Downscaling Global and Regional Climate Models

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ABSTRACT: Statistical Downscaling (SD) methods were first developed for applications in weather forecasting. Numerous methods are now in operation across the world. Since the end of the 1990s, these methods have been used intensively to develop high spatial and temporal resolution climate change information. Climate change scenarios are mainly based on the results of Atmosphere-Ocean Global Climate Models (AOGCMs) and more recently those of Regional Climate Model (RCM) outputs, which operate at horizontal resolutions of 300-km and 45-km, respectively. More reliable information at much finer scales, utilising the appropriate SD approach, is essential for decision-makers and planners tasked with adaptation to climate change. Impact and adaptation solutions are highly demanding in terms of topographic resolution and the representation of physical processes, and neither AOGCMs or RCMs can currently meet those needs. We will therefore require SD applications. Until now, SD methods have mostly downscaled output from AOGCMs, but there is no reason why SD methods could not be applied to higher resolution models. This paper investigates the reliability of atmospheric input variables when used in the SD process, from both AOGCMs, global and regional reanalysis products, and RCMs. This allows us to evaluate the potential added value from particular single site regression-based SD approaches, by comparison with the use of raw AOGCM and RCM outputs over various areas across Canada. This work also investigates the ability of the SD scheme to reproduce observed trends and variability within the predictand under consideration. New developments within multivariate and multisite SD methods are also suggested through on-going projects and collaboration between Environment Canada and various universities across Canada.

Keywords: climate change, statistical downscaling, global climate model, regional climate model, local climate information, predictors and predictand.

1. Introduction

Scientific and socio-economic global climate change research has (thus far) focused mostly upon scenarios of gradual warming, as suggested by Atmosphere-Ocean Global Climate Model (AOGCM) simulations (see IPCC, 2001 and Meehl *et al.*, 2007). However, such scenarios cannot be applied directly at the regional or local scale due to their coarse resolutions. Regionalization techniques are thus needed in order to develop high resolution climate scenarios at the temporal and spatial scales relevant for impact studies: These include Regional Climate Models (RCMs) and Statistical Downscaling (SD) methods. RCMs do not, however, provide information on the scales needed for impact and adaptation solutions, even where they offer improvements over AOGCMs in terms of resolution or representation of physical processes. SD methods are required for the development of local scale information and the higher resolution climate variables (equivalent to point observations) required by many impact applications.

Forecasts of numerical weather prediction (NWP) models have certain defects that can be removed by statistically post-processing their output (Wilks, 1995). Two of the more popular post-processing approaches are Model Output Statistics (MOS) and the Perfect Prog approach (Klein, *et al.,* 1959; Glahn and Lowry, 1972), both of which are based on the idea of relating model forecasts to observations through linear regression. This is the central principle from which SD methods have been developed. Vislocky and Fritsch (1997) included observations as both predictor and predictand, and Marzban (2003) additionally allowed for nonlinear relationships among the various variables. Both techniques have subsequently been inplemented into SD. Numerous methods are now in operation across the world. Since the end of the 1990s, these methods have been used intensively to develop high spatial and temporal resolution climate change information. SD methods are primarily used to relate large scale climate variables drawn from atmospheric and oceanic analyses of temperature, flow, and other quantities, created by processing historical data using fixed state-of-the-art weather forecasting models and data assimilation techniques (i.e., reanalysis products), AOGCMs (for predictors), and local or station scale observations (for predictands). These data sets are used to determine a statistical model that establishes the relationship between large and local scale climate factors. The statistical model is often calibrated and validated under the current climate condition using a reanalysis data set, such as the NCEP (National Centers for Environmental Prediction) reanalysis (Kistler *et al.*, 2001), large-scale outputs of an AOGCM simulation are then fed into the statistical model to estimate (i.e., "downscale") corresponding local and regional climate characteristics for the future. Both NCEP reanalysis and AOGCM output must be screened to produce reliable predictors, in order to prevent the introduction of biases from the host AOGCM to any given SD process. The procedure to select the optimum combination of predictors also needs careful attention. Despite the fact that SD methods have historically been used to downscale from AOGCM output, there is no systematic reason why SD methods could not be applied to higher resolution models, including RCMs. This would allow for the incorporation of more information from regional forcing (not included at the coarse scale of an AOGCM) in the SD process.

SD methods are currently under development at Environment Canada (EC) within the Adaptation and Impacts Research Section (AIRS) in strong collaboration with various universities including McGill/GEC3, the Institut National de la Recherche Scientifique – Eau Terre Environnement, and the University of Regina (see further information at **http://www.cccsn.ca**). These methods complement the impacts, research and adaptation science of EC, specifically in terms of the global and regional climate models developed by the Climate Research Division (CRD, see **www.cccma.bc.ec.gc.ca/**).

This paper gives an overview of current developments within SD research, and investigates the added value of one particular, point-observation, regression-based SD approach, against AOGCM and RCM outputs over various areas across Canada. Benefits to be obtained from the use of RCM, instead of AOGCM, predictors are also suggested, in particular, in terms of potential added value derived from the incorporation of regional scale forcing factors in the downscaling process. The atmospheric variables used to develop the statistical relationships within the SD method are also analysed in order to see if they are statistically significant contributors to the variability in the predictand. Finally, new developments toward multivariate and multisite SD methods are discussed.

The paper is organized as follows, using the various steps presented in Figure 1. Section 2 presents those predictors that are reliably simulated by AOGCMs (compared to those developed from reanalyses), the atmospheric predictors chosen for use in the SD process and the steps required to select the relevant combination of predictors. A new development towards the inclusion of regional scale predictors into the SD process is also presented in Section 2. Section 3 presents the potential for added value or new insight that has been gained through the use of SD methods, rather than raw data directly from AOGCM or RCM output. Section 4 discusses the reproduction of a predictand regime within observed data by the SD model, including trend behaviour as well as the short and long term variability of the predictand. The last section presents the main conclusion, on-going development, and further steps required in SD research.

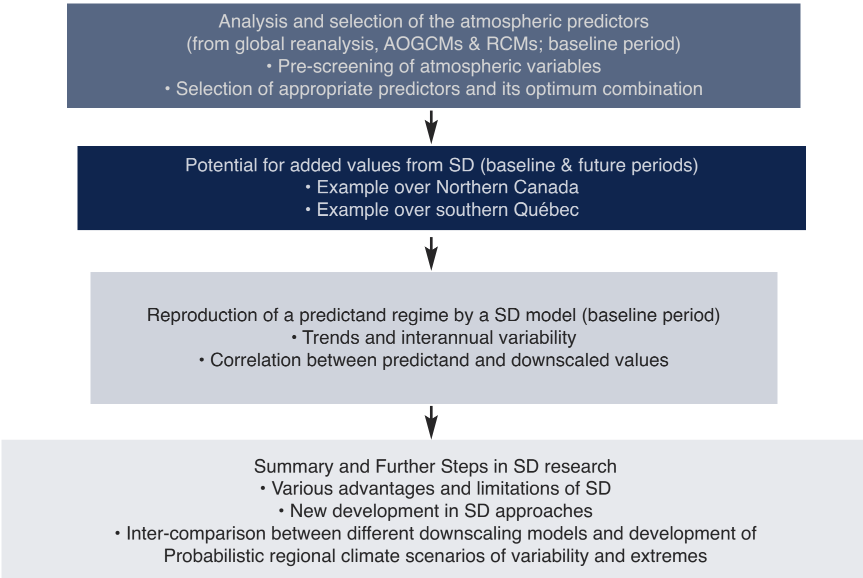


Figure 1 | Chart with the list of the steps followed in the paper.

2. Atmospheric input variables used in the SD process

In principle, all predictors employed in the SD process need to fulfill the following criteria and assumptions: (1) They should show skill in representing large-scale variability as simulated by the AOGCM; (2) They should be statistically significant contributors to the variability in the predictand, or they should represent important physical processes in the context of an enhanced greenhouse effect; (3) They should not be strongly correlated to each other (see further explanations in Wilby *et al.,* 2004, and Benestad *et al.,* 2007). It is also important to limit the set of predictors to only those which are relevant. von Storch *et al.* (2000) list a number of criteria which must be fulfilled for SD: "(1) The predictors are variables of relevance and are realistically modeled by the AOGCM; (2) The transfer function is valid also under altered climatic conditions. This is an assumption that in principle cannot be proven in advance. The observational record should cover a wide range of variations in the past; ideally, all expected future realizations of the predictors should be contained in the observational record; (3) The predictors employed fully represent the climate change signal". It is therefore important to understand the physical mechanisms and connections at work between predictor and predictand. In the following, the main criteria related to the relevance, reliability and optimum combination of various predictors in the SD process are analyzed in further details from AOGCMs and RCMs, as well as from reanalyses products.

From Atmosphere-Ocean Global Climate Model output

In order to follow the suggested criteria concerning predictors and their physical links with the predictand, a systematic assessment of the various candidate predictors is required prior to the development of an SD model (see the works in eastern and northern Canada in Gachon *et al.*, 2005, Gachon and Dibike, 2007, Hessami *et al.*, 2008, and Dibike *et al.*, 2008). Climate model limitations need to be identified when screening potential predictors using both NCEP and AOGCM variables. The variables commonly used as predictors in the downscaling of both temperatures and precipitation are listed in Table 1. From these potential predictors, the first step is to analyze the spatial correlation of these fields with the predictand of interest, and to evaluate the compatibility between NCEP and AOGCM candidate predictors. Indeed, it is necessary to specify the optimum location of the large scale predictor fields to achieve the best performance in downscaling local climate variables (e.g. Wilby *et al.*, 2004). Figures 2 and 3 give an example of a correlation map based around southern Québec, using data observed from a station in Montréal. These plots show correlations between daily precipitation (the predictand) and daily predictors of the mean sea level pressure (MSLP) and the V-component of the wind at 850-hPa (Figure 2), and, between daily maximum temperature (Tmax) and 500-hPa geopotential heights and specific humidity at 850-hPa (Figure 3). These maps suggest higher correlation values for grid points closer to the Montreal area (i.e. the location of the predictand), and stronger correlations for temperature than for precipitation. The selection process for relevant predictors is more complicated for precipitation due to the fact that the explanatory power of individual predictor variables may be low or vary either spatially or temporally (e.g. Wilby *et al.*, 2004; Gachon *et al.*, 2005, and Gachon *et al.*, 2007). Occurrence and intensity of precipitation are controlled by complex mechanisms which may be linked to: large-scale upward or downward motion of a relevant air

Table 1 | List of daily predictor variables commonly used (i.e. not systematically all for all regions and climate conditions across the globe) from AOGCMs and global NCEP reanalysis products in SD models (see www.cccsn.ca). A glossary is added at the end to define all terms listed above.

PREDICTOR VARIABLES	FOR TEMPERATURE			FOR PRECIPITATION		
	Pressure Levels (upper air fields, in hPa)					
	500	850	1000	500	850	1000
Geopotential Height	x	x		x		x
Specific or Relative Humidity		x		x	x	
Wind (U & V components, Speed & Direction)	x				x	
Vorticity	x					
Divergence				x	x	x
Surface or near surface (ex. at 2-m)						
Mean sea level pressure (MSLP)					x	

mass; small-scale processes, such as localised convection; cloud development; turbulent motion of wet or dry air in the boundary layer; orographic effects, including convergence of an air mass, which may induce upward motion on a windward slope area. Simple correlation between predictand and one single, a-priori predictor variable, is therefore not effective for the selection of predictors for downscaling precipitation. This kind of work requires a mechanistic analysis to optimize the choice of individually pertinent predictors. More often, the optimum choice is provided by the right combination of multiple variables linked with the precipitation process (see Choux, 2005). Indeed, the use of a single correlation map can not constitute the only criterion for the selection of predictors over a downscaling area, as partial correlation analysis must also be performed to select the relevant combination of candidate predictors during the downscaling calibration (e.g.,Wilby *et al.*, 2002).

Considering the validation of climate model outputs at the space and time scales used in the SD process, a few grid points surrounding the Montréal area are compared in Figure 4, using both predictor values from NCEP (shown in Figures 2 and 3) and the

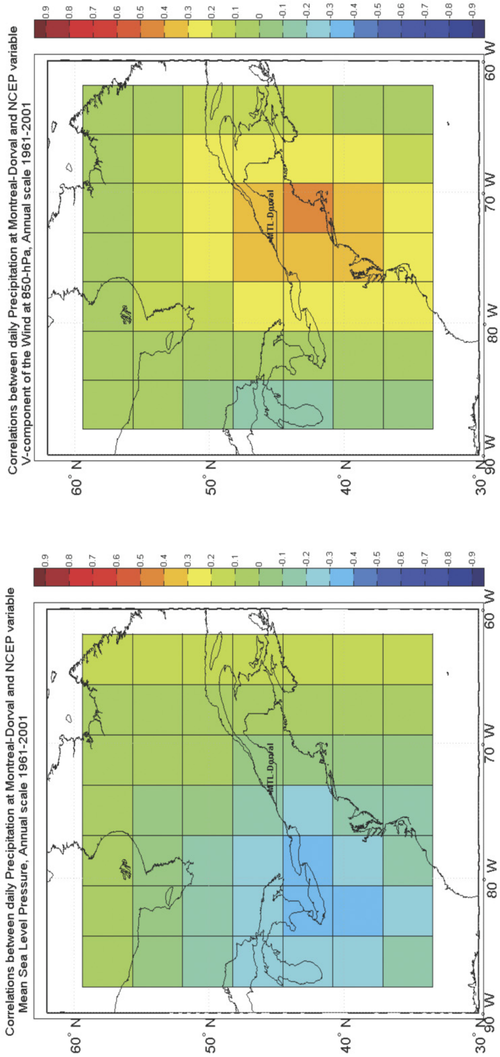


Figure 2 | Correlation map between daily Precipitation at Montréal, Québec and mean sea level pressure (left panel), and between precipitation and the V-component of the wind at 850-hPa (right panel), as derived from the NCEP reanalysis. The correlation is performed with the full inter-annual time series between 1961 and 1990.

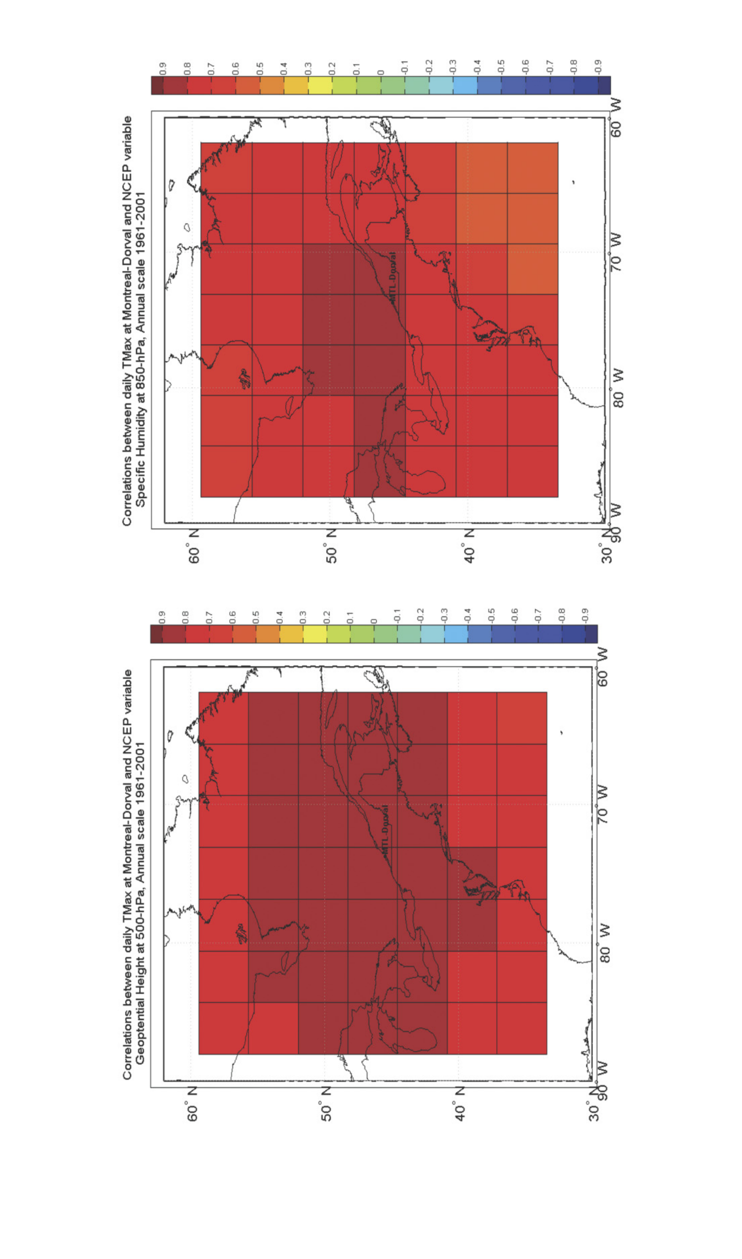


Figure 3 | Correlation maps between daily maximum Temperature (Tmax) at Montreal and geopotential height at 500-hPa (left panel), and between Tmax and specific humidity at 850-hPa (right panel), as derived from the NCEP reanalysis. The correlation is performed with the full inter-annual time series between 1961 and 1990.

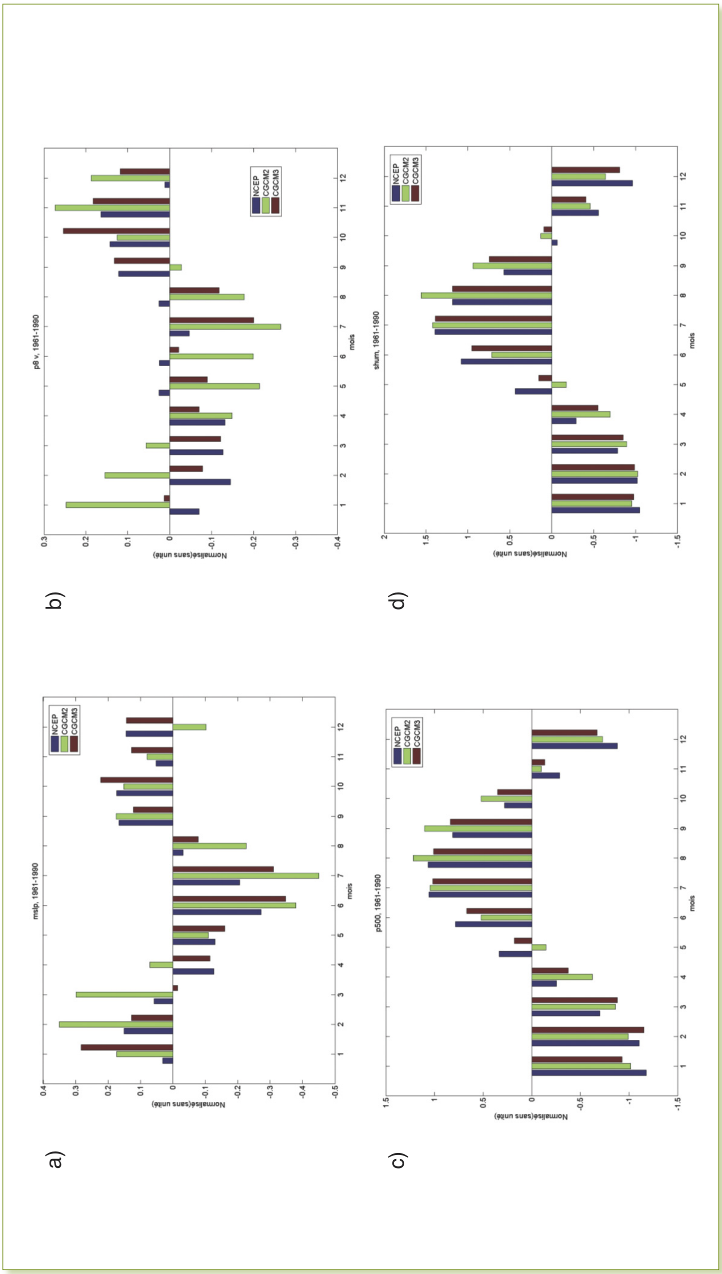


Figure 4 | Monthly evolution (1-12 in panels, i.e., J-D months) of a) mean sea level pressure, b) V-component of the wind at 850-hPa, c) geopotential height at 500-hPa, and d) specific humidity at the 850-hPa level, from NCEP, CGCM2 and CGCM3 predictors. Each plot corresponds to the four grid points closest to the Montréal climate station. All values are normalized with respect to the mean (subtracted) and the standard deviation (divided by) for each series of predictors for the 1961–1990 baseline period.

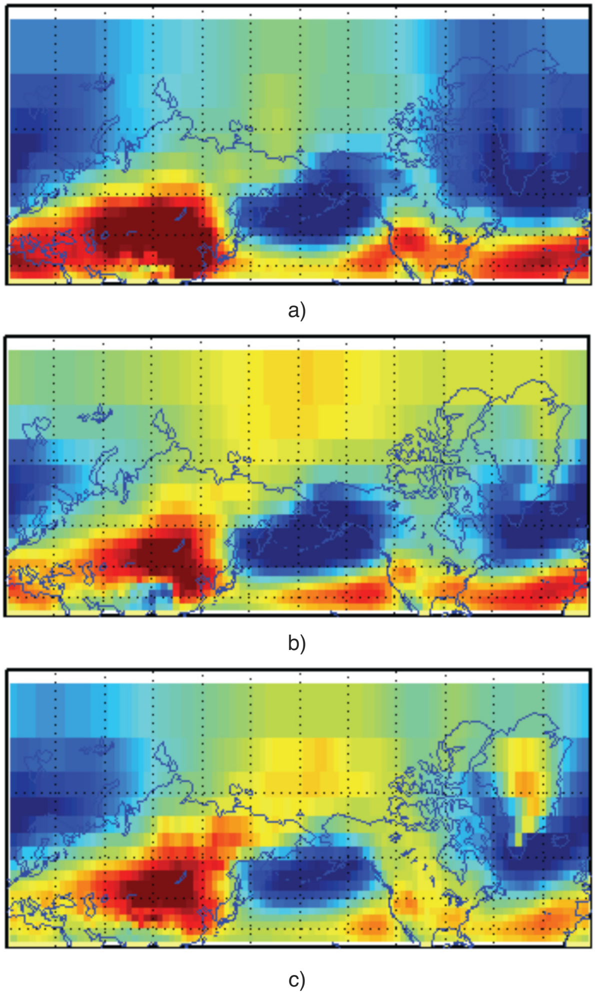


Figure 5 | A comparison of leading modes of variance in mean sea level pressure (annual scale) from a) CGCM2 (96.6% of total variance), b) CGCM3 (96.8%), and c) the NCEP-NCAR reanalysis (97.0%) applied for an area covering all longitudes and above 20°N (Source: Harding *et al.*, 2010).

corresponding values from two AOGCMs (i.e., versions 2 and 3 of the Canadian AOGCM - CGCM2 and CGCM3, Flato and Boer, 2001, and Kim *et al.*, 2002, respectively). Strong biases are revealed in the MSLP of CGCM2 in winter and summer months, and a stronger level of agreement can be seen between CGCM3 values and those from NCEP. The V-component of the wind at 850-hPa is also more strongly biased in the older version of the Canadian AOGCM. For the specific humidity at 850-hPa, values obtained from the CGCM2 are shifted in time, or give a poor estimation of the humidity pattern (and therefore the temperature pattern). This is especially the case in both summer months and for the fall, as also noted in the recent study by Gachon and Dibike (2007) in the northern area of Canada. Figure 5 shows that such inter model variation is not limited to Canada or the mean. Principal components analysis of MSLP reveals that modes of variance are also more accurately captured by CGCM3 than by CGCM2 (see further information in Harding *et al.*, 2010). The systematic discrepancies described above suggest that these variables, when derived from CGCM2, should not be used as predictors, in order to prevent the propagation of discrepancies from the host AOGCM into the SD process (see further explanations in Gachon and Dibike, 2007).

From Regional Climate Model output

Using RCM output instead of AOGCM output for the SD process may constitute a supplementary step in the regionalization procedure. In theory:

- RCMs should perform well in simulating circulation features affecting regional climates (e.g., jet streaks, thermodynamic variables, such as low level air temperature or diabatic fluxes; see definition in the glossary section) due to a resolution of processes that are sub-grid scale for an AOGCM. Hence, more surface or small-scale variables should be available as candidate predictors from an RCM, when compared to AOGCM output;
- Physical parameterizations of RCMs originate from a few "families" and mainly derive from the same AOGCM physical packages. This suggests that RCM and AOGCM outputs are not fully mutually independent, and that errors present in these physical packages or in interpolated atmospheric and oceanic fields from the AOGCM outputs into the RCM grid may propagate or be exacerbated into the RCM domain (i.e. if the RCM is not coupled with a regional-scale oceanic model). For example, surface oceanic conditions are more often taken from the coupled AOGCM and are generally inadequate when representing sea-ice margins or thickness, or sea surface temperature over sub-

arctic basins in regional scale models (see further discussion in Barrow *et al.*, 2004, and in Gachon and Dibike, 2007). The seasonal sea-ice margin and other coastal regions (Canada's coastline is in excess of 5000 km) represent a complex challenge for the development of realistic climate change scenarios at the regional scale; and

- The main advantage of using an RCM is that, for all variables, internal physical consistencies are maintained.

In order to analyze the potential added value for the SD process with respect to downscaling output previously obtained from AOGCMs, a new series of daily variables is under development from RCM runs as well as from regional reanalysis products. This new series of regional predictors is presented in Table 2. Derived values include ground temperature, surface diabatic fluxes, vertical motion and advection terms at various pressure levels, both dynamical (vorticity) and thermodynamical (temperature and humidity). Each of these new predictor variables has the potential to incorporate regional scale forcing factors linked with the evolution of predictand surface variables, such as temperature and precipitation. For example, turbulent fluxes of temperature and humidity play a key role in both temperature change and in the advection of temperature (Gachon *et al.*, 2003). These new variables, derived from 3 or 6-hourly values of both the North American Regional Reanalysis (NARR - Mesinger *et al.,* 2006) and RCM output, will be able to take into account fine scale effects and changes in surface conditions over both land/sea areas and complex coastal or island locations. Regions of highly heterogeneous land-cover or topography are not resolved at the scale of an AOGCM (Barrow *et al.*, 2004; Gachon and Dibike, 2007). The combination of various (vertical motion) predictors from both large-scale and mesoscale influences is particularly crucial to the improvement of our ability to downscale precipitation (compared to temperature, Dibike *et al.*, 2008), which is semi-stochastic in terms of both occurrence and magnitude. Predictors centred around divergence and convergence (linked to large-scale synoptic systems) as well as convective heat and humidity fluxes (in mesoscale weather systems) are inherently important for our ability to capture the variability of occurrence and intensity within any given precipitation regime. As suggested in the studies of Choux (2005), over Montréal, and in Parishkura (2009), over the Sahelian monsoon area, the combination of advection terms of vorticity and humidity have allowed us to improve downscaled precipitation occurrence when using NCEP, coarse-scale, variables. There is, therefore, the potential to improve downscaling of the precipitation regime further using equivalent regional-scale variables. In Figure 6, SD daily precipitation results developed by applying the "Automated Statistical Downscaling" (ASD e.g., Hessami *et al.*, 2008) model to a station in Ottawa, using predictors from NCEP, are compared to those using equivalents from NARR and the Canadian RCM (CRCM). Common variables are used, including specific humidity, vorticity, u-component winds at 850-hPa, and divergence and u-component winds at 500-hPa. The use of regional-scale predictor variables in the SD process allows us to improve both median values and quantile values of daily precipitation and its variability (see Figure 6 a and b, respectively). The use of other variables, including advection terms, is currently under evaluation for application to downscaling precipitation occurrence and intensity.

Table 2 | List of daily predictor variables in development from RCMs and regional re-analysis products (i.e. North American Regional Reanalysis, NARR, e.g. Mesinger *et al.*, 2006) to use in SD models.

PREDICTOR VARIABLES
Pressure Levels (upper air variables, ex. from 1000 to 300 hPa)
Geopotential Height
Differences between 2 consecutive pressure levels (i.e. Thickness)
Specific or Relative Humidity
Wind (U & V components, Speed & Direction)
Vorticity
Divergence
Advection terms (Temperature, Humidity & Vorticity)
Vertical motion
Surface or near surface (low-level air and land surface variables)
Mean sea level pressure
Specific or Relative Humidity
Temperature
Maximum/Minimum of Vorticity (from mesoscale or synoptic weather system)
Diabatic fluxes (radiative, sensible & latent heat release)
Ground Temperature (land & sea surface)

3. Potential for added value from SD

The potential for added value and the strengths and limitations of two particular single site regression-based SD approaches are shown in this section, using AOGCM and RCM outputs over various areas across Canada. A regression-based SDSM model (Wilby *et al.*, 2002) is used to downscale Tmax and Tmin values from two AOGCM

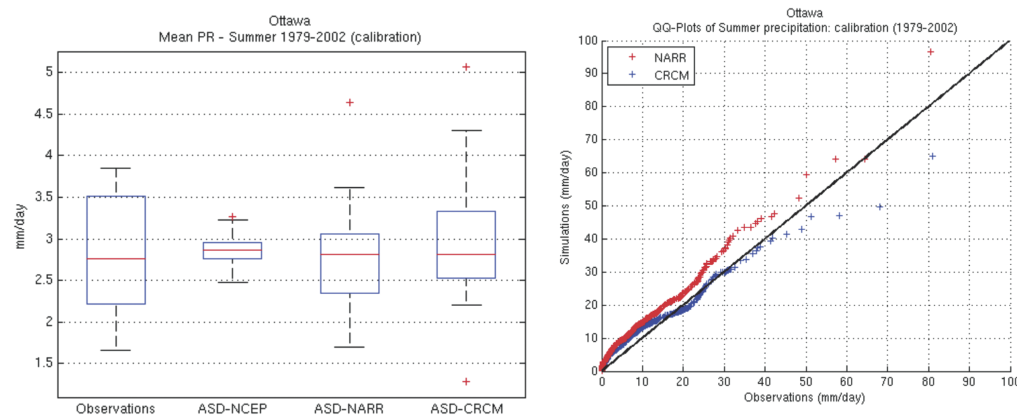


Figure 6 | Comparison between downscaled daily precipitation in summer from the ASD model (e.g. Hessami *et al.*, 2008) at Ottawa using specific humidity, vorticity, and U-component winds at 850 hPa, and divergence and U-component winds at 500-hPa, from a.) NCEP (ASD-NCEP), NARR (ASD-NARR), and the CRCM (ASD-CRCM). (Box plot values for mean daily precipitation) and b.) NARR (ASD-NARR) and the CRCM (ASD-CRCM) (Quantile-Quantile plot). In both graphs, observed values are used as reference (i.e. Observations).

predictor data series (i.e. CGCM2 and HadCM3), for the north Canadian areas used in recent studies by Gachon and Dibike (2007), and Dibike *et al.* (2008). The insight gained through the use of SD methods with respect to the raw-AOGCM data is briefly analyzed over both current and future periods (2080s). The other regression-based model, ASD, is used to downscale daily precipitation from two AOGCMs (CGCM2 and CGCM3), for the southern Québec area. In this latter case, simulations from two generations of the Canadian RCM (CRCM3.7.1 and CRCM4.2.0, see **http://loki.qc.ec.gc.ca/DAI/rcm_CRCM-e.html**), each driven by the relevant Canadian AOGCM (CGCM2 and CGCM3, respectively) are also compared with ASD results, using kriged predictand values over the CRCM 45-km grid. This comparison allows us to evaluate the added value gained through each downscaling technique, and also explores the uncertainty due to the choice of downscaling method using climate change simulations over the 2050s (a period only available from CRCM runs obtained through Ouranos, see **www.cccsn.ca**).

Example over Northern Canada

Over the current period (i.e. 1961-1990 period), Figure 7 reveals that Tmax and Tmin data simulated by two AOGCMs have strong biases (in terms of monthly mean) for the majority of the year (see also Figure 1 in Dibike *et al.*, 2008). The raw-AOGCM data shows a warm bias for the autumn months while the rest of the seasons show cold bias, as also suggested by seasonal Probability Density Functions (PDFs) shown in Figure 8. In general, monthly biases in raw CGCM2 temperature values are higher than those from HadCM3. The CGCM2 monthly temperature bias ranges between 2 and 20°C, while that of HadCM3 is in the order of 2–12°C, suggesting a more systematic problem with surface process representation in CGCM2 when compared against HadCM3 (Dibike *et al.*, 2008). Figure 7 also shows that SD has improved AOGCM output by strongly reducing the temperature biases compared to raw-AOGCM information. However, the downscaled data from CGCM2 does still contain some negative bias in the spring season and positive bias in the autumn months, larger than the bias visible within downscaled values from HadCM3. This is illustrated in more detail through uncertainty analysis in Dibike *et al.* (2008).

For the scenario runs, Figure 8 shows that seasonal changes in the downscaling results for Tmin, except in winter, are essentially due to a single shift of the PDF. In winter, the shift in the median values of downscaled data, with a warming of around 4°C, is associated with a slight increase in the variability due mainly to an extension of the

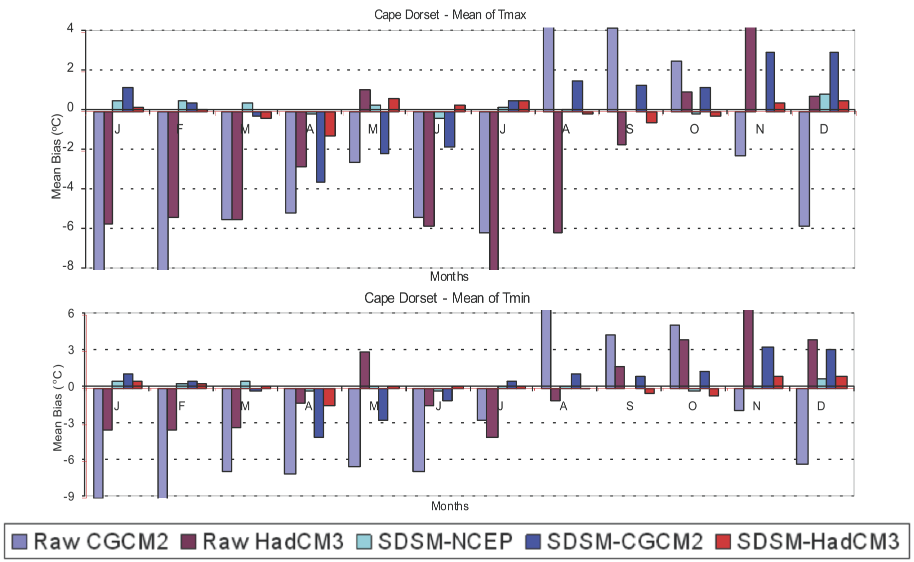


Figure 7 | Histograms of mean biases between the monthly mean values of observed data and the corresponding raw-AOGCMs and SDSM downscaled data of Tmax and Tmin (in °C, upper and bottom panels, respectively) at Cape Dorset over the baseline period (1961–1990). For further information see Dibike *et al.* (2008).

upper tails of the statistical distribution. This suggests a greater probability of hot extremes during winter for the 2080s. In other seasons, no substantial change in variability is shown. Figure 8 also suggests that the statistical distribution from the raw-AOGCM data is strongly biased. Results show a strong shift in median values, the presence of a nearly bimodal distribution in summer, and a strong overestimation in the frequency of 0°C values. These biases are due mainly to an inaccuracy in CGCM2 concerning the timing of the retreat and advance of sea ice and the thawing and the freezing of soil over the adjacent land area. The study of Gachon and Dibike (2007) in northern Canada suggests that the SD model is able to capture the major part of the temperature change signal, with a plausible climatic regime for higher warming in winter than in summer, and for A2 over B2 scenarios. A combination of relevant atmospheric predictors in the SD process is able to take into account most of the key factors in the temperature change signal, with strong convergence in both the magnitude and the timing of the changes across all results. Downscaling signals are more consistent and physically-plausible than the raw AOGCM anomalies.

Example over southern Québec

Over the current period (i.e. 1961-1990), Figure 9 reveals that the two downscaling techniques give quite different results for both wet days and mean intensity per wet day over the majority of the year (example given over southern area of Québec). The SD model is able to reproduce the monthly mean values of wet days and the relevant annual cycle quite well, especially when the SD model is driven by CGCM3 predictors. In the case of the CRCM model, both versions have some difficulty in reproducing the annual cycle. There is a strong overestimation of the wet day regime in spring and in summer, with a shift in the maximum wet day amount as compared to observed values. This behaviour has also been suggested over regions in the eastern United States (Roy, 2009). For the monthly mean intensity per wet day, the SD model reproduces the observed annual cycle, but with a slight overestimation of around 1 mm/day during the majority of the year and of 2 mm/day in May. In the case of the dynamical downscaling model, a systematic underestimation of mean intensity per wet day is revealed for the two versions of the CRCM model, suggesting a problem in reproducing the annual cycle, as for wet days (see Figures 9a and b).

In the scenario mode, Figure 10 reveals an inconsistent signal between the two downscaling methods concerning changes in wet days, mainly through May to December. For SD results, changes are consistently upward, with convergence in the

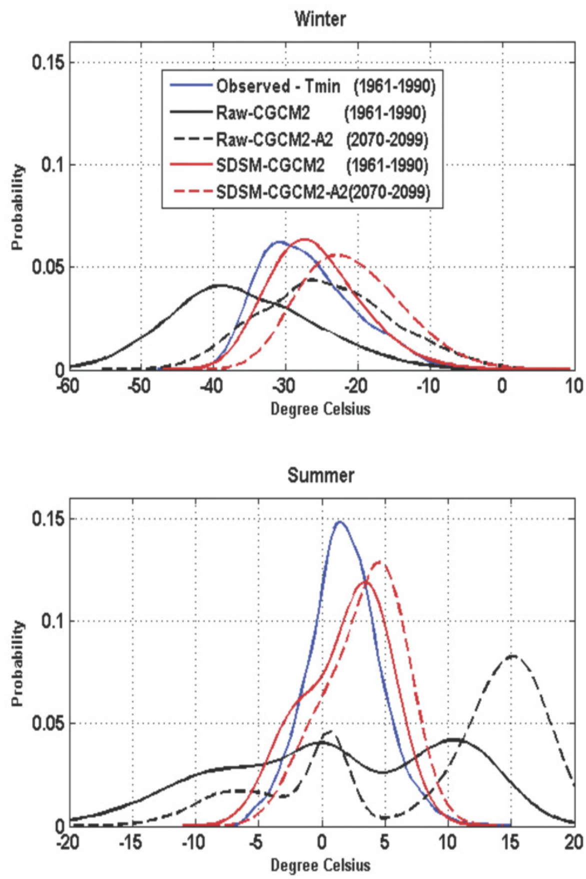


Figure 8 | Comparison of seasonal Probability Density Function (PDF) for Tmin at Cape Dorset for the future (2080s, A2 scenario) and the current (1961–1990) periods between observed, downscaled and AOGCMs values: SDSM with CGCM2 predictors (SDSM-CGCM2) and raw-CGCM2 (CGCM2). For further information see Gachon and Dibike (2007).

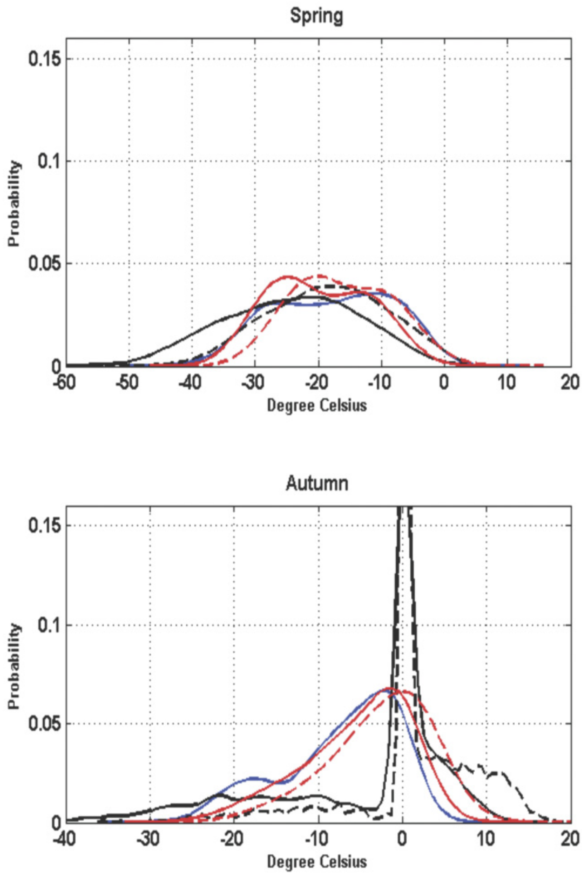


Figure 8 cont... | Comparison of seasonal Probability Density Function (PDF) for Tmin at Cape Dorset for the future (2080s, A2 scenario) and the current (1961–1990) periods between observed, downscaled and AOGCMs values: SDSM with CGCM2 predictors (SDSM-CGCM2) and raw-CGCM2 (CGCM2). For further information see Gachon and Dibike (2007).

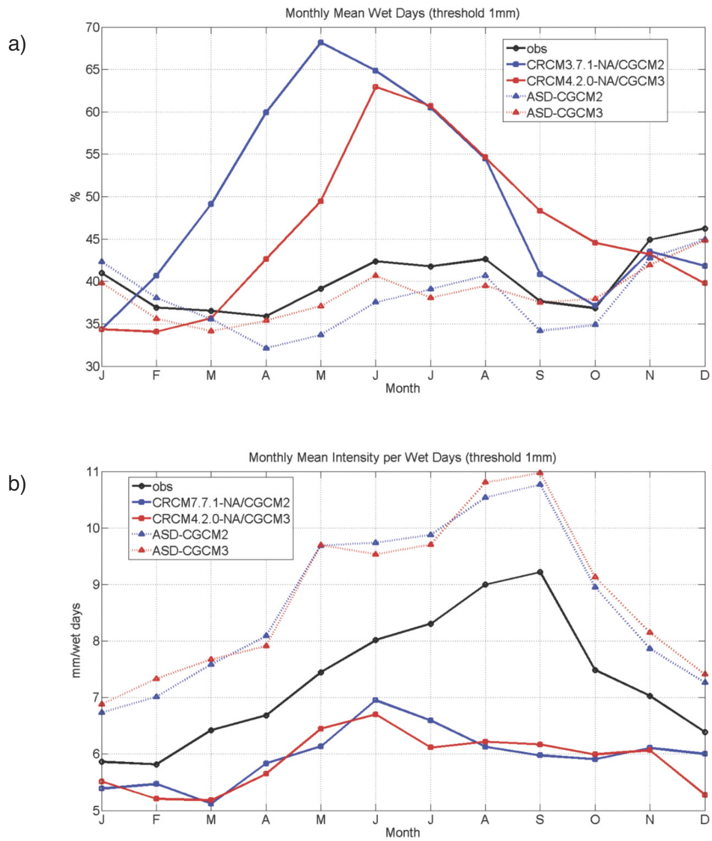


Figure 9 | Monthly mean comparison among kriged observed values (i.e. interpolated on the 45-km grid of the CRCM, see further information about the model versions in **http://loki.qc.ec.gc.ca/DAI/rcm_CRCM-e.html**), SD results using the ASD model (downscaled values over the kriged observed values), and two versions of the CRCM for a) wet day (in %, threshold of 1 mm/day, see Gachon *et al.*, 2005), and b) intensity per wet days (in mm/day). The two downscaling techniques are driven by both CGCM2 and CGCM3 (i.e. ASD-CGCCM2/3 and CRCM3.7.1-CGCM2 and CRCM4.2.0-CGCM3). 10 x 10 grid points from downscaling values are compared over the 1961-1990 period over southern Québec.

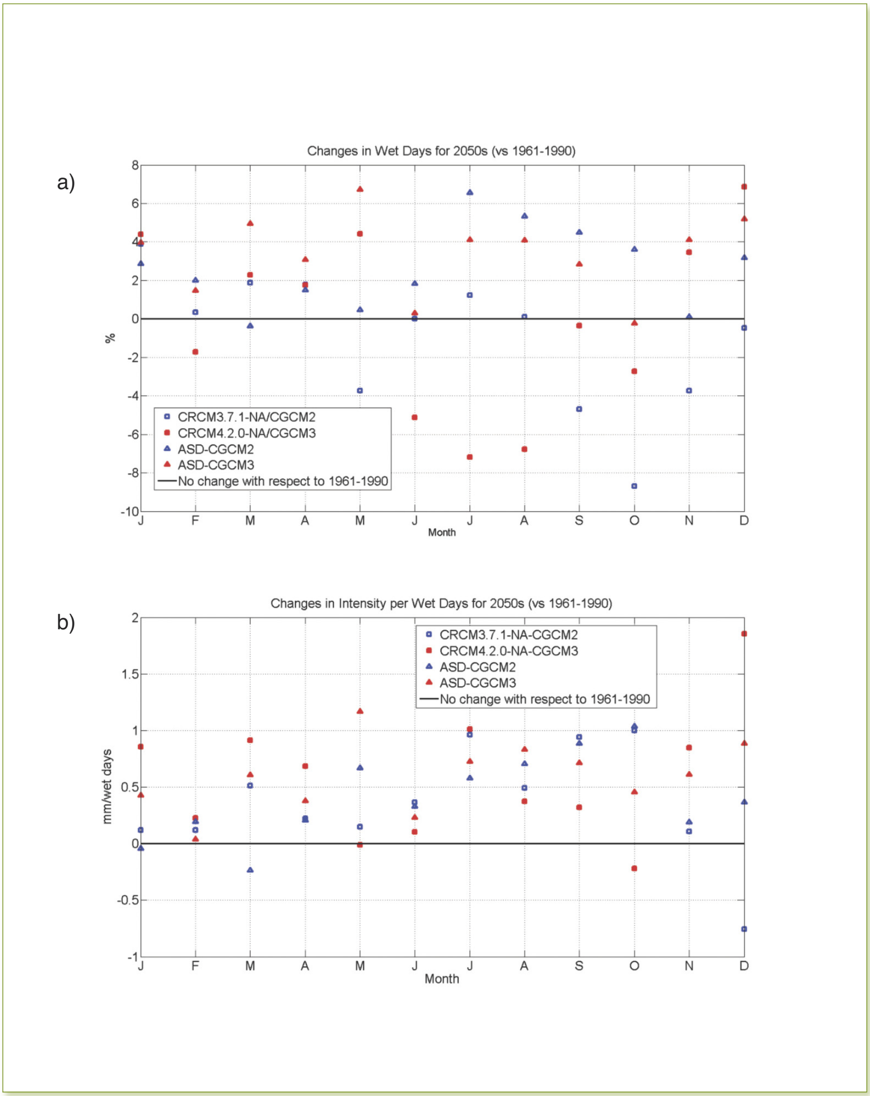


Figure 10 | Monthly changes over the period 2041-2070 (with respect to 1961-1990, A2 scenario) from the ASD model, and two versions of the CRCM for a) wet days (in %), and b) intensity per wet days (in mm/day). The two downscaling techniques are driven by both CGCM2 and CGCM3 (i.e. ASD-CGCCM2/3 and CRCM3.7.1-CGCM2 and CRCM4.2.0-CGCM3). 10 x 10 grid points from downscaling values are compared over southern Québec.

amplitude of the signal over the majority of the year. Results from CRCM3 and CRCM4 are ambivalent, with a change in wet days depending on the month and version of the dynamic model under consideration, especially through May to December. For one of the CRCM versions no change can be seen in August or September. The lack of confidence in either the simulated or historic wet day regime in the CRCM, from both versions of the model, results in strong uncertainties concerning these precipitation outputs. Caution is required when deriving climate change information for local application in impacts studies. For mean intensity per wet day, changes are more consistent and coherent between downscaling models and months, with a quasi-systematic increase in intensity of daily precipitation. This increase is largely greater during summer and fall, regardless of the AOGCM driven conditions (i.e., for both CGCM2 and CGCM3). The usefulness of this comparison, between the two downscaling schemes, is that the confidence in estimates of regional or local climate change will only be improved by the convergence between dynamical and statistical signals or by the emergence of clear evidence supporting the use of a single preferred method (Murphy, 2000).

4. Reproduction of a predictand regime by a SD model

The reproduction of a climate regime of a predictand using an SD model constitutes one of the most important criteria in the evaluation of any downscaling model, and in the selection of the preferred method to develop scenario information. The ability of the downscaling scheme to reproduce observed trends and variability for a given predictand is paramount. Not all models are able to reproduce (partially or entirely) observed climatic trends, or inter-annual variability, over short (seasonal) and long (decadal) timescales, apparent in the observed data series. As suggested in section 2, the selected predictors need to be statistically significant contributors to the variability in the predictand, or they should represent important physical processes in the context of the main fluctuations of the predictand. It is particularly important to observe whether or not the statistical model can be extrapolated to situations where local climate is warmer, cooler, drier or wetter than the climatic conditions for which the SD model has been calibrated. An example follows concerning northern Canada, where changes in temperature are inherently greater at all timescales than in other regions of Canada. This amplification of fluctuation is due to significant changes in surface albedo, mainly from changes in the snow cover, and also due to modifications in surface diabatic fluxes (i.e. sensible and latent heat fluxes) over oceanic areas, according to the state of sea-ice extent and thickness.

In order to analyze the effects of fluctuations in large-scale circulation indices on local predictands, a comparison is made in Figure 11 between interannual fluctuations of the North Atlantic Oscillation (NAO) index and Tmax and Tmin from both observed and SD values at Iqaluit (see its location in southwestern Baffin Bay, in Figure 1 in Gachon and Dibike, 2007). Mean seasonal values of Tmax and Tmin are analyzed alongside cold and warm extremes (i.e. 10th percentile of Tmin, and 90th percentile of Tmax, respectively) over the winter season (DJF). Figure 11 confirms strong links suggested by previous authors (see Hurrell and Van Loon, 1997) between the positive (negative) phase of the NAO and the cooling (warming) of temperatures in northeastern Canada. Recent observed shifts in winter extreme events are related to the strengthening of the winter time NAO, with a strong negative correlation between the NAO and temperature values close to -0.7 (except for Tmin 10th percentile at -0.52, see Table 3). As also shown in SD results using NCEP predictors (see the choice of predictors in Gachon and Dibike, 2007), downscaled values reproduce both trends and the interannual anomalies of both mean values of temperatures and extremes of Tmin and Tmax. A range of correlation close to 0.81-0.92 is obtained between downscaled values and observed values, suggesting that the SD model with the right combination of predictors is able to maintain and develop the main forcing mechanism responsible for the winter variability of temperature. The SD model is also able to reproduce the correlation between Tmax and Tmin time series with NAO interannual anomalies with a range of correlation between -0.52 and -0.75 (Table 3). For the other stations in the North and for other seasons this relationship is less sensitive. The link between the NAO and changes in temperature is less pronounced, and the spatial influences of the NAO index decrease, over the rest of Canada. It is also worth noting that the NAO mainly affects the winter months through November to March. It is difficult to reproduce the exact evolution of the NAO in AOGCMs (see IPCC, 2007; Harding *et al.*, 2010), for several reasons. Mainly, it is due to the chaotic nature of this event and model misrepresentation associated with the low resolution of ocean dynamics, ocean-atmosphere coupling, sea-ice, and topography. Greenland, for example, is largely "smooth" at the scale of an AOGCM, whereas its landmass plays an important role in storm tracks and the blocking of pressure systems over the North Atlantic, all of which affect the NAO pattern (see Hurrell and Van Loon, 1997).

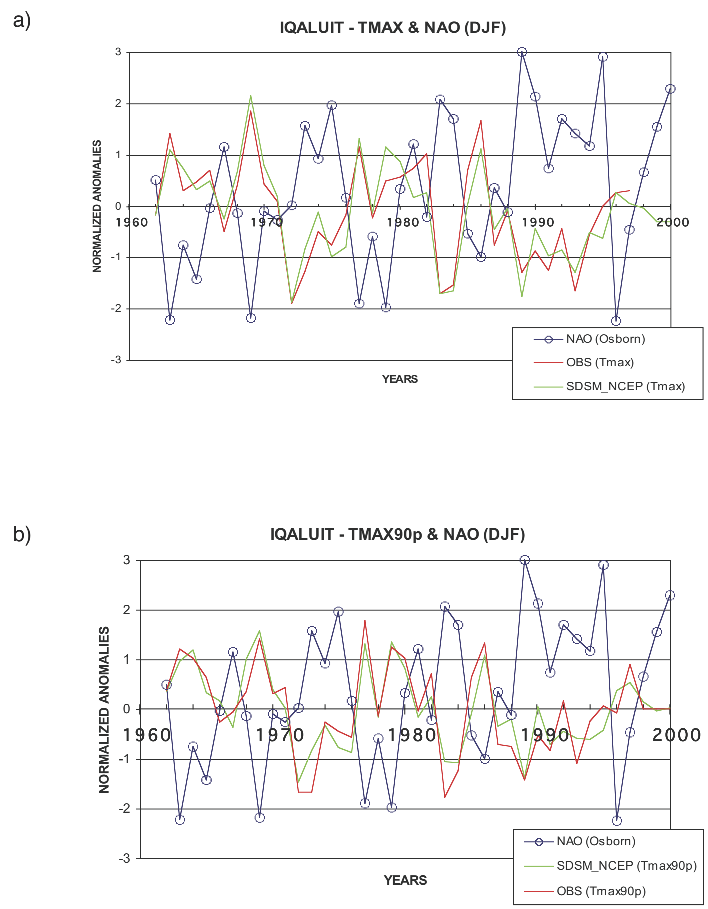
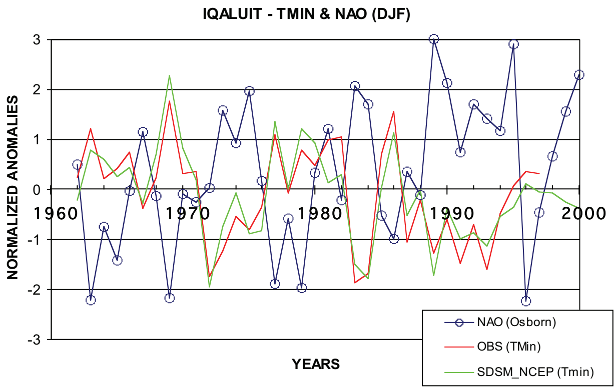


Figure 11 | Comparison of interannual winter normalized anomalies over the period 1961-2000 (with respect to 1961-1990) between observed and SD values of temperatures, and with the NAO index at Iqaluit, Nunavut for a) the mean daily Tmax, b) the 90th percentile

cont.

c)



d)

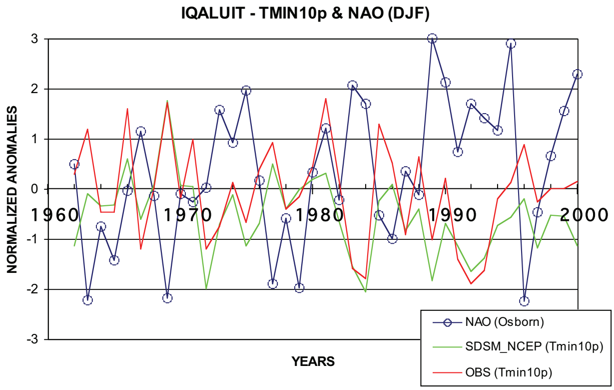


Figure 11 cont... | of daily Tmax, c) the mean daily Tmin, and d) the 10th percentile of daily Tmin. All temperatures and NAO values are averaged over the three winter months of December, January and February (DJF, respectively). The NAO index is defined from Osborn *et al.* (1999).

Table 3 | Temporal correlation values between the observed (i.e. predictand) and SD (i.e. downscaled values from SDSM using NCEP predictors) values of temperatures, and the NAO index (from Osborn, e.g. Osborn *et al.*, 1999) for the winter (DJF) season at Iqaluit, Nunavut (located in southern Baffin Island). Tmax and Tmax90p correspond to the mean value and the 90th percentile of daily maximum temperatures, and Tmin and Tmin10p to the mean value and the 10th percentile of daily minimum temperatures, respectively. The correlation is made using normalized values. NB: the correlation between the downscaled values and each respective predictand is high, i.e. between 0.81 and 0.92. All correlations are statistically significant at the 95% level.

OBSERVED & SD VALUES	NAO INDEX (OSBORN)
Predictand (Tmax)	-0.7
SDSM_NCEP (Tmax)	-0.75
Predictand (Tmax90p)	-0.69
SDSM_NCEP (Tmax90p)	-0.72
Predictand (Tmin)	-0.69
SDSM_NCEP (Tmin)	-0.71
Predictand (Tmin10p)	-0.52
SDSM_NCEP (Tmin10p)	-0.61

5. Conclusion and Further Steps in SD research

SD methods offer various advantages and constitute some useful alternative techniques for climate modelers and impact researchers, mainly because they are:

- Much less computationally demanding than RCMs, and can easily produce ensemble runs of high resolution climate scenarios;
- Able to employ a full range of available, physically appropriate predictor variables (both from AOGCMs and RCMs), as long as a pre-screening of predictors is conducted;
- Able to adequately reproduce a predictand climatic regime in terms of explained variance, correlation, and statistical distribution;
- Able to reproduce the trend (if any) and interannual variability of a predictand, for seasons where the predictand is strongly linked with the large-scale behaviour of selected predictors, i.e., this is not true for all seasons or locations, or where links with atmospheric circulation indices are less clear;
- Able to take into account non-stationarity in predictor/predictand relationships with the relevant combination of predictors, but this needs to be explored with a large variety of long data series and climate regimes.

However, as for other downscaling methods, SD methods have their own limitations, namely:

- Specialist knowledge is required to apply these techniques correctly;
- The relationships for some variables may lie outside the range of the calibration period;
- It may not be possible to derive significant relationships for some variables (e.g., extremes of precipitation);
- The degree of stationarity in the relationship under consideration may constitute a limitation for the downscaling of extremes (precipitation), especially with linear SD methods.

The need to improve and develop more sophisticated SD approaches has hence emerged in order to:

- Develop more spatial coherence (i.e. regional-scale physical distribution of the considered variable over the targeted area) within the downscaling of precipitation (i.e., no spatial coherence is obtained from a single site SD approach);
- Develop a multisite & multivariate SD model using various approaches, be they multi-linear, machine learning based, kernel-gaussian, etc., in order to evaluate the potential added values from each;
- Develop non-linear regression or other approaches with genetic algorithm, or weather typing approach to improve the relevant combination of predictors;
- Develop and identify links between local predictands and regional-scale predictors from RCM runs and other sources in order to gain information on links with extremes and stationarity issues;
- Develop ensemble runs with various AOGCM/RCM driven conditions to construct probabilistic scenarios.

An on-going project in which Environment Canada is engaged with partners at Universities across Canada (namely McGill, UQÀM, INRS-ETE, University of Toronto, University of British Columbia), under the NSERC-SRO (Natural Sciences and Engineering Research Council of Canada, Special Research Opportunity) initiative will allow us to develop new SD methods. i.e. multivariate and multisite statistical approaches. This project on the "Probabilistic assessment of regional changes in climate variability and extremes" is developed in collaboration with European and US colleagues through the ENSEMBLES **http://www.ensembles-eu.org/** and US NARCCAP **http://www.narccap.ucar.edu/** projects, in which a large variety of downscaling models are inter-compared. In order to more coherently address regional climate change and the associated uncertainties, these coordinated efforts will improve the integrated hierarchy of models, will help to evaluate different methodologies, and to apply both dynamical and statistical downscaling approaches in a comprehensive strategy over various regions of interest.

Finally, the internal climate variability of northern Canada's nordic conditions is huge compared to other temperate regions in the Northern Hemisphere. This issue needs to be carefully addressed, especially through downscaling methods applied to a more systematic analysis of the stability in relationships between predictors and predictands with time. Further research is also required in order to distinguish large versus regional scale influences on both climate variability and change. This is true for regions in which low and high frequency variability in the atmosphere and ocean affect the mean climate state and related physical processes at the regional scale, both linked to the occurrence and frequency of extreme events. Plausible causes for changes in the timing and magnitude of these climatic events need to be urgently addressed at high spatial resolution. They are of primary importance for impacts studies, environmental modeling and risk assessments.

Glossary

- Geopotential Height : a physical height measurement representative of air thickness beneath a given pressure level.
- Vorticity : spin of airflow.
- Divergence : outflow or inflow of an airstream.
- Diabatic fluxes: heating or cooling rate of an air parcel due to divergence or exchange of energy from various processes, i.e. through latent heat release, radiative transfer and/or divergence of sensible heat.

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