INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **32**: 1151–1163 (2012)
Published online 17 May 2011 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.2343

Future changes in intense precipitation over Canada assessed from multi-model NARCCAP ensemble simulations

Alain Mailhot,[a]* Ian Beauregard,[a] Guillaume Talbot,[a] Daniel Caya,[b] and Sébastien Biner[b]
[a] *Centre Eau Terre Environnement, Institut national de la recherche scientifique, 490, de la Couronne, Québec, G1K 9A9, Canada*
[b] *Consortium Ouranos, 550 Sherbrooke Ouest, 19e étage, Tour Ouest, Montréal (Québec), H3A 1B9, Canada*

ABSTRACT: Annual maxima (AM) series of precipitation from 15 simulations of the North American Regional Climate Change Assessment Program (NARCCAP) have been analysed for gridpoints covering Canada and the northern part of United States. The NARCCAP Regional Climate Models' simulations have been classified into the following three groups based on the driving data used at the RCMs boundaries: (1) NCEP (6 simulations); (2) GCM-historical (5 simulations); and (3) GCM-future (4 simulations). Historical simulations are representative of the 1968-2000 period while future simulations cover the 2041-2070 period. A reference common grid has been defined to ease the comparison. Multi-model average intensities of AM precipitation of 6-, 12-, 24-, 72-, and 120-h for 2-, 5-, 10-, and 20-year return periods have been estimated for each simulation group. Comparison of results from NCEP and GCM-historical groups shows good overall agreement in terms of spatial distribution of AM intensities. Comparison of GCM-future and GCM-historical groups clearly shows widespread increases with median relative changes across all gridpoints ranging from 12 to 18% depending on durations and return periods. Fourteen Canadian climatic regions have been used to define regional projections and average regional changes in intense precipitation have been estimated for each duration and return period. Uncertainties on these regional values, resulting from inter-model variability, were also estimated. Results suggest that inland regions (e.g. Ontario and more specifically Southern Ontario, the Prairies, Southern Quebec) will experience the largest relative increases in AM intensities while coastal regions (e.g. Atlantic Provinces and the West Coast) will experience the smallest ones. These projections are most valuable inputs for the assessment of future impact of climate change on water infrastructures and the development of more efficient adaptation strategies. Copyright © 2011 Royal Meteorological Society

KEY WORDS intense rainfall; regional climate model; global climate model; climate change; NARCCAP; multi-model ensemble

Received 13 November 2010; Revised 14 March 2011; Accepted 20 March 2011

1. Introduction

Climate change (CC) is expected to cause an increase in evaporation and precipitation, leading to an intensification of the water cycle (Huntington, 2006). It is expected that this intensification will have consequences on the availability of water resources and also on the intensity and frequency of occurrence of extreme events (Trenberth, 1999; Emori and Brown, 2005; Allan and Soden, 2008). These conclusions are supported by observed trends and simulations from climate models (Frei *et al*., 2006; Vincent and Mekis, 2006; Fowler *et al*., 2007; Hayhoe *et al*., 2007; Alexander and Arblaster, 2008).

The chaotic nature of the climate system, the important feedbacks between its components, our incomplete and/or approximate representation of this very complex system and its intrinsic variability make the assessment of the uncertainties a required step in any climate projections in order to completely assess CC impacts and develop more efficient adaptation strategies (Bronstert *et al*., 2007; New *et al*., 2007; Stainforth *et al*., 2007; Kundzewicz *et al*., 2008). Information transfer from the scientific realm to water managers is critical as climate sciences and available projections are rapidly evolving (Milly *et al*., 2008). Assumptions underlying the available projections as well as their inherent uncertainties should be conveyed to communities that would be impacted and who would have to adapt to CC. A few studies assessing CC impacts have recently been published where uncertainties are explicitly considered (e.g. Cantelaube and Terres, 2005, in agricultural sciences; Thomson *et al*., 2006, in health science; Graham *et al*., 2007, in hydrology and water management). The authors think that uncertainty analysis should be part of every CC impacts analysis.

Various approaches have been proposed to deal with uncertainties in climate projections and impact studies. Among these uncertainties, the 'structural uncertainties' of the models have been identified as the most significant ones (e.g. Frei *et al*., 2006; Räisänen, 2007; Tebaldi and Knutti, 2007; de Elía *et al*., 2008). The multi-model ensemble approach has been developed to combine simulations from different models using various initial conditions (ensemble members) and therefore take into

* Correspondence to: Alain Mailhot, Centre Eau Terre Environnement, Institut national de la recherche scientifique, 490, de la Couronne, Québec, G1K 9A9, Canada. E-mail: Alain.Mailhot@ete.inrs.ca

consideration structural as well as uncertainties associated to the natural variability in the climate system (Hagedorn *et al*., 2005; Palmer *et al*., 2005; Kharin *et al*., 2007; Meehl *et al*., 2007; Tebaldi and Knutti, 2007; Laprise, 2008). It has been argued that the combination of results from various models leads to more consistent and reliable forecasts by reducing the characteristic biases and uncertainties of any individual model (Hagedorn *et al*., 2005).

The North American Regional Climate Change Assessment Program (NARCCAP) aims at producing simulations generated by a set of regional climate models (RCMs) on a common period and domain (Mearns *et al*., 2009). The NARCCAP Regional Climate Models' simulations provide the required data to address the assessment of CC signal and its associated uncertainty. Some encouraging results using NARCCAP ensemble of regional model have been reported. For example, Gutowski *et al*. (2010) showed that models accurately reproduce several features of observed extreme monthly precipitation, defined as the top 10% of monthly precipitation in the cold half of the year (October–March) for the 1982–1999 period.

Basing on available NARCCAP simulations, this study intends to combine projections to get a multi-model mean (MMM) of future change in annual maxima (AM) precipitation over Canada and to get an estimate of the associated uncertainty. The simulations analysed in the present investigation have been classified into three groups based on the driving data used to supply the RCMs boundary conditions: (1) NCEP (6 simulations); (2) GCM-historical (5 simulations); and (3) GCM-future (4 simulations). Historical simulations are representative of the 1968–2000 period while future simulations cover the 2041–2070 period. A common reference grid has been defined to ease the comparison. Multi-model mean intensities of AM precipitation of 6-, 12-, 24-, 72-, and 120-h for 2-, 5-, 10-, and 20-year return periods have been estimated for each simulation group. Comparison with observed AM series across Canada is also achieved in order to help establish the degree of confidence one might have in projections of climate change.

This paper is organized as follows. Section 2 gives an overview of the available simulations and observed data. Experimental setup and preliminary analysis appear in Section 3 (selection of the reference grid, projection of the various results on this reference grid, trend analysis, implementation of the multi-model approach). Intra-group variability is investigated in Section 4, while comparison between NCEP and GCM-historical simulation groups is presented in Section 5. Section 6 provides a description of the comparison of observed and simulated extreme precipitation. Finally, results of the comparison between simulated series (future *vs* historical driven by GCM) at the grid-point scale are described in Section 7, while results from the regional analysis are presented in Section 8.

Table I. The NARCCAP simulations used in the present study.

Group	RCM	Driving	Simulation period
NCEP	ECPC	NCEP	1982–2005
	HRM3	NCEP	1982–2004
	MM5I	NCEP	1982–2004
	RCM3	NCEP	1982–2004
	WRFP	NCEP	1982–2004
	CRCM	NCEP	1982–2003
GCM-historical	HRM3	HadCM3	1971–2000
	MM5I	CCSM	1971–1999
	RCM3	CGCM3	1971–2000
	RCM3	GFDL	1971–2000
	CRCM	CGCM3	1971–2000
GCM-future	HRM3	HadCM3	2041–2070
	RCM3	CGCM3	2041–2070
	RCM3	GFDL	2041–2070
	CRCM	CGCM3	2041–2070

2. Available simulation series and observed data

Fifteen multi-decade simulations from the NARCCAP archive have been analysed (Table I; see the NARCCAP website http://www.narccap.ucar.edu for detailed information on the project and for a description of the participating RCMs and GCMs). NARCCAP involves six RCMs (identified as CRCM, ECPC, MM5I, RCM3, WRFP, and HRM3) using a similar 50-km horizontal resolution grid. In the NARCCAP framework, each RCM has to be driven by the NCEP reanalysis and by two distinct GCMs data (Mearns *et al*., 2009). Every future simulation in NARCCAP follows greenhouse gas and aerosol concentrations from the SRES A2 scenario (IPCC, 2000). For the analysis carried out in the present article, the NARCCAP simulations were classified in three distinct groups: (1) NCEP (simulations in historical climate driven by NCEP/DOE Reanalysis II data; Kanamitsu *et al*., 2002); (2) GCM-historical (simulations in current climate by a GCM that follows historical GHG concentrations); and (3) GCM-future (simulations in future climate driven by a GCM with GHG concentrations based on the SRES A2 emission scenario). It is important to note that the first three years of each simulation has been discarded (spin-up period) and that the period indicated in Table I corresponds to the period actually considered in this study.

The comparison of simulated data with observations for the historical period is made against daily data from 432 stations across Canada (a map showing the location of the stations can be seen in Zhang *et al*., 2000; only stations with 15 years of data or more have been retained). The stations' data is provided by Environment Canada and have been adjusted for possible bias due to winds, wetting losses, evaporation, etc. (Mekis and Hogg, 1999, for a description of the adjustment method). Data were available for the period from 1900 to 2007 for the more densely urbanized parts of Canada (essentially the southern regions), while they covered the 1950–2007 period for the other regions.

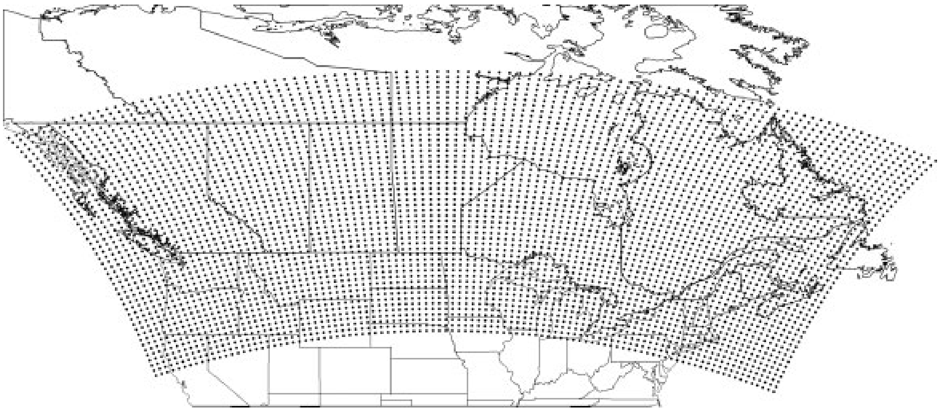

Figure 1. Reference grid used in this study.

3. Experimental setup and statistical analysis

For each model, AM series for 6-, 12-, 24-, 72-, and 120-h durations were constructed for each simulation (precipitation depth is available for each 3-h time interval) on each of the model native grids. The Generalized Extreme Value (GEV) distribution was used and parameters were estimated by the L-moments method (Hosking and Wallis, 1997). Precipitation intensities associated to 2-, 5-, 10-, and 20-year return periods were estimated (Mailhot *et al*., 2007, for details on the methodology).

Since the NARCCAP RCMs used distinct horizontal grids (each grid have a common 50-km resolution but uses a different projection on the spherical Earth), a common reference grid needed to be defined in order to combine results from the various simulations. All grids having comparable horizontal resolution of 50 km, the reference grid was defined in such a way that each of its gridpoints is located at the geometrical average location of the neighbouring RCMs gridpoints. The resulting grid is presented in Figure 1. It covers the southern part of Canada and the northern United States. A correspondence between each reference gridpoint and native RCM gridpoints was established by locating, for each RCM, the nearest native gridpoints to a given reference gridpoint. Group-average precipitation intensity for a given duration and return period on each cell of the common reference grid is obtained by averaging the corresponding values from native RCM gridpoint. These average values on the reference grid are hereafter referred as Multi-Model Mean (MMM) values.

Trend analysis was performed on RCMs gridpoint series using the Mann-Kendall test (Mann, 1945; Kendall, 1975). For each of the NARCCAP simulation, less than 10% of gridpoint AM series (all durations included) display significant trends at the 95% level, with an average over all simulation series of 5.9% of gridpoints with significant trends. Basing on the trend analysis result, all series were assumed stationary for both NCEP and GCM driven historical climate (1982–2004 period for NCEP-driven runs and 1971–2000 for GCM-driven runs) and the future climate (2041–2070 period).

4. Intra-group variability

The intra-group variability is estimated to assess the overall coherence of the simulated climate between the different RCMs and to estimate the level of inter-model variability in the simulations as part of the overall uncertainty in climate simulations. In order to assess inter-model variability among results from simulations belonging to a given group, coefficients of variation (CV) at each gridpoint were estimated within that group. For a given duration and return period, the CV is defined at each gridpoint as the ratio between the standard deviation of AM simulated precipitation intensities within a given group to the corresponding group mean value. Investigation of the intra-group variability shows that:

- All three simulation groups predominantly show relatively low CV values (most of CV values are within the (15, 30%) interval), which means that results from the various simulations are reasonably consistent at the gridpoint scale even in future climate (Figure 2);
- Variability among simulation results is higher for the western part of the studied area (values between 0.2 and 0.3) while it is lower for the eastern part (this result is valid for all simulation groups; Figure 3). Spatial patterns blur out as the return period increases.
- For all groups, median values of the CV distribution over all gridpoint slightly increase as the return period increases for a given duration, this effect being more pronounced for both GCM-driven groups (Figure 2a). CV distributions also spread out with increasing return period for GCM-driven simulations (present and future);
- For all three groups, given a return period, duration seems to have a negligible effect on the distribution of the CV values over all gridpoints.

The westward CV gradient on Figure 3 could be due to the fact that on the West Coast the precipitation is dominated by large-scale systems hitting the coastal range and the Rockies. This could emphasize the differences between the large-scale fields and the topography representation of the different RCM/GCM combinations. These differences could affect the lee-side cyclogenesis

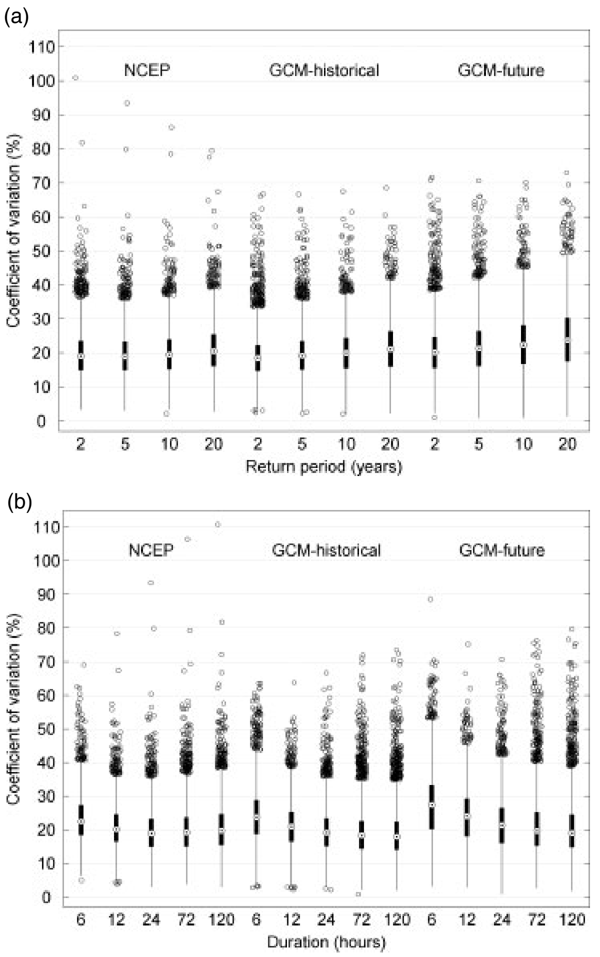

Figure 2. Box-plots of gridpoint CV values for the three simulation groups: (a) 24-h AM precipitation; (b) 5-year return period precipitation.

and propagate eastward before they eventually attenuate over Ontario. Part of the higher CV values found over the northern United States and Canadian prairies could also be linked to differences in the treatment of moisture by the RCMs over that region and by differences in the moisture influx from the Gulf of Mexico.

5. Comparison between NCEP and GCM-historical simulation groups

It is believed that reanalysis provides the most accurate global description of the historical weather events time series. Comparison between NCEP- and GCM-driven RCM simulations is therefore achieved to estimate the effect of moving from observed boundary conditions to GCMs' simulated ones.

The RCMs' simulations in the NCEP and GCM-historical groups display similar spatial patterns of extreme precipitation. Figure 4 presents maps of relative differences between NCEP and GCM-historical MMM gridpoint values for the 2- and 20-year return periods for the 24-h AM precipitation depths while Figure 5 presents the box plots of these relative differences. NCEP and GCM-historical estimates are globally in good agreement with relative differences typically ranging from −30 to 30% and a distribution centred near zero (similar results are obtained for the other durations and return periods). The dispersion of the differences slightly increases with return period (Figure 5a) while it remains unchanged with duration (Figure 5b). The spatial distribution of these values reveals that GCM-historical values estimates tend to slightly overestimate NCEP values for the southcentral and the southwestern portions of the study area while they globally underestimate NCEP values for the northern part (Figure 4). As the return period increases, relative differences increase with no noticeable change in spatial distribution (Figure 4a and b).

6. Comparison of observed and simulated extreme precipitation depth

Annual maxima for 24-, 72-, and 120-h durations were extracted from the available observed series of daily precipitation. It is important to note that, since only daily precipitation series are available, these values correspond to the AM values of total precipitations occurring during one day, three or five consecutive days. In the analyses of the previous sections, sliding windows of 24, 72, or 120 h were used to construct AM series since NARCCAP

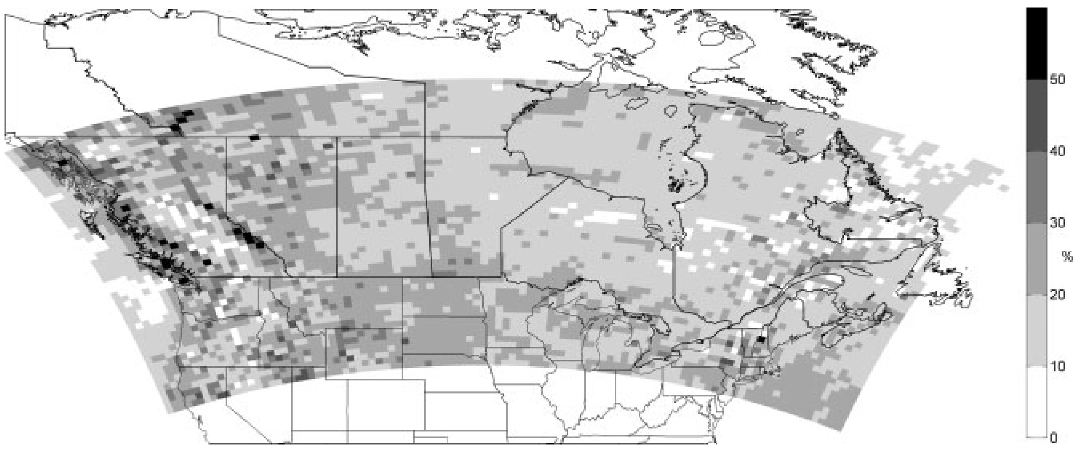

Figure 3. Gridpoint CV values for 24-h 2-year return period AM precipitation for GCM-historical group.

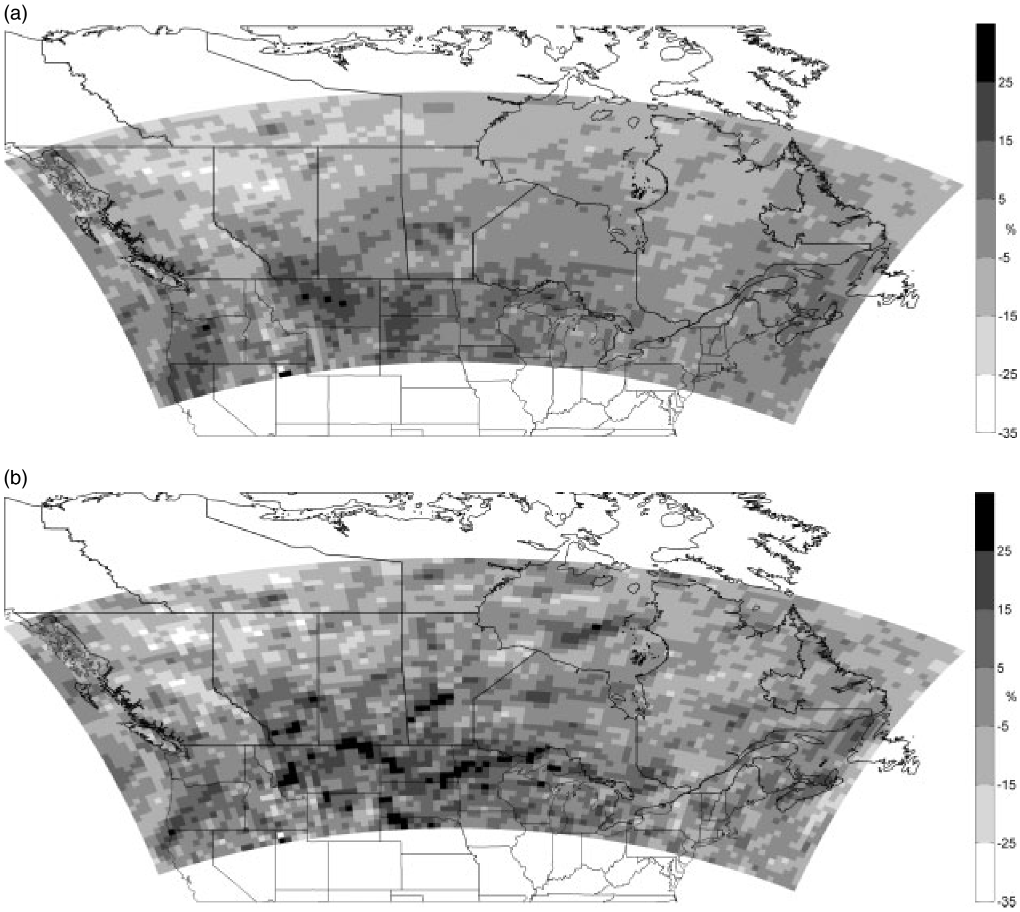

Figure 4. Maps of relative differences between NCEP and GCM-historical MMM gridpoint precipitation depths ([GCM-historical−NCEP]/NCEP) for 24-h: (a) 2-year return period; (b) 20-year return period.

series are recorded at a 3-h time interval. In order to have a common basis of comparison, NARCCAP simulations data were aggregated at a daily time step and AM series for 1-, 3-, and 5-day precipitation depths were constructed for each simulation. Precipitation depths for the various durations and return periods were estimated using the L-moments method and assuming a GEV distribution for both observed and simulated series. MMM values are estimated as in previous sections.

Comparison is made by averaging observed AM precipitation estimates for stations enclosed within a gridpoint. Ratios between the MMM gridpoint values and the corresponding average observed precipitation depths (for a given duration and return period) are then evaluated. These ratios can somehow be related to the Areal Reduction Factor (ARF) since it is generally recognized that the gridpoint precipitation simulated by GCMs and RCMs has the spatial characteristics of areal averages (Osborn and Hulme, 1997). Accordingly, the NARCCAP RCMs operate in a world drawn by 50×50 km pixels (Fowler *et al*., 2005). ARFs are used to relate the maximum areal average precipitation rate to the maximum rate observed at a point within that area (Allen and DeGaetano, 2002; 2005). It has been shown that ARFs vary with duration and size of the averaging area (Srikanthan, 1995). For example, ARFs will decrease when, for a fixed area, AM of shorter durations (less than 24 h) are considered, since systems involved in shorter duration extreme precipitation are spatially smaller than those involved in longer duration extreme precipitations (Srikanthan, 1995).

In the present study, ARF is defined as the ratio of MMM GCM-historical precipitation depth to mean precipitation depth estimated from observed series. Figure 6 presents maps of the ARF values estimated for grid tiles enclosing one or more stations and box plots of ARF values for the territory under study are displayed in Figure 7. Results indicate that:

- ARF values and their dispersion slightly increase with duration, getting globally closer to one (Figure 7b);
- Globally ARF values slightly decrease when return period increase for a given duration (Figure 7a);
- Spatially, the most important differences are seen in British Columbia where ARF values, for many gridpoints, range from 1.1 to 1.4, meaning that observed AM estimates are much smaller than gridpoint estimates (Figure 6), these differences being more pronounced for 5 days AM precipitation (Figure 6b).

These results are coherent with the hypothesis that short duration AM precipitation are generated by more localized meteorological systems not explicitly captured

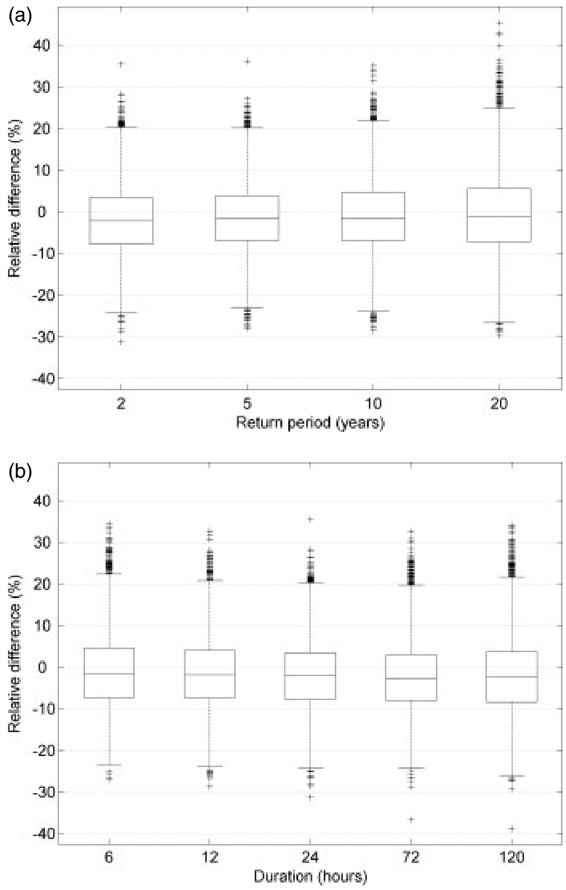

Figure 5. Box plots of relative differences between NCEP and GCM-historical MMM gridpoint precipitation depths ([GCM-historical−NCEP]/NCEP) for: (a) 24-h; (b) 2-year return period.

by the RCMs and, therefore, leading to smaller ARF values as duration decreases (for a given return period). The resulting ARF values seem reasonable and are consistent with what has been reported in the literature (e.g. Allen and DeGaetano, 2002, 2005), assuming RCMs generate average areal precipitation (to our knowledge, no ARF values have been estimated for the area under study essentially because the network density is too low to provide reliable ARF values built on observations).

7. Future projections for extreme precipitation – gridpoint analysis

Relative differences between gridpoint MMM precipitation depth estimated from GCM-future and GCM-historical groups were calculated. These values correspond to the projected changes in AM precipitation depth between the historical (pre-2005) and the future (2041–2070) MMM values. Figure 8 presents some results for 24-h AM precipitation. The largest increases are observed for Ontario and the Prairies (similar patterns of change are observed for other durations and return periods). While most regions will experience an increase, it is interesting to note that some regions in British Columbia and in the Northwest Territories may experience a decrease in AM precipitation. Projected changes increase with return period while regional patterns seem to blur out. Looking at the global picture, median values of the distribution of relative projected changes range from 12 to 18% (Figure 9). Dispersion among gridpoint relative changes increases with the return period while projected changes decrease with duration.

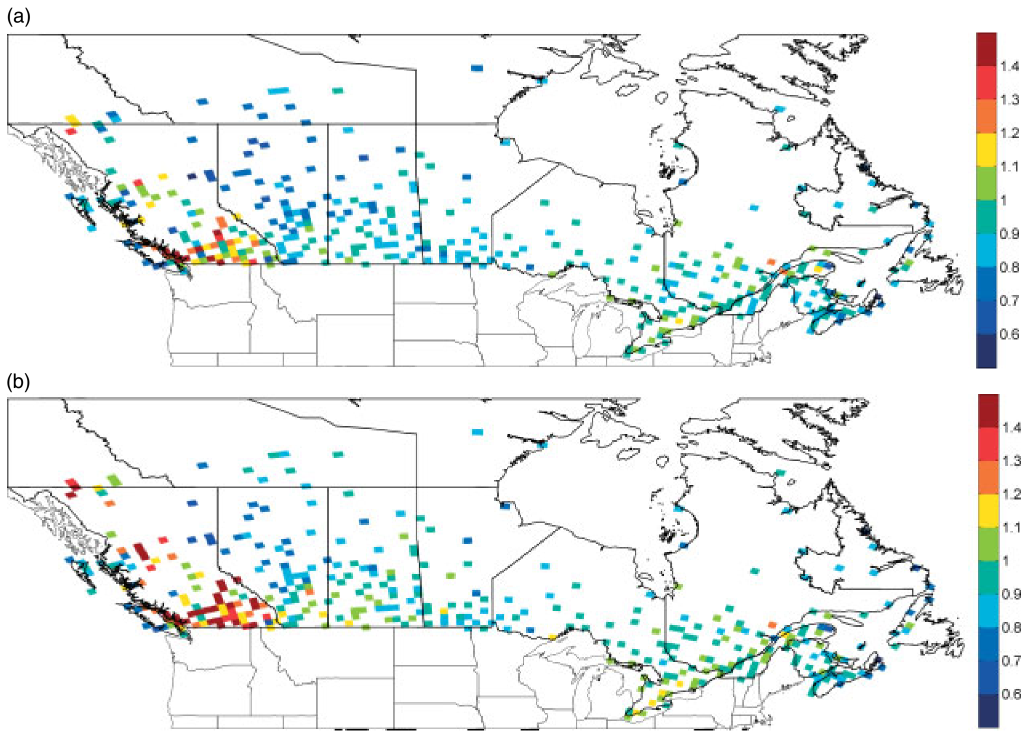

Figure 6. Maps of ARF values for 2-year return period: (a) daily AM precipitation; (b) 5-day AM precipitation (observed versus GCM-historical group). ARF <1 indicates that simulated values underestimate observed ones.

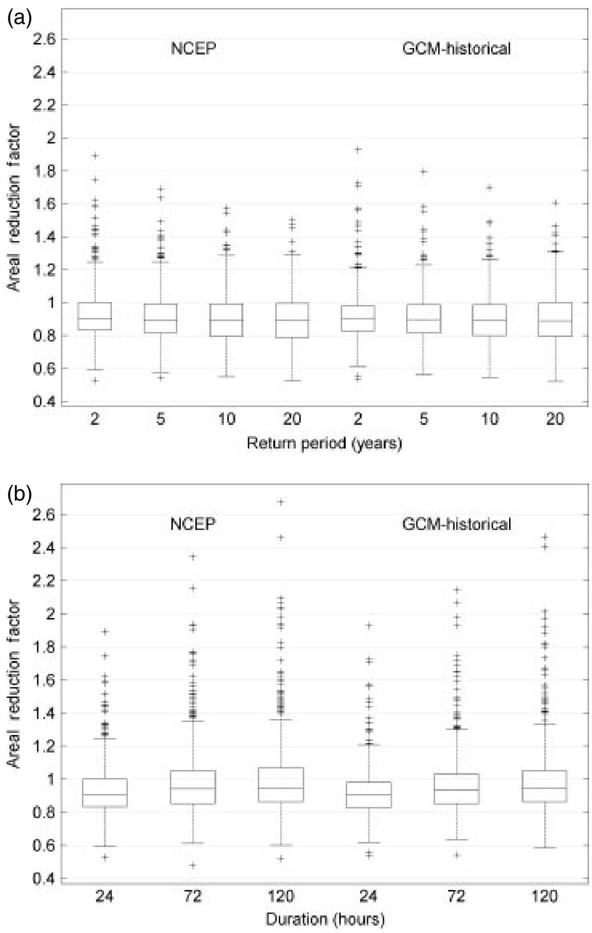

Figure 7. Box-plots of ARF values (observed *vs* GCM-historical and NCEP groups) for: (a) 24-h AM precipitation; (b) 2-year return period AM precipitation.

8. Future projections for extreme precipitation – regional analysis

In order to get a regional overview of the expected changes, climatic regions of Canada were considered. Some of these regions were subdivided to improve the regional homogeneity of simulated MMM AM precipitation. Fourteen climatic regions were defined accordingly (Figure 10 and Table II.). Regional average MMM of AM precipitation depth for a given duration and a given return period are obtained by averaging MMM values for gridpoints included in the region. Denoting by $\overline{MMM}_{i,s}$ the MMM values at gridpoint i for group s, the regional average MMM value is defined as:

$$\overline{MMM}_{R_j,s} = \frac{1}{n_j}\sum_{i\in R_j}\overline{MMM}_{i,s} \tag{1}$$

The sum is over gridpoints included in region R_j and n_j is the number of gridpoints in region R_j. The sample standard deviation on MMM gridpoint values, defined as $\sigma_{\overline{MMM}_i}$, account for the dispersion among the estimates from the various simulations at a gridpoint (inter-model or inter-simulation variability within a group). Standard errors on regional average MMM values for GCM-future, $\sigma_{R_j,f}$, and GCM-historical groups, $\sigma_{R_j,h}$, are then computed. Assuming that gridpoint MMM values correspond to independent normally distributed variables (the dispersion being due to inter-model variability), the regional variance is given by (Hogg *et al*., 2004):

$$\sigma^2_{R_j,s} = \frac{1}{n^2_{R_j}}\sum_{i\in R_j}\sigma^2_{\overline{MMM}_{i,s}} \tag{2}$$

Relative changes between future and historical climate for region R_j, $\delta_{R_j,f-h}$, were finally estimated using:

$$\delta_{R_j,f-h} = \frac{\overline{MMM}_{R_j,f}}{\overline{MMM}_{R_j,h}} - 1 \tag{3}$$

Standard deviation on $\delta_{R_j,f-h}$ was estimated assuming that $\overline{MMM}_{R_j,f}$ and $\overline{MMM}_{R_j,h}$ are both normally distributed with standard deviation given by $\sigma_{R_j,f}$ or $\sigma_{R_j,h}$. The expression derived by Hinkley (1969) to estimate the variance in the ratio of two normally distributed variables was used. Standard deviation on $\delta_{R_j,f-h}$ accounts for regional uncertainty due to inter-model (or inter-simulation) variability at the gridpoint scale.

Regional homogeneity can be accessed through the estimation of the regional coefficient of variation defined as the ratio between the standard deviation on MMM gridpoint values for a given region to the corresponding mean value (Equation (1)). Figure 10 displays the CV values for 24-h precipitation with a 20-year return period (these values are representative of CV values of other durations and return periods). As can be seen, western regions are more heterogeneous than central or eastern regions. This result is not surprising considering the heterogeneous topography of Western Canada.

Figure 11 gives an overview of regional estimates revealing a number of interesting features. It shows that Canadian regions will be diversely affected by climate change in terms of expected variations in intense precipitation. A general observation is that inland regions localized in mid-latitudes (NEFN, NEFS, NWF) and Southern Canada (GLSLO, GLSLQ, P) will experience large increases of AM rainfall depths for all durations and return periods. The most affected region being the GLSLO region with increases up to approximately 25% for 20-year return period AM precipitation of all durations. Regional changes in AM precipitation (for all durations) either increase (especially for short durations) or remain unchanged as return period increases. Similarly, for a given return period, relative changes in AM precipitation either increase or remain approximately unchanged as duration decreases, the shorter duration AM precipitation therefore being, for many regions and return periods, more affected by climate change. SBC is the region with the most diverse response with respect to duration (e.g. for 20-year return period AM, an 18% increase is expected for the 6-h duration while it is close to 0% for the 120-h duration). Error bars on regional AM precipitation are smaller than estimated changes except for NBCC (the most heterogeneous region; Figure 10), PC

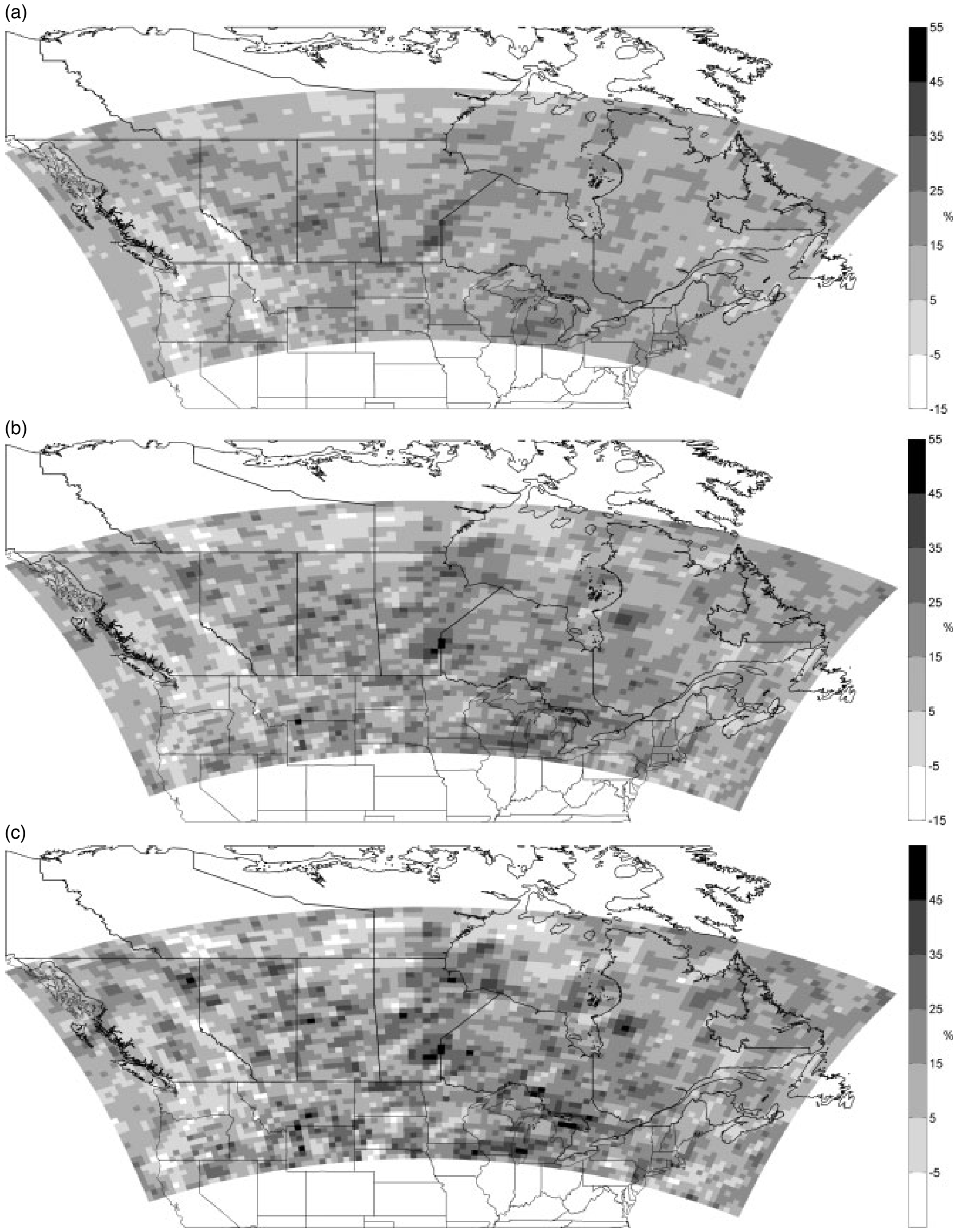

Figure 8. Maps of projected relative changes for MMM gridpoint precipitation between the historical (pre-2000) and the future (2041–2070) periods for 24-h AM precipitation ([GCM future–GCM-Historical]/GCM-Historical): (a) 2-year; (b) 10-year; (c) 20-year return period.

(also very heterogeneous) and SBC (for which no changes are expected for the 120-h duration).

9. Summary and conclusion

Important differences in projected climate can occur between models mainly due to different representations (e.g. spatial and temporal discretisations of the simulation domains; parameterisation of the sub-grid scale physical processes involved) of the climatic system adopted by each model. The internal variability associated to the chaotic and nonlinear nature of the climate system must also be considered. Assessment of uncertainties in climatic projections is therefore essential in a context where adaptation strategies are needed to minimize the vulnerability of our societies to CC (Lemmen *et al*., 2008). Uncertainties in future projections are usually assessed through the combination and comparison of simulation results using approaches such as the multimodel ensemble approach. Furthermore, assessment of the consistency among variables as simulated by different climate models, for example, through the comparison and

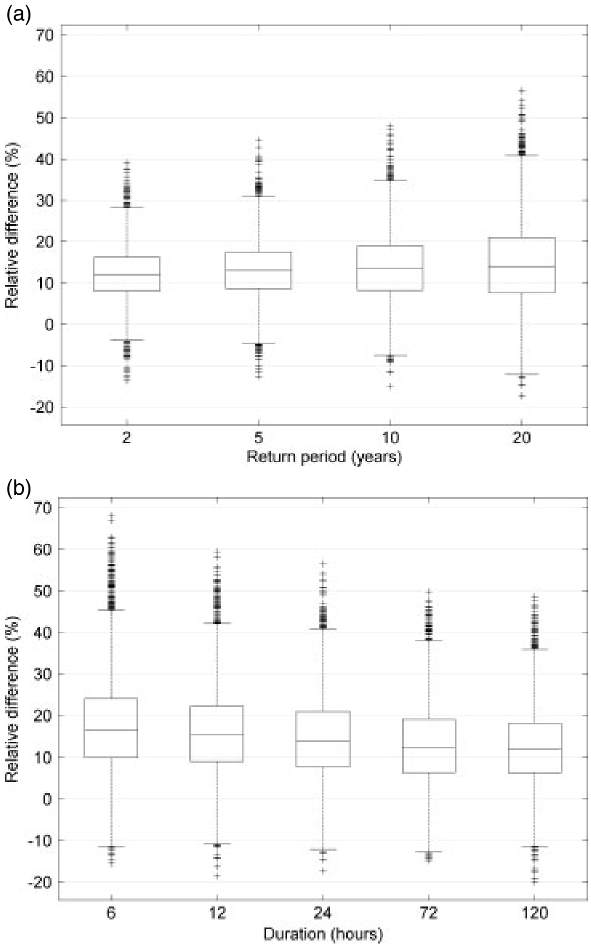

Figure 9. Box plots of projected relative changes in precipitation between the historical (pre-2000) and the future (2041–2070) periods ([GCM-future–GCM-historical]/GCM-historical): (a) 24-h (*vs* return period); (b) 20-year return period (*vs* duration).

Table II. Climatic regions.

Name	Acronym
North British Columbia (Coast)	NBCC
Pacific Coast	PC
North British Columbia (Inland)	NBCI
South British Columbia	SBC
South Mackenzie District	SMD
Northwestern Forest	NWF
Prairies	P
Southern Arctic Tundra	SAT
Northeastern forest (South)	NEFS
Northeastern forest (North)	NEFN
Great Lakes St-Lawrence (Ontario)	GLSLO
Great Lakes St-Lawrence (Quebec)	GLSLQ
Northeastern forest (St Lawrence Estuary)	NEFSLE
Atlantic Canada	AC

combination of simulation results provided by available RCM-GCM pairings, even though not a strict demonstration of the models' ability to simulate future climatic conditions (e.g. if structural errors are shared by all models) is also essential as it gives some clues on the model reliability (Räisänen, 2001). Assessment of the model consistency (not identical results) could strengthen our confidence in projections, help to investigate potential vulnerabilities (e.g. for water resources) and help to identify adequate adaptation measures.

Annual maxima (AM) series from the available subset of the NARCCAP ensemble of simulations have been analysed and compared to historical series from the Canadian monitoring network. NARCCAP simulations have been classified according to the source of the data used to drive the RCM. Three groups have been defined: (1) NCEP (6 simulations); (2) GCM-historical (pre-2000 period; 5 simulations); and (3) GCM-future (2041–2070 period; 4 simulations). AM series for 6, 12, 24, 72, and 120 h have been considered and AM intensities associated with 2-, 5-, 10-, and 20-year return periods have been estimated. Analysis has been first performed at the gridpoint scale and secondly at the regional scale. Canadian climatic regions have been used for the regional analysis.

Good agreement in terms of the spatial pattern of AM precipitation for all durations and return periods is observed between NCEP and GCM-historical groups. This good agreement is strengthening the confidence that one can put in the ability of GCMs to emulate historical conditions for the simulation domain under study.

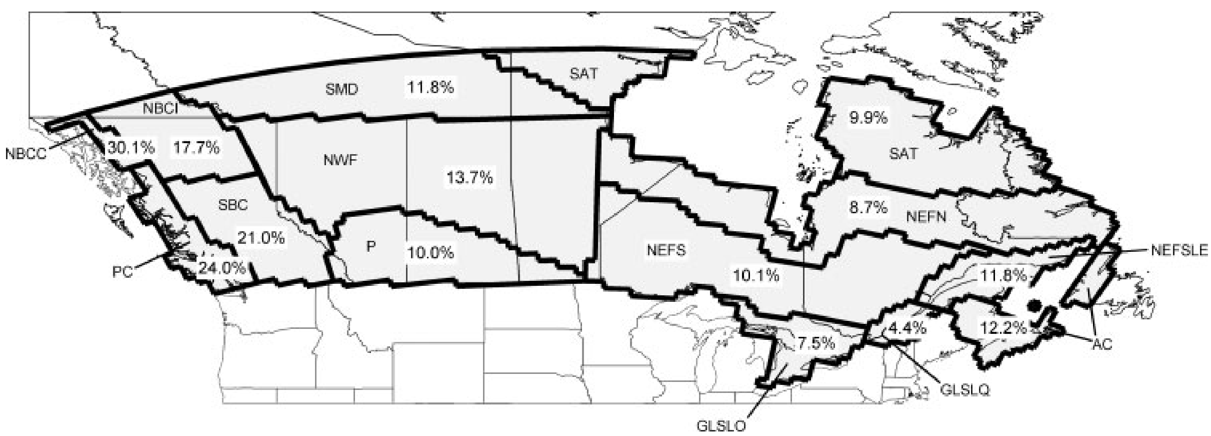

Figure 10. Climatic regions with regional CV for 24-h, 20-year return period AM precipitation (GCM-historical group).

Comparison of AM precipitation estimated from observed series and from GCM-historical group was also achieved. Available series at stations were preferred to gridded series to avoid any possible smoothing effect of interpolation. The ratio between simulated and observed intensities (for a given duration and a given return period) has been used, ratio that can be assimilated to the Areal Reduction Factor (ARF) under the hypothesis of RCMs having the spatial characteristics of areal averages (Osborn and Hulme, 1997). Results are intuitively consistent with this hypothesis (most grid tiles with one or more stations have ARF values slightly smaller than one) even if, strictly speaking, no ARF values are available in Canada for comparison (a monitoring network of higher density would be necessary to estimate ARF values).

Actual estimated changes in AM precipitation between historical and future climates are based on simulated precipitation at the gridpoint scale (50×50 km). Since ARF values depend on the proportions of convective and stratiform precipitation and on the spatial scale of events, they can change in future climate if the spatial scale of precipitation events changes (Osborn, 1997). The actual spatial resolution of RCMs is possibly still too low to resolve short-scale and localized extreme precipitation events, but it is believed that the representation of these will become more realistic as grid meshes become finer. However, since these eventual modifications cannot be confirmed or quantified at that time, analyses of future precipitation extremes are usually based on the assumption that, for a given area, duration, and return period, ARF will not change in a future climate (Ekström *et al*., 2005; Fowler *et al*., 2005). The practitioners must, therefore, be aware that using actual projections may underestimate future changes, especially for extreme events of short duration.

Regional averages were estimated. The defined regions are a subdivision of the Canadian climatic regions. Results show that Canadian regions will be diversely affected in terms of changes in extreme precipitation induced by climate change. Globally, all regions will experience an increase in AM precipitation, central and southern regions being more affected while Atlantic provinces and Coastal British Columbia will experience small changes. Future work includes the investigation

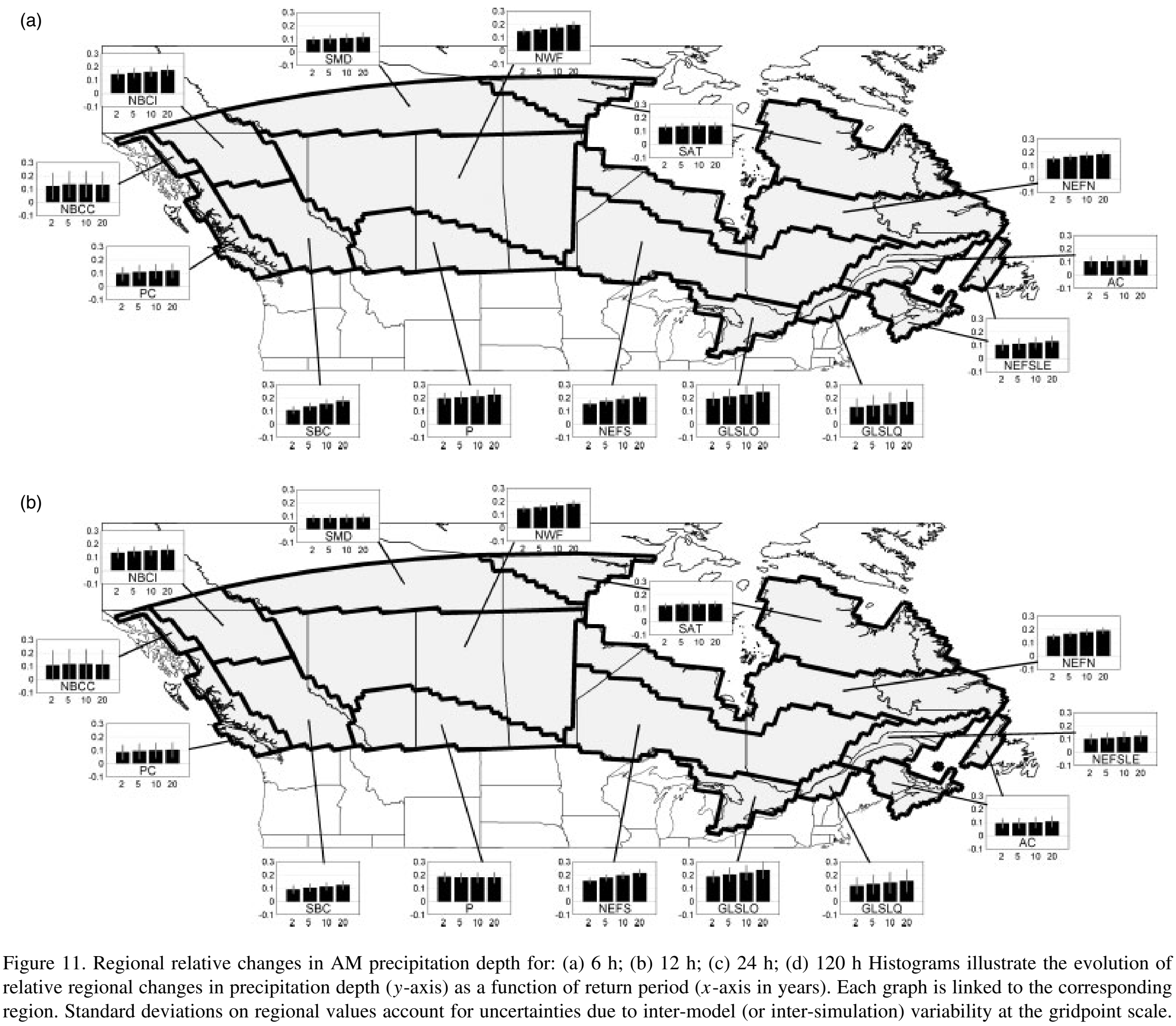

Figure 11. Regional relative changes in AM precipitation depth for: (a) 6 h; (b) 12 h; (c) 24 h; (d) 120 h Histograms illustrate the evolution of relative regional changes in precipitation depth (y-axis) as a function of return period (x-axis in years). Each graph is linked to the corresponding region. Standard deviations on regional values account for uncertainties due to inter-model (or inter-simulation) variability at the gridpoint scale.

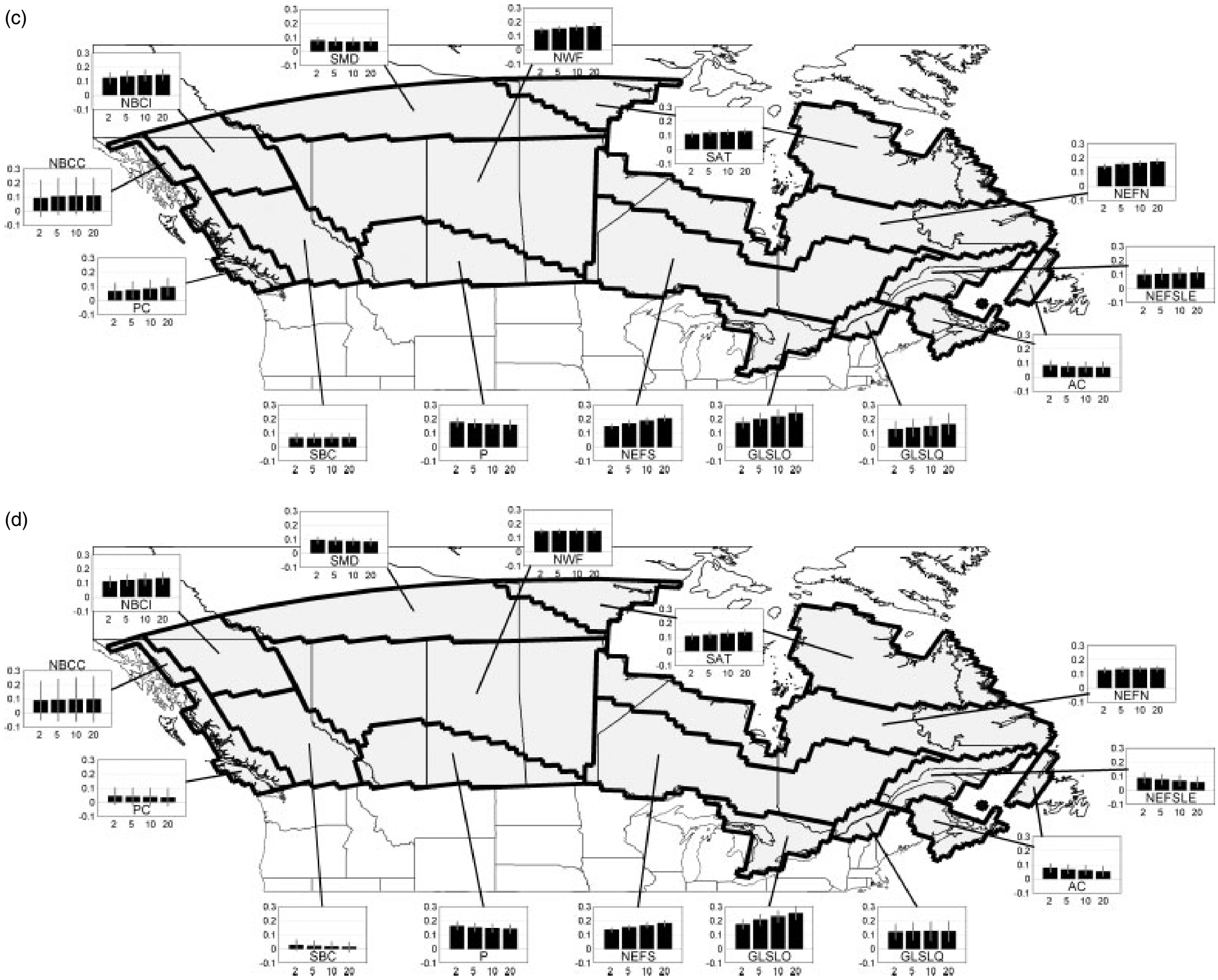

Figure 11. (*Continued*).

of possible shifts in seasonal patterns of occurrence of annual maxima in a future climate.

Uncertainties reported in this study account for inter-model uncertainties referring to the combined uncertainties of GCM and RCM. However, internal variability could not be explored through the available series (only one simulation is available for each GCM-RCM combination), meaning, that total uncertainties (model uncertainties plus internal variability) may be underestimated. Hawkins and Sutton (2009, 2010) showed that, for annual and seasonal precipitations simulated by GCM, internal variability can contribute to 50–90% of the total uncertainties for short term projections (the next 2–3 decades, depending on the region). Model uncertainty contributions to total uncertainties increase while internal variability decreases for long-term projections. For a vast majority of the Canadian territory (except the southern part along the United States border), contributions from model uncertainties will dominate for projections over the 2030–2100 period. Following Hawkins and Sutton's analysis, the contribution from internal variability to total uncertainties may be significant for some regions and therefore underestimated by the reported results.

Estimates of future increases for 2- to 25-year return period AM values reported in this study can be used for the design of infrastructures with life expectancy extending over the 2040–2070 period. Revised design criteria are important since not including climate change may lead to undersized infrastructures and could result in significant reduction of service level over time. Assessing uncertainties on projected future extreme rainfall is important in developing adaptation strategies. Uncertainties may guide decision makers in their ranking of adaptation strategies. How this could be done remains a subject of debate (e.g. Lempert *et al*., 2004; and Hallegatte, 2009).

Acknowledgements

The authors thank Ms Eva Mekis from Environment Canada who kindly made the historical precipitation data available. This work was part of a project funded by the Québec Government and Ouranos (Action Plan on Climate Change 2006-2012 (PACC) of the Québec Government). The authors also thank Mr Blaise Gauvin-St-Denis from the consortium Ouranos who provided the data from the NARCCAP. The authors also wish to thank the North American Regional Climate Change Assessment Program (NARCCAP) for providing the data used in this paper. NARCCAP is funded by the National Science Foundation (NSF), the US Department of Energy (DoE), the National Oceanic and Atmospheric Administration (NOAA), and the US Environmental Protection Agency Office of Research and Development (EPA). The authors thank Valérie Garant for correcting and editing the manuscript.

References

Alexander LV, Arblaster JM. 2008. Assessing trends in observed and modelled climate extremes over Australia in relation to future projections. *International Journal of Climatology* published online, DOI:10.1002/joc.1730.

Allan RP, Soden BJ. 2008. Atmospheric warming and the amplification of precipitation extremes. *Science* **321**: DOI:10.1126/science.1160787.

Allen RJ, DeGaetano AT. 2002. Re-evaluation of extreme rainfall areal reduction factors. In: 13th Conf. Applied Meteorology, American Meteorological Society, May 13–14, 2002, Oregon.

Allen RJ, DeGaetano AT. 2005. Areal reduction factors for two eastern United States regions with high rain-gauge density. *Journal of Hydraulic Engineering* **10**(4): 327–335.

Bronstert A, Kolokotronis V, Schwandt D, Straub H. 2007. Comparison and evaluation of regional climate scenarios for hydrological impact analysis: General scheme and application example. *International Journal of Climatology* **27**: 1579–1594, DOI:10.1002/joc.1621.

Cantelaube P, Terres J-M. 2005. Seasonal weather forecasts for crop yield modelling in Europe. *Tellus A* **57**: 476–487, DOI:10.1111/j.1600-0870.2005.00125.x.

de Elía R, Caya D, Côté H, Frigon A, Biner S, Giguère M, Paquin D, Harvey R, Plummer D. 2008. Evaluation of uncertainties in the CRCM-simulated North American climate. *Climate Dyn*amics **30**: 113–132, DOI:10.1007/s00382-007-0288-z.

Ekström M, Fowler HJ, Kilsby CG, Jones PD. 2005. New estimates of future changes in extreme rainfall across the UK using regional climate model integrations. 2. Future estimates and use in impact studies. *Journal of Hydrology* **300**: 234–251.

Emori S, Brown SJ. 2005. Dynamic and thermodynamic changes in mean and extreme precipitation under changed climate. *Geophysical Review Letters* **32**: L17706, DOI:10.11029/2005GL023272.

Fowler HJ, Ekström M, Kilsby CG, Jones PD. 2005. New estimates of future changes in extreme rainfall across the UK using regional climate model integrations – 1. Assessment of control climate. *Journal of Hydrology* **300**: 212–233.

Fowler HJ, Ekström M, Blenkinsop S, Smith AP. 2007. Estimating change in extreme European precipitation using a multimodel ensemble. *Journal of Geophysical Research* **112**: D18104, DOI:10.1029/2007JD008619.

Frei C, Schöll R, Fukutome S, Schidli J, Vidale PL. 2006. Future change of precipitation extremes in Europe: Intercomparison of scenarios from regional climate models, *Journal of Geophysical Research* **111**: D06105, DOI:10.1029/2005JD005965.

Graham LP, Andréasson J, Carlsson B. 2007. Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods – a case study on the Lule River basin. *Climate Change* **81**: 293–307, DOI:10.1007/s10584-006-9215-2.

Gutowski Jr. WJ, Arritt RW, Kawazoe S, Flory DM, Takle ES, Biner S, Caya D, Jones RG, Laprise R, Leung LR, Mearns LO, Moufouma-Okia W, Nunes AMB, Qian Y, Roads JO, Sloan LC, Snyder MA. 2010. Regional, Extreme Monthly Precipitation Simulated by NARCCAP RCMs. Submitted to *Journal of Hydrometeorology*.

Hagedorn R, Doblas-Reyes FJ, Palmer TN. 2005. The rationale behind the success of multi-model ensembles in seasonal forecasting. – I. Basic concepts. *Tellus* **57A**: 219–233.

Hallegatte S. 2009. Strategies to adapt to an uncertain climate change. *Global Environmental Change* **19**: 240–247.

Hawkins E, Sutton R. 2009. The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society* **90**: 1095–1107, DOI:10.1175/2009BAMS2607.1.

Hawkins E, Sutton R. 2010. The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics*, DOI:10.1007/s00382-0.10-0810-6 (available online *http://www.springerlink.com/content/g3m4q2613571094j/*).

Hayhoe K, Wake CP, Huntington TG, Luo L, Schwartz MD, Sheffield J, Wood E, Anderson B, Bradbury J, DeGaetano A, Troy TJ, Wolfe D. 2007. Past and future changes in climate and hydrological indicators in the US Northeast. *Climate Dynamics* **28**: 381–407.

Hinkley DV. 1969. On the ratio of two correlated normal random variables. *Biometrika* **56**(3): 635–639.

Hogg RV, McKean JW, Craig AT. 2004. *Introduction to Mathematical Statistics*, Upper Saddle River, N.J., Pearson Education: 6th edn, p. 704.

Hosking JRM, Wallis JR. 1997. *Regional Frequency Analysis: An Approach Based on L-moments*. Cambridge University Press: Cambridge, UK; p. 224.

Huntington TG. 2006. Evidence for intensification of the global water cycle: Review and synthesis. *Journal of Hydrology* **319**: 83–95.

IPCC 2000. *Emissions scenarios. Summary for policymakers. Special report of Intergovernmental Panel on Climate Change Working Group III*. IPCC: Geneva, Switzerland; p. 21.

Kanamitsu M, Ebisuzaki W, Wollen J, Yang SK, Hnilo JJ, Fiorino M, Potter GL. 2002. NCEP/DOE AMIP-II reanalysis (R-2). *Bulletin of the American Meteorological Society* **82**: 1631–1643.

Kendall MG. 1975. *Rank correlation measures*. Charles Griffin: London.

Kharin VV, Zwiers FW, Zhang XB, Hegerl GC. 2007. Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations. *Journal of Climate* **20**(8): 1419–1444.

Kundzewicz ZW, Mata LJ, Arnell NW, Döll P, Jimenez B, Miller K, Oki T, Şen Z, Shiklomanov I. 2008. The implications of projected climate change for freshwater resources and their management, *Hydrological Science Journal* **53**(1): 3–10.

Laprise R. 2008. Regional climate modelling. *Journal of Computational Physics* **227**(7): 3641–3666. 10.1016/j.jcp.2006.10.024.

Lemmen DS, Warren FJ, Lacroix J, Bush E. 2008. From Impacts to Adaptation: Canada in a changing climate 2007, Government of Canada, Ottawa (Ontario), p. 448.

Lempert R, Nakicenovic N, Sarewitz D, Schlesinger M. 2004. Characterizing climate-change uncertainties for decision-makers – An editorial essay. *Climatic Change* **65**: 1–9.

Mailhot A, Duchesne S, Caya D, Talbot G. 2007. Assessment of future change in Intensity-Duration-Frequency (IDF) curves for Southern Quebec using the Canadian Regional Climate Model (CRCM). *Journal of Hydrology* **347**(1–2): 197–210, DOI:10.1016/j.jhydrol.2007.09.019.

Mann HB. 1945. Nonparametric tests against trend. *Econometrica* **13**: 245–259.

Mearns LO, Gutowski WJ, Jones R, Leung L-Y, McGinnis S, Nunes AMB, Qian Y. 2009. A regional climate change assessment program for North America. *EOS*, **90**: 311–312.

Meehl GA, Covey C, Delworth T, Latif M, McAvaney B, Mitchell JFB, Stouffer RJ, Taylor KE. 2007. The WCRP CMIP3 multimodel dataset – A new era in climate change research. *Bulletin of the American Meteorological Society* **88**: 1383–1394.

Mekis E, Hogg WD. 1999. Rehabilitation and analysis of Canadian daily precipitation time series. *Atmosphere-Ocean* **37**(1): 53–85.

Milly PCD, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz ZW, Lenttemaier DP, Stouffer RJ. 2008. Stationarity is dead: Whither water management? *Science* **319**: 573–574, DOI:10.1126/science.1151915.

New M, Lopez A, Dessai S, Wilby R. 2007. Challenges in using probabilistic climate change information for impact assessments: an example from the water sector. *Philosophical Transactions of the Royal Society of London, Series A* **365**: 2117–2131, DOI:10.1098/rsta.2007.2080.

Osborn TJ. 1997. Areal and point precipitation intensity changes: implications for the application of climate models. *Geophysical Reviews Letters* **24**: 2829–2832.

Osborn TJ, Hulme M. 1997. Development of a relationship between station and grid box rainday frequencies for climate model validation. *Journal of Climate* **10**: 1885–1908.

Palmer TN, Doblas-Reyes FJ, Hagedorn R, Weisheimer A. 2005. Probabilistic prediction of climate using multi-model ensembles: from basics to applications. *Philosophical Transactions of the Royal Society of London, Series B* **360**: 1991–1998, DOI:10.1098/rstb.2005.1750.

Räisänen J. 2001. CO_2-Induced climate change in CMIP2 experiments: quantification of agreement and role of internal variability. *Journal of Climate* **14**: 2088–2104.

Räisänen J. 2007. How reliable are climate models? *Tellus* **59A**: 2–29, DOI:10.1111/j.1600-0870.2006.00211.x.

Srikanthan RA. 1995. Review of the Methods for Estimating Areal Reduction Factors for Design Rainfalls. Report 95/3, Cooperative Research Centre for Catchment Hydrology, Melbourne, Australia, p. 36.

Stainforth DA, Allen MR, Tredger ER, Smith LA. 2007. Confidence, uncertainty and decision-support relevance in climate predictions. *Philosophical Transactions of the Royal Society of London, Series A* **365**: 2145–2161, DOI:10.1098/rsta.2007.2074.

Tebaldi C, Knutti R. 2007. The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society of London, Series A* **365**: 2053–2075, DOI: 10.1098/rsta.2007.2076.

Thomson MC, Doblas-Reyes FJ, Mason SJ, Hagedorn R, Connor SJ, Phindela T, Morse AP, Palmer TN. 2006. Malaria early warnings based on seasonal climate forecasts from multi-model ensembles. *Nature* **439**: 576–579, DOI:10.1038/nature04503.

Trenberth KE. 1999. Conceptual framework for changes of extremes of the hydrological cycle with climate change. *Climate Change* **42**: 327–339.

Vincent LA, Mekis E. 2006. Changes in daily and extreme temperature and precipitation indexes for Canada over the 20th century. *Atmosphere-Ocean* **44**(2): 177–193.

Zhang X, Vincent LA, Hogg WD, Niitsoo A. 2000. Temperature and precipitation trends in Canada during the 20th century. *Atmosphere-Ocean* **38**(3): 395–429.

