

1 Title: Hydrological impacts of warmer and wetter climate in Troutlake
2 and Sturgeon River basins in central Canada

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7 Running title: Hydrological impacts in central Canada

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24

25 **Abstract**

26

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

39

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

41

42 **1 Introduction**

43
44 The impact of climate change on water resources is an important issue in Canada, including in the
45 province of Manitoba which has a considerable amount of surface water and an important
46 hydropower industry. However, relatively few studies have addressed climate change impacts on
47 the hydrology of Manitoba. Choi *et al* (2009) found that mean runoff in two basins in central
48 Manitoba is projected to increase as a result of climate change. Shrestha *et al* (2011) studied
49 climate-induced hydrological changes in the Lake Winnipeg basin, with focus on two river basins
50 in southeastern Saskatchewan and southern Manitoba, and also found that total runoff is likely to
51 increase and the spring freshet likely to occur earlier in the future. Other studies (e.g. Burn *et al*
52 2008; St. George 2007; Sushama *et al* 2006; Yulianti and Burn 1998) have examined the
53 hydrology or hydrological impacts of climate change for the Canadian Prairie region in general.
54 Except for the global-scale study by Hamududu and Killingtveit (2012) and continental-scale
55 study by Sushama *et al* (2006), there is limited research relevant to mid-sized basins contributing
56 to Lake Winnipeg.

57
58 The present study focuses on the impact of climate change on the runoff regime of two mid-sized
59 catchments within the Winnipeg River basin. The Winnipeg River, located primarily in
60 southeastern Manitoba and northwestern Ontario, is a major source of inflow to Lake Winnipeg.
61 The general methodology employed here involves running a hydrological model with future
62 climate scenarios simulated by a global climate model (GCM). Due to their global nature, GCMs
63 have coarse spatial resolutions, typically in the order of several hundred kilometers, and most
64 GCMs have significant biases, especially in precipitation output. It is therefore necessary to
65 perform some post-processing of simulated precipitation and temperature in order to use these
66 variables as input to hydrologic models (Mareuil *et al* 2007). Methods for downscaling GCM
67 output are commonly classified as dynamic or statistical. Dynamic downscaling methods involve
68 the use of high-resolution regional climate models set up for the domain of interest, with the
69 GCM providing the necessary boundary conditions. Statistical downscaling methods use
70 relatively simple statistical models to relate large-scale atmospheric variables, presumably well
71 simulated by the GCM, to temperature and precipitation at the location of interest. Statistical
72 downscaling is computationally cheaper and easier to implement than dynamic downscaling, and

73 can often be designed to produce unbiased simulations for specific locations which is not always
74 possible with dynamic downscaling models. A general review of downscaling methods, including
75 their relative advantages and disadvantages, is provided by Fowler *et al* (2007). Statistical
76 downscaling methods are commonly divided into three classes (Wilby and Wigley 1997): transfer
77 function models, weather generators, and weather-typing models. Some downscaling methods are
78 hybrids of these classes. In the present study, three statistical downscaling methods representing
79 different classes were employed. More specifically, we used the Statistical DownScaling Model
80 (SDSM, Wilby *et al* 2002), which falls into the category of transfer function models, the Long
81 Ashton Research Station Weather Generator (LARS-WG, Semenov and Barrow 1997) which is a
82 weather generator, and nearest neighbor resampling (NNR, Gangopadhyay *et al* 2005), a non-
83 parametric method that can be viewed as a special case of weather typing.

84

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

92

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

100

101 **2 Methods**

102 *2.1 Study basins*

103 The study focuses on two river basins, Sturgeon and Troutlake, located in northwestern Ontario
104 (Figure 1). The watersheds are part of the Winnipeg River basin, which in turn is part of the
105 greater Nelson River basin. The region is sparsely populated and the landscape is typical for the
106 Canadian Shield, characterized by coniferous forest and numerous lakes. The drainage areas
107 upstream of the hydrometric stations are 4450 km² for the Sturgeon River and 2370 km² for the
108 Troutlake River.

109
110 There are two weather stations in the vicinity of the sub-basins (Red Lake and Sioux Lookout)
111 (Figure 1). The average annual precipitation is 640 mm, and the annual mean temperature is
112 0.9°C at Red Lake Airport over the period 1971-2000. Sioux Lookout Airport has a similar
113 climate, albeit slightly wetter and warmer. The average discharge at Troutlake, measured over the
114 period 1970-2008, is 17.0 m³s⁻¹, with spring peak flow usually occurring in late May. The
115 Sturgeon River has a similar seasonal pattern with an average discharge of 39.3 m³s⁻¹ during the
116 period 1961-2008. There are several control structures in the Winnipeg River basin, but the two
117 basins selected for this study have natural flow regimes.

118

119 *2.2 Hydrological modeling*

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

129

130 The land cover data for the study basins were obtained from the Advance Very High Resolution
131 Radiometer via GeoGratis (<http://geogratis.cgdi.gc.ca/geogratis/en/index.html>) with a scale of
132 1:2M. The digital elevation model with a resolution of 3 arc seconds was obtained from the
133 National Aeronautics and Space Administration Shuttle Radar Topography Mission via the U.S.
134 Geological Survey (<http://seamless.usgs.gov>). Based on the GIS analysis, the Sturgeon River
135 basin was divided into seven ASAs and the Troutlake basin into four (Figure 1).

136
137 Daily time series of temperature, precipitation, and relative humidity were obtained from
138 Environment Canada for the two weather stations shown in Figure 1. Both weather stations are
139 reasonably close to their respective watersheds and provide the most representative information
140 available. Solar radiation data, extracted from the North American Regional Reanalysis (NARR;
141 Mesinger *et al* 2006), were used in place of bright sunshine hours that are not available at the
142 weather stations in the region.

143
144 The SLURP model was set up for each river basin and calibrated using measured streamflow data
145 for the years 1995-1997 (Sturgeon) and 1994-1996 (Troutlake). The automatic optimization tool
146 embedded in SLURP was used first and later some parameters were adjusted manually to
147 improve the model performance in terms of relative errors and goodness-of-fit. Three
148 performance statistics were considered in the calibration: deviation of volume (D_v), Nash-
149 Sutcliffe efficiency (E), and mean absolute error (MAE). These measures were chosen based on
150 the recommendation by Legates and McCabe (1999). Daily scale E values were 0.71 (Sturgeon)
151 and 0.66 (Troutlake), D_v was under +/- 10%, and MAE values were $9.7 \text{ m}^3\text{s}^{-1}$ (Sturgeon) and 3.1
152 m^3s^{-1} (Troutlake). The calibration periods were selected based on the availability of weather data.
153 The E values are reasonable and typical for this type of watersheds where weather stations are
154 limited in numbers and the watersheds are characterized by many lakes. MAE values are around
155 25% of the mean observed streamflow.

156 157 *2.3 Downscaling methods*

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

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

170
171 SDSM is a statistical downscaling technique based on multiple regression models between large-
172 scale atmospheric variables (predictors) and local-scale variables (predictands). Three
173 predictands, daily maximum temperature, minimum temperature and precipitation, were modeled
174 by SDSM for the baseline and future periods for this study. The general procedure to set up
175 SDSM is described in Wilby and Dawson (2004). SDSM was calibrated for Sioux Lookout using
176 the National Centers for Environmental Prediction-National Center for Atmospheric Research
177 global reanalysis data (Kistler *et al* 2001). Twenty-five predictor variables were initially
178 considered (details in Koenig 2008). The model was calibrated for the period 1961-1990 and
179 validated for the 1991-2000-period. CGCM3.1 was used to obtain predictors for the baseline and
180 future periods. Due to the lack of observed climate data, SDSM could not be implemented for the
181 Red Lake station. Instead, the mean monthly differences in observed temperature and
182 precipitation were calculated between the Sioux Lookout and Red Lake stations, and the
183 differences were superposed on the SDSM parameters for Sioux Lookout to generate SDSM data
184 for Red Lake.

185
186 LARS-WG is a stochastic weather generator that can produce synthetic series of daily
187 precipitation, maximum temperature (Tmax), minimum temperature (Tmin), and solar radiation.
188 In LARS-WG, the occurrence of daily precipitation is modeled as alternating sequences of dry
189 and wet spells. The daily weather variables – Tmax, Tmin, solar radiation and precipitation
190 amount – are then simulated conditional on whether precipitation occurs or not. To generate

191 future scenarios, LARS-WG uses changes in daily weather variables determined from the GCM
192 baseline and future periods to revise parameters to represent the future climate. LARS-WG
193 requires observed Tmax, Tmin, and precipitation data as input. LARS-WG was implemented for
194 the location of the Sioux Lookout weather station to generate precipitation, Tmax, Tmin, and
195 solar radiation. As in the case of the SDSM model, the results were transferred to Red Lake. Data
196 from 1961-1990 were used for the calibration while the period of 1991-2000 was used for
197 validation (Koenig 2008).

198
199 NNR is a non-parametric method that produces local weather data by resampling from the record
200 of observed weather variables, based on the similarity of the daily large-scale atmospheric
201 patterns of a GCM and the corresponding observed patterns. The basic idea is that by comparing
202 large-scale atmospheric variables from a GCM for a given simulation day with the same variables
203 in the historical record, days with similar large-scale variables (nearest neighbors) can be
204 identified in the historical record. The comparison between the simulation day and the historical
205 record is done using a vector of variables referred to as the feature vector. The number of
206 variables included in the vector may vary, and Buishand and Brandsma (2001) obtained the best
207 results with 2 and 5 after trying 2, 5, 20, and 50. Using a pre-defined metric, the distance between
208 the feature vector for a given simulation day and feature vectors in the historical record can be
209 determined, and the group of the k most similar days can be identified. One of these is selected at
210 random to provide the local weather data for the simulation day. A higher selection probability is
211 given to the closer days by using a decreasing kernel density function. The NNR method requires
212 large-scale atmospheric variables for the feature vector and corresponding historical weather data.
213 The large-scale variables considered here are surface temperature, 500 hPa temperature, 850 hPa
214 temperature, 500 hPa geopotential height, and 850 hPa geopotential height covering a significant
215 area over west-central Canada.

216

217 **3 Results**

218 *3.1 Comparison of statistical downscaling methods for the baseline period*

219 The three downscaling methods produced temperature and precipitation series for the baseline
220 period (1971-2000) both for Sioux Lookout and Red Lake. The results were evaluated by

221 comparing downscaled temperature and precipitation statistics with those observed at the Sioux
222 Lookout station. The results for the Red Lake station show a similar pattern between downscaling
223 methods. As seen in Table 1, all downscaling methods result in mean annual temperatures that are
224 higher than the observed (Station), but only SDSM annual temperature is significantly different
225 from the station at the 5% significance level. This difference is largely due to the fact that SDSM
226 annual temperatures were higher than Station annual temperatures in most of the 1990s, the
227 validation period for SDSM. LARS-WG is closest to the station data in terms of mean annual
228 temperature. The interannual variability of temperature is somewhat underestimated in the
229 statistical downscaling results, which is common in observation-model comparisons. The 95th and
230 5th percentile of daily temperature values are fairly similar among the data sets. The difference
231 between the three downscaling methods is more pronounced in the case of precipitation statistics,
232 although none of the downscaled annual total precipitations are significantly different from
233 Station. All downscaling methods underestimate the observed interannual variability, and the
234 underestimation is particularly severe in SDSM. Maximum daily precipitation is different by as
235 much as 14.7 mm (between SDSM and LARS-WG), but the 95th percentile of daily precipitation
236 is very similar among the data sets.

237

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

249

250 The SLURP model was run with input data generated by each downscaling method for the period
251 1970-2000, and the result for the year 1970 was dropped from the analysis to eliminate the impact

252 of initial conditions. The distribution of simulated annual mean discharge is shown in Figure 3.
253 The median annual runoff simulated with input data from NNR is consistently lower than runoff
254 simulated with SDSM or LARS-WG data. The largest variability among the downscaling
255 methods, in terms of the range of the whiskers, is observed with LARS-WG, while the median
256 streamflow with NNR are significantly lower than the other two methods. The result generally
257 reflects the precipitation statistics in Table 1. All the simulations with the downscaled GCM data
258 resulted in smaller interannual variability than the observed streamflow.

259
260 Overall, all the methods produce similar results for temperature, whereas LARS-WG produce
261 better results for precipitation than SDSM and NNR. There are some studies that report similar
262 results to the present one. Dibike and Coulibaly (2005) report that LARS-WG is better than
263 SDSM for wet- and dry-spell length, which has important implications for runoff generation.
264 Khan *et al* (2006) analyzed uncertainty from three statistical downscaling methods, SDSM,
265 LARS-WG and an artificial neural network (ANN) model, and conclude that LARS-WG and
266 SDSM are better than the ANN model in reproducing important statistics such as daily
267 precipitation, and maximum and minimum temperatures in a Quebec basin. They also found that
268 LARS-WG worked better for daily precipitation than SDSM. The characteristics of weather
269 generators that employ empirical distributions of precipitation variables are believed to contribute
270 to the better performance of LARS-WG relative to SDSM.

271
272 The underestimation of annual precipitation amount and variability by NNR is not entirely
273 unexpected. One of the drawbacks of NNR is that it merely resamples values from the observed
274 data (Sharif and Burn 2006). What is somewhat surprising however is the result from the
275 hydrological modeling with NNR-downscaled scenarios. NNR underestimates mean annual
276 precipitation by about 4% of the station data and about 8% relative to SDSM- or LARS-WG-
277 downscaled scenarios, but the runoff totals produced using the NRR method is 21% and 9%
278 lower than the runoff produced by SDSM in Sturgeon and Troutlake, respectively. Cunderlik and
279 Simonovic (2005, 2007) used NNR-downscaled scenarios to run a hydrological model but did not
280 elaborate on the bias of NNR and its effect on hydrological simulations, making it impossible to
281 compare with the present study.

282

283 3.2 *Projected changes in annual and monthly temperature, precipitation, and*
284 *runoff*

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

300
301 Figure 4 shows the changes in mean monthly temperature and precipitation from the baseline
302 climate by the 2050s at Sioux Lookout, for each downscaling method and emission scenario.
303 There is a noticeable discrepancy among downscaling methods and emission scenarios both in
304 temperature and precipitation changes. The temperature changes for summer months from SDSM
305 is roughly twice or more than those from LARS-WG and NNR in each emission scenario,
306 whereas LARS-WG- and NNR-downscaled scenarios show higher temperatures than SDSM for
307 January, February, and March. Warming is projected year round, which could lead to earlier
308 snowmelt, higher evaporation, and reduced snowpack storage. For March, April, and May, wetter
309 climate is generally projected with LARS-WG and NNR and drier with SDSM. The results for
310 Red Lake are fairly similar and thus not shown here.

311
312 Figure 5 shows changes of mean monthly runoff between the baseline and 2050s periods,
313 simulated with downscaled input data for each emission scenario. Under the A1B scenario,

314 LARS-WG results in runoff increases throughout the year, with the highest increase in April due
315 to increased precipitation and earlier snowmelt, and moderate increases in other months, largely
316 due to increased evaporation offsetting the effects of precipitation increases. On the other hand,
317 SDSM results mostly in decreases, and NNR shows more mixed results. Mean monthly runoff
318 changes to some extent resemble the pattern of mean monthly precipitation changes due to the
319 relatively small size of the catchments (Figure 4), but with amplified decreases in runoff with
320 SDSM and NNR. For months with small precipitation increases in SDSM- and NNR-downscaled
321 scenarios, runoff is projected to decrease, and for months with large increases (e.g. SDSM for
322 August), runoff increases moderately. Even though the precipitation changes in NNR- and
323 SDSM-downscaled scenarios are similar at the annual scale, the NNR-downscaled scenarios
324 show large increases in springtime precipitation whereas the SDSM-downscaled scenarios show
325 smaller increases or decreases (Figure 4). As a result, NNR results in smaller annual runoff
326 decreases than SDSM because spring runoff increases partially offset decreases in other seasons.
327 With the A2 and B1 scenarios, the overall pattern of changes is similar but of smaller magnitude.

328
329 Projected annual runoff changes between the baseline period and the 2050s for the Sturgeon basin
330 are presented as cumulative distribution functions (CDF) in Figure 6(a), grouped into emissions
331 scenarios. The results are similar for Troutlake, thus not shown. For a given emission scenario,
332 there are considerable differences between downscaling methods, suggesting that a substantial
333 uncertainty is associated with the choice of downscaling method. In all cases, increases are
334 predominant with LARS-WG, indicated by the curves located mostly on the right-hand side of
335 zero on the abscissae. This is not surprising given that precipitation is projected to increase by
336 about 20% with LARS-WG in all scenarios (Table 2). With the A1B scenario, SDSM mostly
337 shows decreases, and NNR is a mix between increases and decreases, reflecting the small average
338 changes shown in Table 2. With the A2 scenario, LARS-WG shows very large increases in some
339 years, easily exceeding 100%. Even though annual mean changes are similar between A1B and
340 A2 with LARS-WG, interannual variability is much larger with A2. Decreases are of similar
341 magnitudes between downscaling methods, but increases vary widely. The changes are more
342 modest with the B1 scenario. Figure 6(b) shows, for given downscaling methods, the differences
343 in runoff projections resulting from different emission scenarios. There appears to be much less
344 variability in runoff projections, suggesting that there is more uncertainty associated with the

345 choice of downscaling method than with the choice of emission scenario. Of course, this
346 conclusion is specific to the methods used here.

347
348 Mean monthly runoff from all future simulations (three downscaling methods and three emission
349 scenarios) are presented in Figure 7 along with the baseline simulations with the observed climate
350 data. The future mean monthly runoff shows a great degree of uncertainty between the
351 simulations, and for every calendar month, the range of changes covers both negative and
352 positive values. April is the only month where increases are predominant in both basins and this
353 is due to the earlier snowmelt. In September, October and November, decreases are predominant
354 due to warmer temperatures and small precipitation changes resulting in increased evaporation.
355 Summertime runoff shows a great deal of variability and has fairly equal probabilities for
356 increases and decreases.

357
358 The present study found larger uncertainty from the statistical downscaling methods than from
359 emission scenarios in terms of climate change impacts on mean runoff. This finding is in line
360 with Wilby and Harris (2006, p. 7) who suggest the following order of significance as a source of
361 uncertainty for low flow modeling in a UK basin: GCM > downscaling method > hydrological
362 model structure > hydrological model parameters > emission scenario. They adopted a
363 probabilistic approach for each source of uncertainty and considered a limited number of cases
364 for each source, which is a different approach than used here. However, the way they measured
365 the magnitude of uncertainty from each source is similar to this study in the sense that relative
366 changes of hydrological variables are compared among the cases of each uncertainty source.
367 Their finding is also in line with those of Boé *et al* (2009) who found larger uncertainty
368 associated with climate models than with downscaling methods and Menzel *et al* (2006) who
369 found much larger uncertainty with GCM-downscaling combinations than hydrological
370 modeling. Therefore, the importance of considering GCM-related uncertainty is emphasized.

371

372 **4 Conclusions**

373 This study used three different statistical downscaling methods for the CGCM3.1 output under
374 three different greenhouse gas emission scenarios to create climate scenarios for central Canadian
375 basins, and simulated hydrological processes with the scenarios using the SLURP hydrological

376 model. Major findings from the study includes: (1) the climate is projected to be generally
377 warmer (from 2.1 to 3.6 ° C increases in annual mean temperature) and wetter or slightly drier
378 (from -6.8 to +22.1% in annual total precipitation) in the studied basins in the 2050s; (2) runoff is
379 projected to change with a wide range across downscaling methods and emission scenarios, but
380 LARS-WG produced most consistent results across emission scenarios—increases in mean
381 annual runoff by 13-27%; and (3) statistical downscaling methods have greater uncertainty than
382 emission scenarios in projecting future water availability. To the extent that the GCM used in the
383 study provides a reasonable projection of climate change, our results suggest that there a good
384 likelihood that the region will see more runoff in the future although changes in seasonal runoff
385 remain rather uncertain.

386

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388

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391

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393

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494

495

496 **Tables**

497
 498 *Table 1. Temperature and precipitation variables from observation (Station) and each statistical*
 499 *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 |
| 95 th percentile of daily temperature (°C) | 20.9 | 20.6 | 20.8 | 20.8 |
| 5 th 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 |
| 95 th percentile of daily precipitation (mm) | 10.8 | 9.8 | 10.7 | 10.1 |

500 ^a SD stands for standard deviation

501

502

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

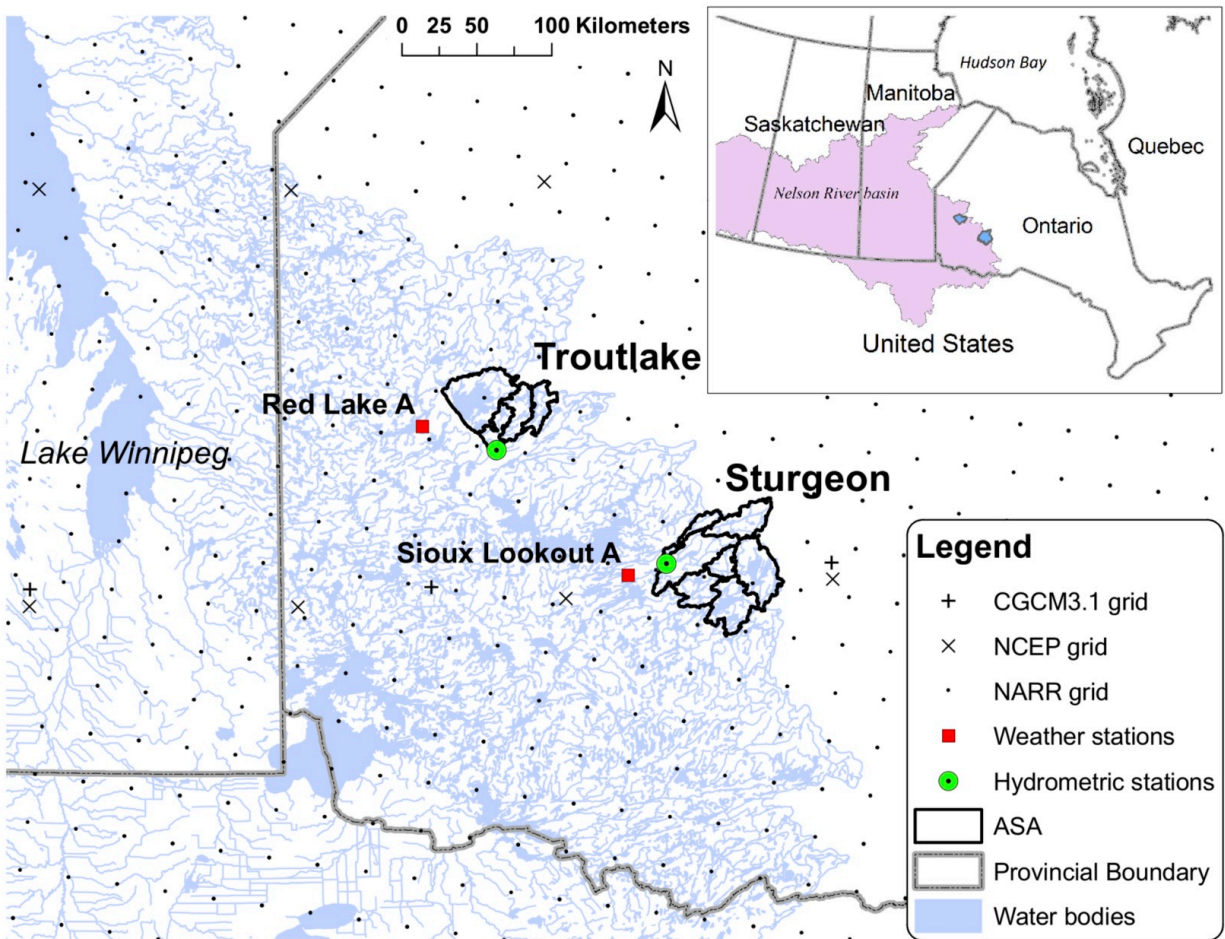
| | T change (°C) | | | | P change (%) | | | | Q change (%) | | |
|-----------|---------------|------------|------------|------------|--------------|------------|-------------|------|--------------|-------------|-------|
| | CGCM3.1 | SDSM | WG | NNR | CGCM3.1 | SDSM | WG | NNR | SDSM | WG | NNR |
| Sturgeon | | | | | | | | | | | |
| 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 | | | | | | | | | | | |
| 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 |

506

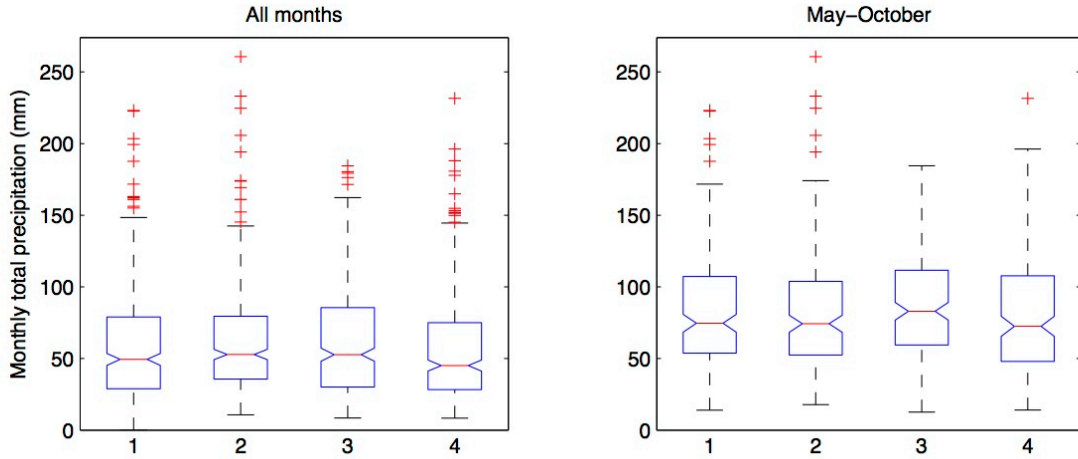
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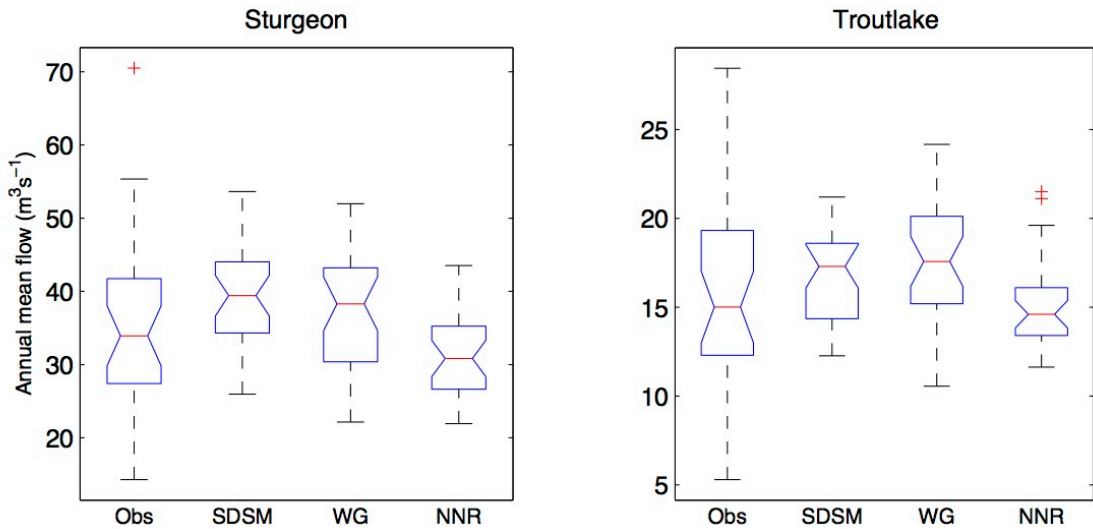
509 **Figures**



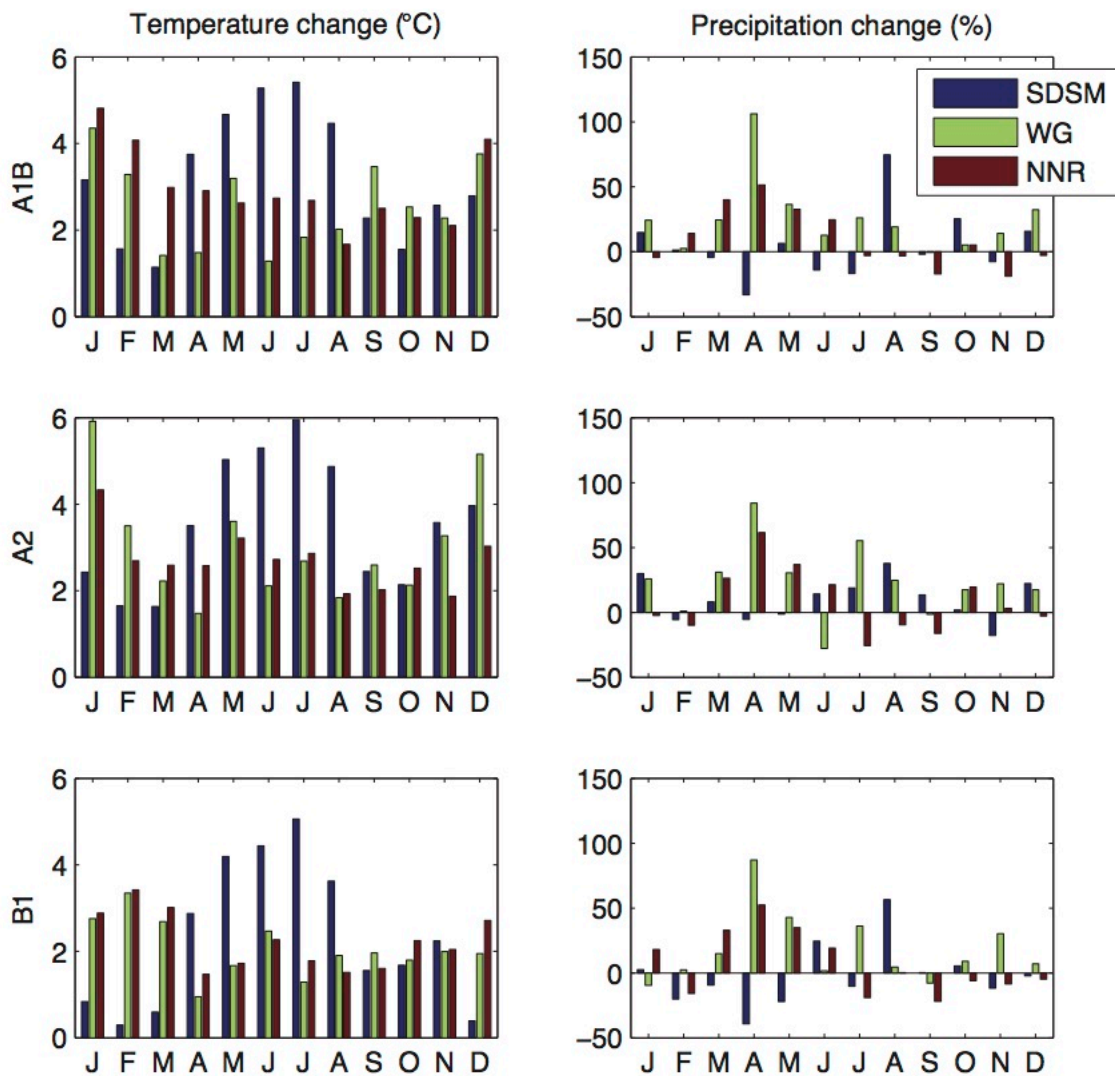
510
511 Figure 1. Aggregated simulations areas (ASA) of the Sturgeon and Troutlake River basins for
512 hydrological modeling. Point symbols are the location where climatic and hydrometric data are
513 available. The inset map shows the two basins and the Nelson River basin where the two basins
514 are nested.



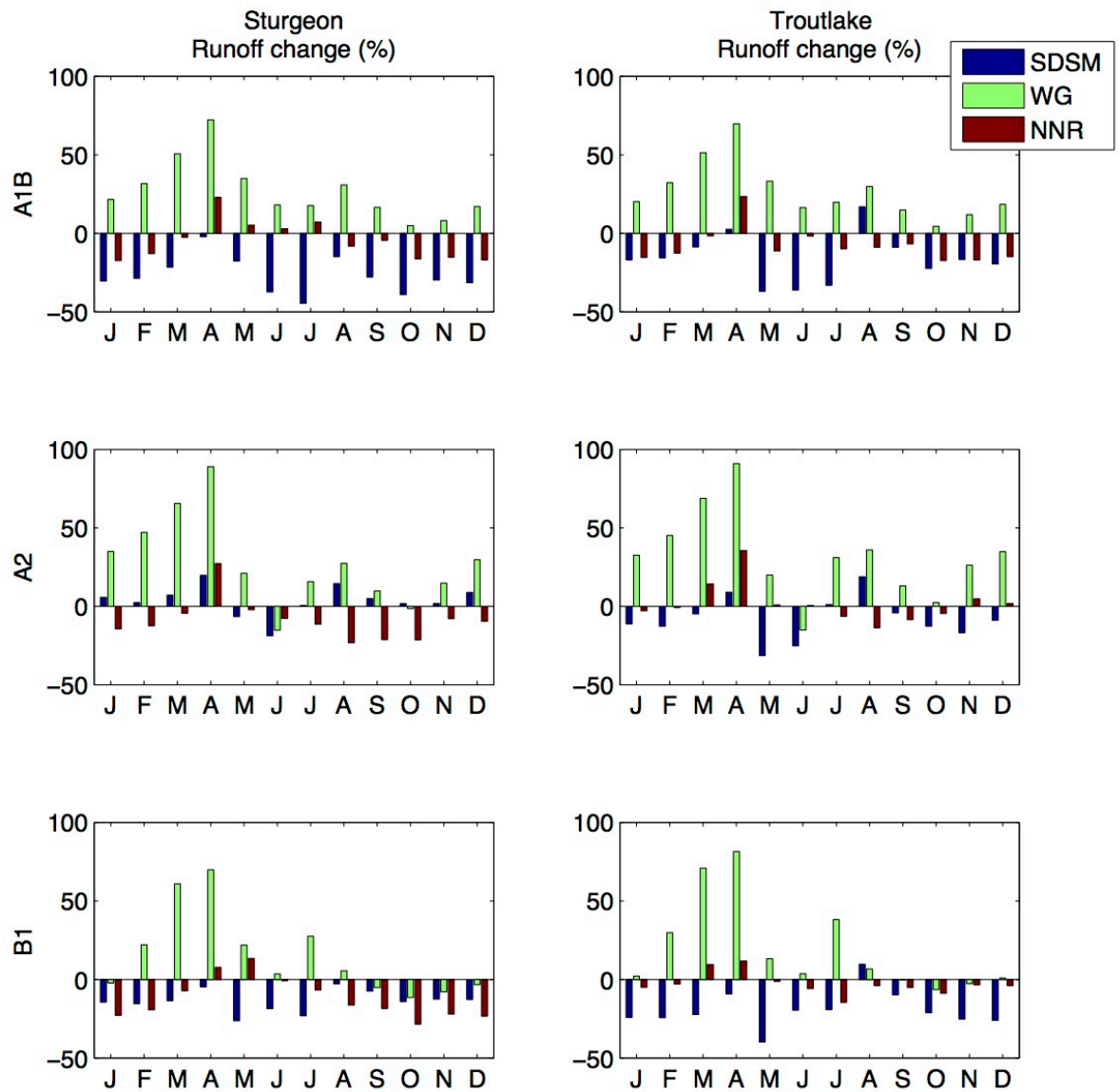
515
 516 Figure 2. Distribution of monthly total precipitation values for all months and May-October from
 517 Station and each statistical downscaling method at Sioux Lookout A, 1971-2000. 1: Station, 2:
 518 SDSM, 3: LARS-WG, and 4: NNR. The boxes have lines at the lower quartile, median, and
 519 upper quartile values. Whiskers extend from each end of the box to the most extreme values
 520 within 1.5 times the interquartile range. Plus (+) signs denote outliers. Non-overlapping notch
 521 intervals indicate that the medians are significantly different ($\alpha = 0.05$). Same for other box plots.



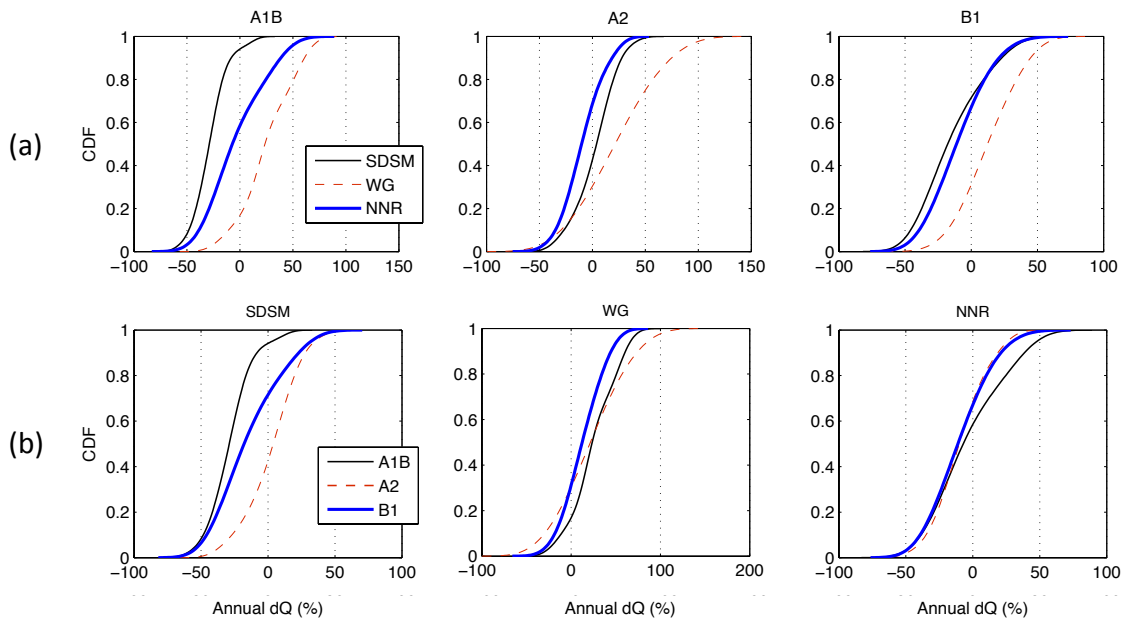
522
 523 Figure 3. Boxplots of annual mean flow simulated with observed climate data (Obs) and
 524 downscaled CGCM data for the baseline period. The plots indicate the interannual variability of
 525 annual mean flow.



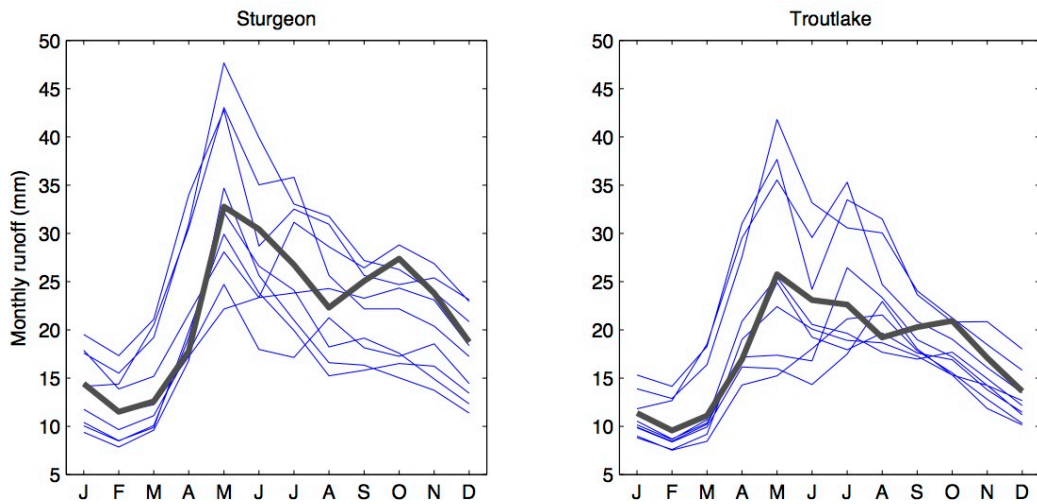
526
 527 Figure 4. Mean monthly temperature (left panel) and precipitation (right panel) changes for Sioux
 528 Lookout A from the baseline period by the 2050s.



529
 530 Figure 5. Mean monthly runoff changes for Sturgeon (left panel) and Troutlake (right panel) from
 531 the baseline period by the 2050s, simulated with statistically downscaled climate scenarios.



532
 533 Figure 6. Cumulative distribution functions (CDFs) of annual runoff changes (dQ) for the
 534 Sturgeon basin between the 2050s and the baseline periods reflecting uncertainty in the
 535 downscaling methods (a) and emissions scenarios (b).



536
 537 Figure 7. Mean monthly runoff from the simulations with the baseline climate data (thick grey
 538 line) and with future climate data (thin blue lines) from all downscaling methods and emission
 539 scenarios.