that the low annual precipitation from NNR shown in Table 1 is largely due to low precipitation during dry months. LARS-WG was better than others for interannual variability at the annual scale, but not at the monthly scale. Dibike and Coulibaly (2005) report that both SDSM and LARS-WG simulated precipitation reasonably well for a basin in Quebec, but do not comment on variability.

The SLURP model was run with input data generated by each downscaling method for the period 1970-2000, and the result for the year 1970 was dropped from the analysis to eliminate the impact of initial conditions. The distribution of simulated annual mean discharge is shown in Figure 3. The median annual runoff simulated with input data from NNR is consistently lower than runoff simulated with SDSM or LARS-WG data. The largest variability among the downscaling methods, in terms of the range of the whiskers, is observed with LARS-WG, while the median streamflow with NNR are significantly lower than the other two methods. The result generally reflects the precipitation statistics in Table 1. All the simulations with the downscaled GCM data resulted in smaller interannual variability than the observed streamflow.

Overall, all the methods produce similar results for temperature, whereas LARS-WG produce better results for precipitation than SDSM and NNR. There are some studies that report similar results to the present one. Dibike and Coulibaly (2005) report that LARS-WG is better than SDSM for wet- and dry-spell length, which has important implications for runoff generation. Khan *et al* (2006) analyzed uncertainty from three statistical downscaling methods, SDSM, LARS-WG and an artificial neural network (ANN) model, and conclude that LARS-WG and SDSM are better than the ANN model in reproducing important statistics such as daily precipitation, and maximum and minimum temperatures in a Quebec basin. They also found that LARS-WG worked better for daily precipitation than SDSM. The characteristics of weather generators that employ empirical distributions of precipitation variables are believed to contribute to the better performance of LARS-WG relative to SDSM.

The underestimation of annual precipitation amount and variability by NNR is not entirely unexpected. One of the drawbacks of NNR is that it merely resamples values from the observed data (Sharif and Burn 2006). What is somewhat surprising however is the result from the hydrological modeling with NNR-downscaled scenarios. NNR underestimates mean annual precipitation by about 4% of the station data and about 8% relative to SDSM- or LARS-WG-downscaled scenarios, but the runoff totals produced using the NRR method is 21% and 9% lower than the runoff produced by SDSM in Sturgeon and Troutlake, respectively. Cunderlik and Simonovic (2005, 2007) used NNR-downscaled scenarios to run a hydrological model but did not elaborate on the bias of NNR and its effect on hydrological simulations, making it impossible to compare with the present study.

3.2 Projected changes in annual and monthly temperature, precipitation, and runoff

The three downscaling methods were applied to the future period of 2046-2065 (2050s) using output from the CGCM3.1 model, and the downscaled climate data were used for SLURP simulations. Table 2 shows the changes in annual temperature, precipitation, and runoff for all basins, emission scenarios, and downscaling methods. The changes in temperature and precipitation from the raw CGCM3.1 data are also shown, and are the same for the two basins. The differences between projected temperature changes are small at the annual level, but the differences in precipitation changes are quite large, especially between downscaling methods. Changes in annual mean temperatures are all statistically significant ($p < 0.01$). LARS-WG results in large precipitation increases which are all statistically significant ($p < 0.01$), whereas SDSM and NNR result in inconsistent directions of change with much smaller magnitudes. Generally, LARS-WG results in larger precipitation increases and smaller temperature increases than CGCM3.1, both of which favor runoff increases. On the other hand, SDSM- and NNR-downscaled scenarios have precipitation changes with smaller magnitudes than CGCM3.1. Therefore, SDSM and NNR generally show changes in the same direction – decrease – whereas LARS-WG results in increases.

Figure 4 shows the changes in mean monthly temperature and precipitation from the baseline climate by the 2050s at Sioux Lookout, for each downscaling method and emission scenario. There is a noticeable discrepancy among downscaling methods and emission scenarios both in temperature and precipitation changes. The temperature changes for summer months from SDSM is roughly twice or more than those from LARS-WG and NNR in each emission scenario, whereas LARS-WG- and NNR-downscaled scenarios show higher temperatures than SDSM for January, February, and March. Warming is projected year round, which could lead to earlier snowmelt, higher evaporation, and reduced snowpack storage. For March, April, and May, wetter climate is generally projected with LARS-WG and NNR and drier with SDSM. The results for Red Lake are fairly similar and thus not shown here.

Figure 5 shows changes of mean monthly runoff between the baseline and 2050s periods, simulated with downscaled input data for each emission scenario. Under the A1B scenario, LARS-WG results in runoff increases throughout the year, with the highest increase in April due to increased precipitation and earlier snowmelt, and moderate increases in other months, largely due to increased evaporation offsetting the effects of precipitation increases. On the other hand, SDSM results mostly in decreases, and NNR shows more mixed results. Mean monthly runoff changes to some extent resemble the pattern of mean monthly precipitation changes due to the relatively small size of the catchments (Figure 4), but with amplified decreases in runoff with SDSM and NNR. For months with small precipitation increases in SDSM- and NNR-downscaled scenarios, runoff is projected to decrease, and for months with large increases (e.g. SDSM for August), runoff increases moderately. Even though the precipitation changes in NNR- and SDSM-downscaled scenarios are similar at the annual scale, the NNR-downscaled scenarios show large increases in springtime precipitation whereas the SDSM-downscaled scenarios show smaller increases or decreases (Figure 4). As a result, NNR results in smaller annual runoff decreases than SDSM because spring runoff increases partially offset decreases in other seasons. With the A2 and B1 scenarios, the overall pattern of changes is similar but of smaller magnitude.

Projected annual runoff changes between the baseline period and the 2050s for the Sturgeon basin are presented as cumulative distribution functions (CDF) in Figure 6(a), grouped into emissions scenarios. The results are similar for Troutlake, thus not shown. For a given emission scenario, there are considerable differences between downscaling methods, suggesting that a substantial uncertainty is associated with the choice of downscaling method. In all cases, increases are predominant with LARS-WG, indicated by the curves located mostly on the right-hand side of zero on the abscissae. This is not surprising given that precipitation is projected to increase by about 20% with LARS-WG in all scenarios (Table 2). With the A1B scenario, SDSM mostly shows decreases, and NNR is a mix between increases and decreases, reflecting the small average changes shown in Table 2. With the A2 scenario, LARS-WG shows very large increases in some years, easily exceeding 100%. Even though annual mean changes are similar between A1B and A2 with LARS-WG, interannual variability is much larger with A2. Decreases are of similar magnitudes between downscaling methods, but increases vary widely. The changes are more modest with the B1 scenario. Figure 6(b) shows, for given downscaling methods, the differences in runoff projections resulting from different emission scenarios. There appears to be much less variability in runoff projections, suggesting that there is more uncertainty associated with the choice of downscaling method than with the choice of emission scenario. Of course, this conclusion is specific to the methods used here.

Mean monthly runoff from all future simulations (three downscaling methods and three emission scenarios) are presented in Figure 7 along with the baseline simulations with the observed climate data. The future mean monthly runoff shows a great degree of uncertainty between the simulations, and for every calendar month, the range of changes covers both negative and positive values. April is the only month where increases are predominant in both basins and this is due to the earlier snowmelt. In September, October and November, decreases are predominant due to warmer temperatures and small precipitation changes resulting in increased evaporation. Summertime runoff shows a great deal of variability and has fairly equal probabilities for increases and decreases.

The present study found larger uncertainty from the statistical downscaling methods than from emission scenarios in terms of climate change impacts on mean runoff. This finding is in line with Wilby and Harris (2006, p. 7) who suggest the following order of significance as a source of uncertainty for low flow modeling in a UK basin: GCM > downscaling method > hydrological model structure > hydrological model parameters > emission scenario. They adopted a probabilistic approach for each source of uncertainty and considered a limited number of cases for each source, which is a different approach than used here. However, the way they measured the magnitude of uncertainty from each source is similar to this study in the sense that relative changes of hydrological variables are compared among the cases of each uncertainty source. Their finding is also in line with those of Boé *et al* (2009) who found larger uncertainty associated with climate models than with downscaling methods and Menzel *et al* (2006) who found much larger uncertainty with GCM-downscaling combinations than hydrological modeling. Therefore, the importance of considering GCM-related uncertainty is emphasized.

4 Conclusions

This study used three different statistical downscaling methods for the CGCM3.1 output under three different greenhouse gas emission scenarios to create climate scenarios for central Canadian basins, and simulated hydrological processes with the scenarios using the SLURP hydrological model. Major findings from the study includes: (1) the climate is projected to be generally warmer (from 2.1 to 3.6 ° C increases in annual mean temperature) and wetter or slightly drier (from –6.8 to +22.1% in annual total precipitation) in the studied basins in the 2050s; (2) runoff is projected to change with a wide range across downscaling methods and emission scenarios, but LARS-WG produced most consistent results across emission scenarios—increases in mean annual runoff by 13-27%; and (3) statistical downscaling methods have greater uncertainty than emission scenarios in projecting future water availability. To the extent that the GCM used in the study provides a reasonable projection of climate change, our results suggest that there a good likelihood that the region will see more runoff in the future although changes in seasonal runoff remain rather uncertain.

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Tables

Table 1. Temperature and precipitation variables from observation (Station) and each statistical downscaling method for Sioux Lookout A, 1971-2000

	Station	SDSM	WG	NNR
Mean annual temperature (°C)	1.6	2.2	1.8	2.0
SD[a] of annual mean temperature	1.1	1.1	0.6	0.8
Maximum daily temperature (°C)	30.3	26.9	30.3	27.9
95th percentile of daily temperature (°C)	20.9	20.6	20.8	20.8
5th percentile of daily temperature (°C)	-24.0	-21.0	-22.5	-22.7
Minimum daily temperature (°C)	-38.4	-34.1	-41.6	-37.8
Mean of annual total precipitation (mm)	717	746	744	689
SD of annual precipitation	127	75	101	88
Maximum daily precipitation (mm)	71.0	89.6	64.9	80.0
95th percentile of daily precipitation (mm)	10.8	9.8	10.7	10.1

[a] SD stands for standard deviation

Table 2. Projected changes in mean annual temperature (T), total precipitation (P) and total runoff (Q) by the 2050s. Bold fonts indicate statistical significance (α = 0.05) from the baseline period according to the t-test.

	T change (°C)				P change (%)				Q change (%)		
Sturgeon	CGCM3.1	SDSM	WG	NNR	CGCM3.1	SDSM	WG	NNR	SDSM	WG	NNR
A1B	**2.8**	**3.2**	**2.6**	**3.0**	**15.9**	**4.5**	**22.0**	6.3	**–28.3**	**25.1**	–3.3
A2	**3.1**	**3.6**	**3.0**	**2.7**	**10.0**	11.4	**20.2**	4.2	2.3	**22.0**	–9.4
B1	**2.3**	**2.3**	**2.1**	**2.2**	6.8	1.1	**16.9**	2.8	**–14.5**	**12.8**	–10.1
Troutlake	CGCM3.1	SDSM	WG	NNR	CGCM3.1	SDSM	WG	NNR	SDSM	WG	NNR
A1B	**2.8**	**3.2**	**2.6**	**2.9**	**15.9**	–5.3	**22.1**	–0.7	**–18.2**	**25.3**	–7.8
A2	**3.1**	**3.6**	**3.0**	**2.6**	**10.0**	2.3	**20.4**	3.8	–8.8	**26.6**	0.6
B1	**2.3**	**2.3**	**2.1**	**2.3**	6.8	–6.8	**17.1**	0.2	**–19.2**	**17.0**	–3.6

Figures

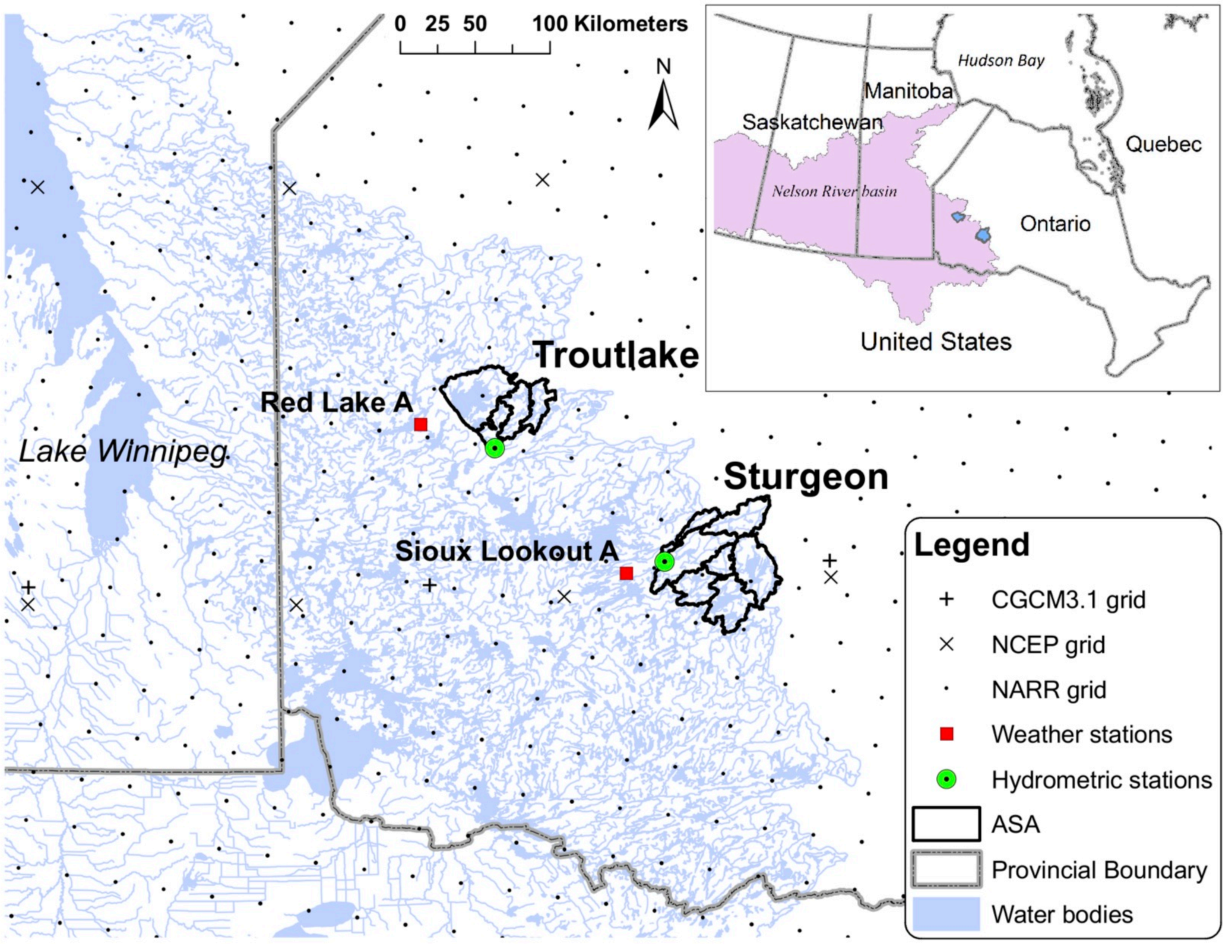

Figure 1. Aggregated simulations areas (ASA) of the Sturgeon and Troutlake River basins for hydrological modeling. Point symbols are the location where climatic and hydrometric data are available. The inset map shows the two basins and the Nelson River basin where the two basins are nested.

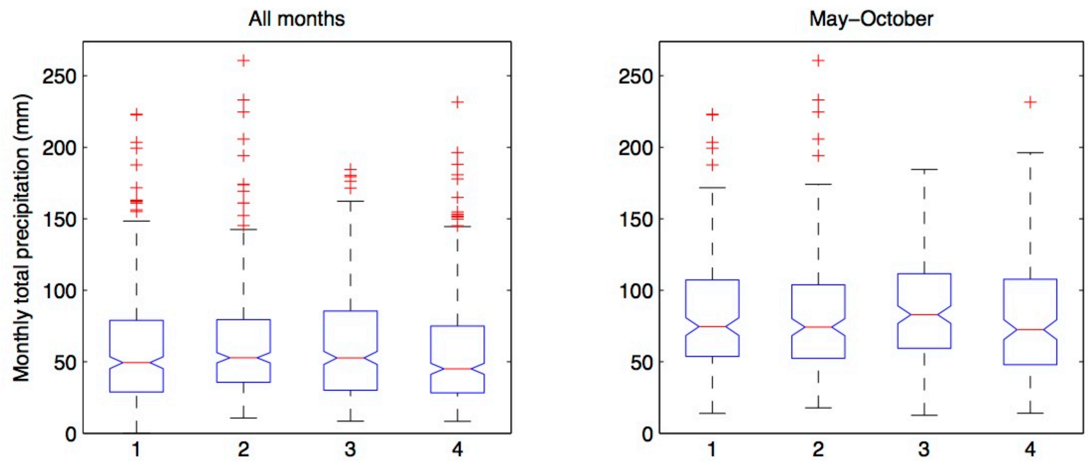

Figure 2. Distribution of monthly total precipitation values for all months and May-October from Station and each statistical downscaling method at Sioux Lookout A, 1971-2000. 1: Station, 2: SDSM, 3: LARS-WG, and 4: NNR. The boxes have lines at the lower quartile, median, and upper quartile values. Whiskers extend from each end of the box to the most extreme values within 1.5 times the interquartile range. Plus (+) signs denote outliers. Non-overlapping notch intervals indicate that the medians are significantly different (α = 0.05). Same for other box plots.

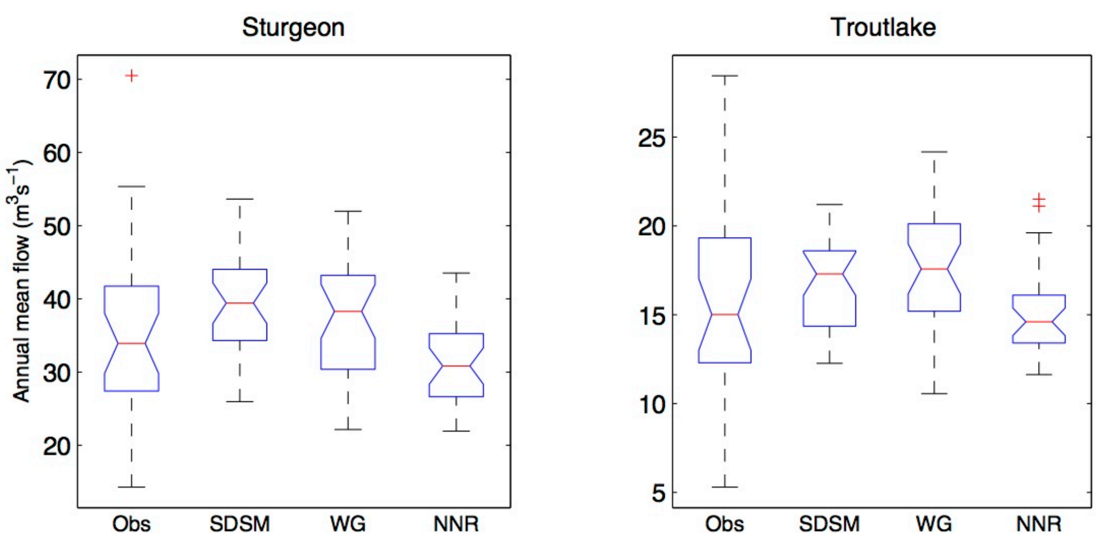

Figure 3. Boxplots of annual mean flow simulated with observed climate data (Obs) and downscaled CGCM data for the baseline period. The plots indicate the interannual variability of annual mean flow.

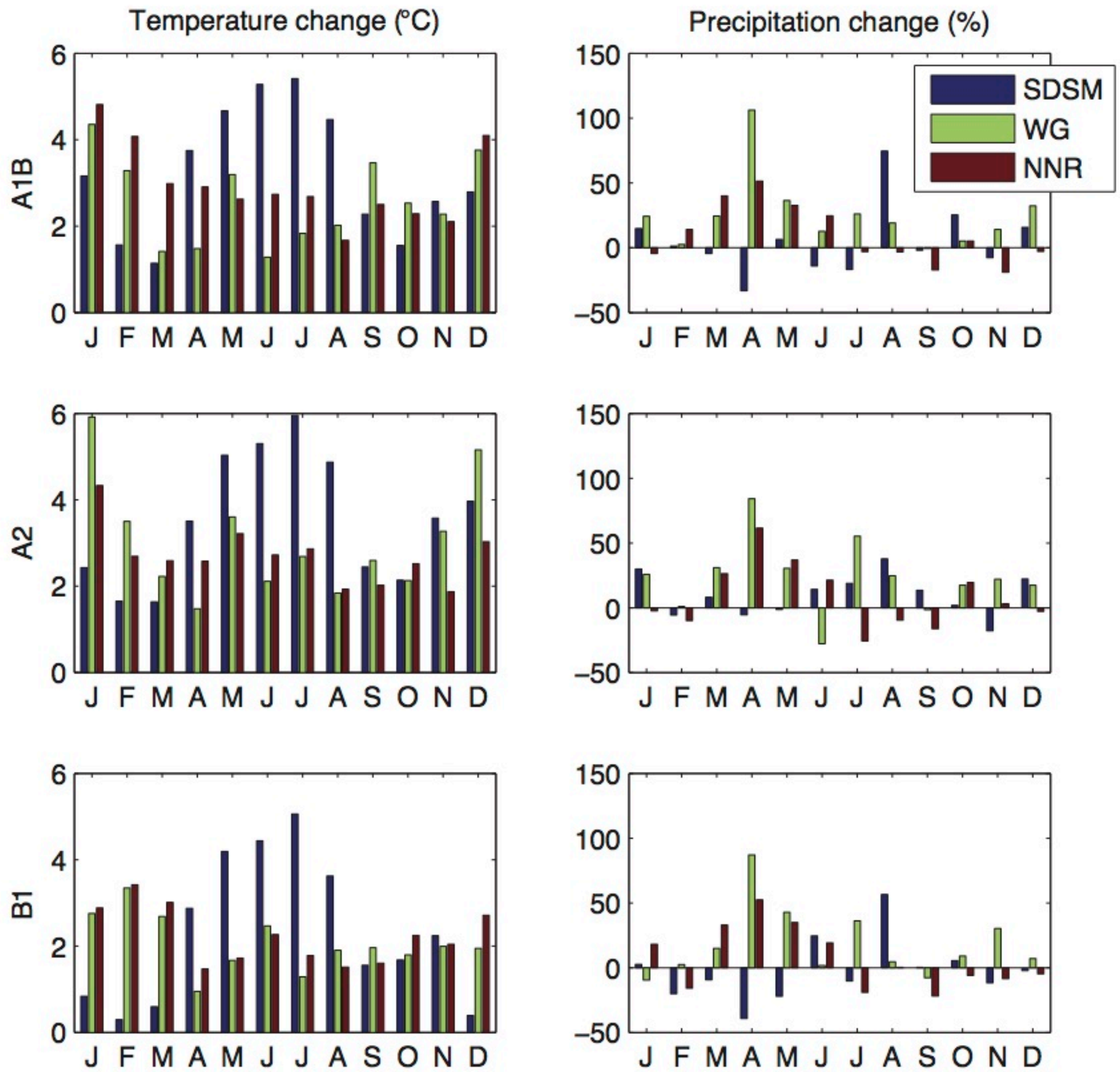

Figure 4. Mean monthly temperature (left panel) and precipitation (right panel) changes for Sioux Lookout A from the baseline period by the 2050s.

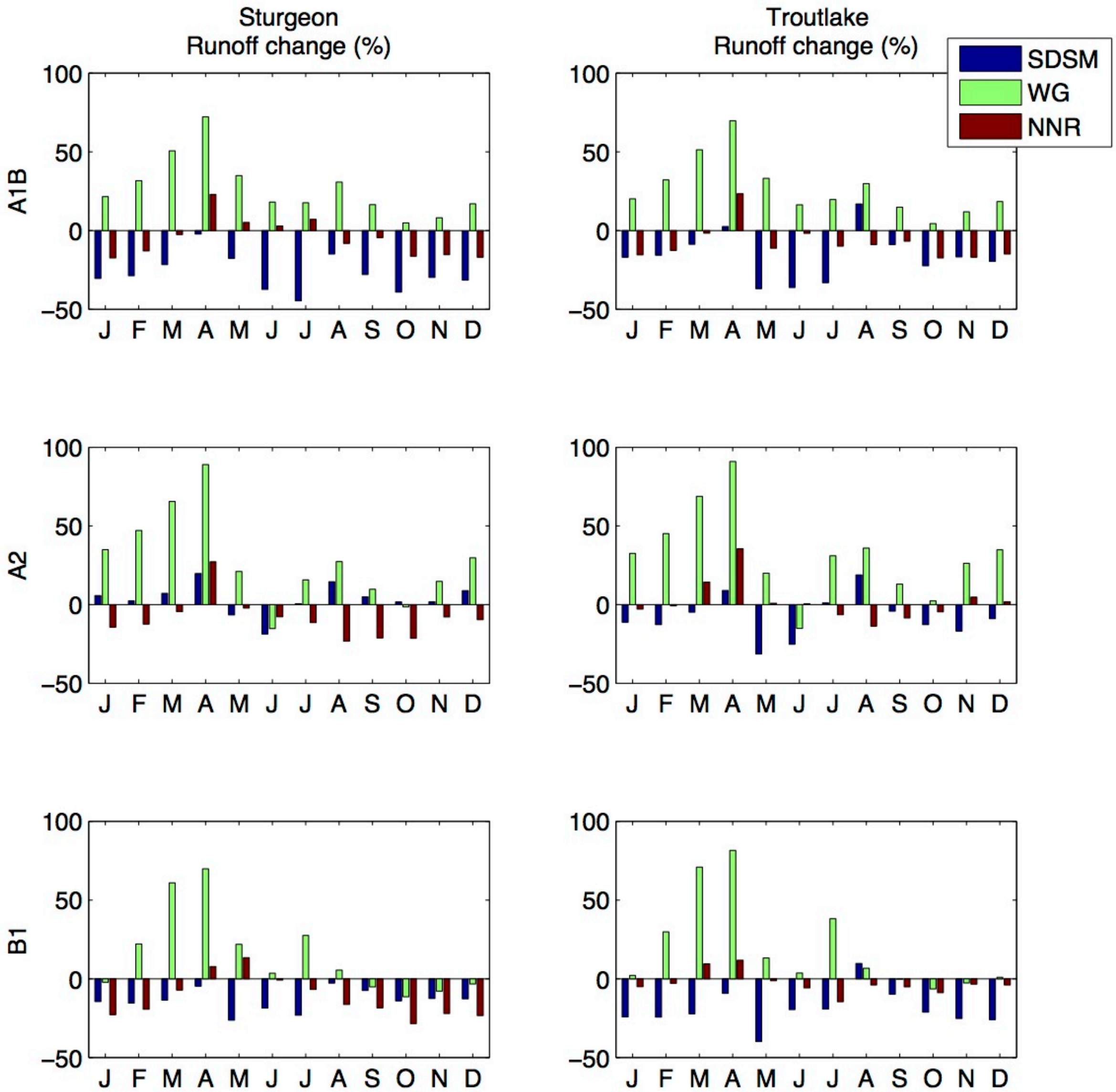

Figure 5. Mean monthly runoff changes for Sturgeon (left panel) and Troutlake (right panel) from the baseline period by the 2050s, simulated with statistically downscaled climate scenarios.

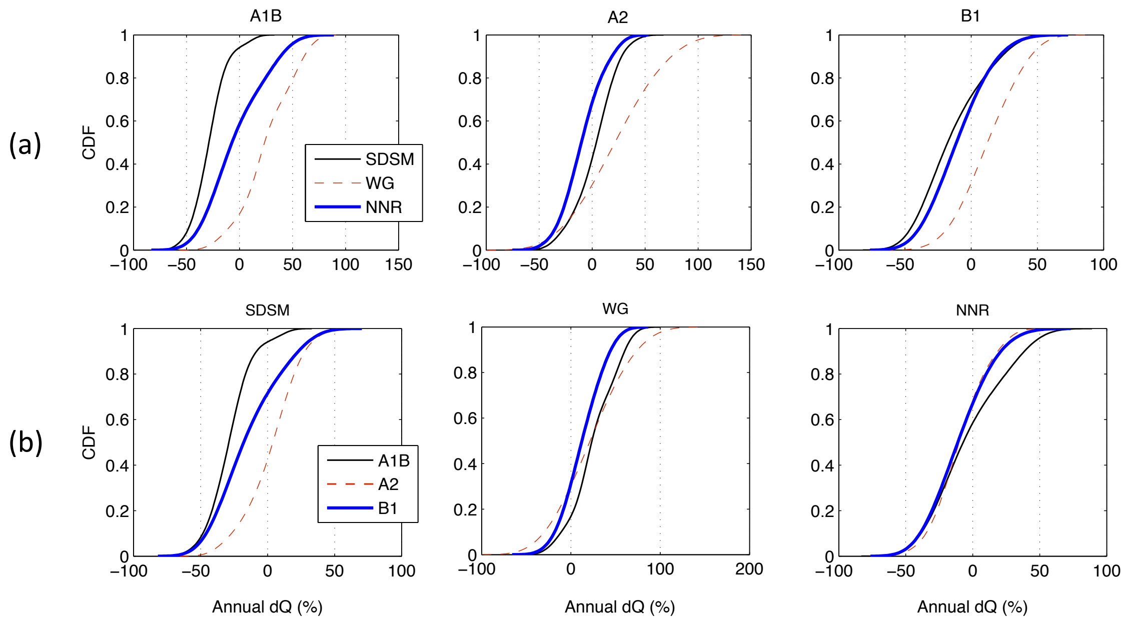

Figure 6. Cumulative distribution functions (CDFs) of annual runoff changes (dQ) for the Sturgeon basin between the 2050s and the baseline periods reflecting uncertainty in the downscaling methods (a) and emissions scenarios (b).

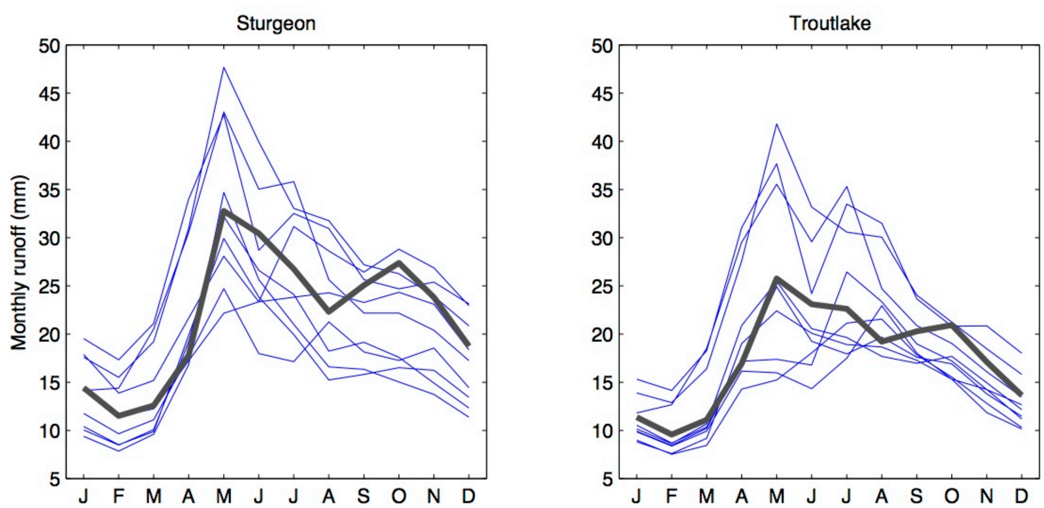

Figure 7. Mean monthly runoff from the simulations with the baseline climate data (thick grey line) and with future climate data (thin blue lines) from all downscaling methods and emission scenarios.