Regional Climate Projections of Extreme Heat Events in Nine Pilot Canadian Communities for Public Health Planning

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ABSTRACT

Public health planning needs the support of evidence-based information on current and future climate, which could be used by health professionals and decision makers to better understand and respond to the health impacts of extreme heat. Climate models provide information regarding the expected increase in temperatures and extreme heat events with climate change and can help predict the severity of future health impacts, which can be used in the public health sector for the development of adaptation strategies to reduce heat-related morbidity and mortality. This study analyzes the evolution of extreme temperature indices specifically defined to characterize heat events associated with health risks, in the context of a changing climate. The analysis is performed by using temperature projections from the Canadian Regional Climate Model. A quantile-based statistical correction is applied to the projected temperatures, in order to reduce model biases and account for the representativeness error. Moreover, generalized Pareto distributions are used to extend the temperature distribution upper tails and extrapolate the statistical correction to extremes that are not observed in the present but that might occur in the future. The largest increase in extreme daytime temperatures occurs in southern Manitoba, Canada, where the already overly dry climate and lack of soil moisture can lead to an uncontrolled enhancement of hot extremes. The occurrence of warm nights and heat waves, on the other hand, is already large and will increase substantially in the communities of the Great Lakes region, characterized by a humid climate. Impact and adaptation studies need to account for the temperature variability due to local effects, since it can be considerably larger than the model natural variability.

1. Introduction

Climate model projections show consensus on the increase of temperatures and occurrence of extreme heat events (EHE) in terms of frequency, intensity, and duration, with enhanced greenhouse gas (GHG) emissions (Solomon et al. 2007; Field et al. 2012). In a special issue on climate change and health published by The Lancet, it has been recognized that most populations will be affected by direct or indirect health effects of climate change in the coming decades and it has been concluded that “climate change is potentially the biggest global health threat in the 21st century” (Costello et al. 2009, p. 1728). EHE are considered as a direct health effect of climate change and constitute a potential source of environmental health risks that have already caused thousands of deaths. In western Europe, the severe EHE that occurred in the summer of 2003 (Schär et al. 2004; Fischer et al. 2007b) resulted in more than 70000 excess deaths (Robine et al. 2008); more recently, the Russian 2010 EHE, with more than 28 consecutive days of high temperatures above 30°C, caused approximately 56000 fatalities (United Nations 2011). In North America, several periods of EHE have been recorded and caused many deaths and illnesses. For example, the city of

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Chicago, Illinois, experienced in 1995 a period of extreme heat (Meehl and Tebaldi 2004) during which more than 600 deaths and over 3300 excess emergency department visits were registered (Dematte et al. 1998). In 2009, British Columbia has registered more than 200 excess deaths due to one week of high temperatures (Kosatsky 2010). Another example comes from Montreal, Quebec, Canada, where 106 heat-related deaths were recorded after a 3-day heat event in July 2010 (Bustinza et al. 2013). In response to EHE risks, several communities and countries have implemented Heat Alert and Response plans, in order to raise awareness of heat health risks among the general public, to help reduce heat-related morbidity and mortality among the vulnerable categories of the population. In this context, Health Canada is working, through a Heat Resiliency Program (HRP), with key partners and stakeholders to support the development and implementation of heat alert and response systems in at-risk communities and to help Canadians adapt to extreme heat events (Health Canada 2010). These efforts need the support of evidence-based information on current and future climate at the local and regional scale that could be used by public health professionals and decision makers to better understand and respond to the health impacts of extreme heat.

Future projections from both global and regional climate models (GCMs and RCMs, respectively; Meehl et al. 2007b; Christensen et al. 2007) show that for several regions around the globe, extreme hot temperatures are expected to increase more than average temperatures because of an increase of temperature variability (Seneviratne et al. 2012; Della Marta et al. 2007; Della Marta and Beniston 2007; Sterl et al. 2008; Clark et al. 2006; Fischer et al. 2007a). In North America, climate models project hot spots in the Great Lakes region and in the U.S.–Canadian plains (Sterl et al. 2008; Clark et al. 2006; Orlowsky and Seneviratne 2011). Some of the most severe health hazards arise from multiday heat waves, associated with both hot daytime and warm nighttime temperatures, and enhanced by a high relative humidity (Fischer and Schär 2010). The Great Lakes region is characterized by a humid climate and a large population: this region is therefore considered particularly vulnerable from the health perspective, and could suffer from severe health impacts in a warming climate. Several climate studies demonstrate that the interactions between land and atmosphere physical processes, and in particular the (lack of) soil moisture, can play a fundamental role in enhancing hot temperature extremes (Seneviratne et al. 2010; Sterl et al. 2008; Fischer et al. 2007a; Fischer and Schär 2009; Clark et al. 2006). The overly dry climate and lack of soil moisture of the North American plains could lead to unprecedented future hot temperature extremes in this region, with severe effects on the ecosystem, the agricultural sector, and human health.

The importance of considering changes in temperature variability, as well as changes in the mean climate, for the assessment of future heat-related mortality has been highlighted also in health-impact studies. As an example, Gosling et al. (2009b) estimate future heat-related mortality from the Hadley Centre Coupled Model, version 3 (HadCM3) temperature projections, and propose a delta method that accounts for changes in both the temperature average and variability. Their results demonstrate that a higher heat-related future mortality is attributed to the increase of both mean and variability of temperature with climate change, rather than to the increase of mean temperature alone. Martin et al. (2012) discuss the effects of temperature variability on extreme temperatures and the consequent possible enhancement of future temperature-related mortality. However, based on historical records for 56 Canadian cities, they found no strong evidence of an increase of temperature variability in the past century, so they consider solely changes in the seasonal average temperatures for the future projections.

One of the goals of this study is to show the outcome of a multidisciplinary effort in which several extreme temperature indices relevant for the public health sector are analyzed in the context of a changing climate. Both analysis setup and definition of the extreme temperature indices are tailored to respond to the needs of public health planning, for the assessment of heat-related impacts and the development of public health adaptation strategies, in Canada. This cross-domain collaboration brings together expertise from both the Canadian public health sector and the climate model community, highlights some of the respective needs and limitations, and hopefully helps enhance the exchange of knowledge, approaches, and results between the two communities.

Many studies in the literature have examined the association between temperature and mortality during the summer and found a significant increase of mortality above a specific temperature threshold (Curriero et al. 2002; Medina-Ramon and Schwartz 2007; Anderson and Bell 2009; Williams et al. 2012; Schwartz 2005). The identification of these thresholds depends on many factors such as the local climate, local effects (e.g., heat urban spots), community size, and vulnerable population. The analysis shown in this study is hence performed at the level of the community for nine Canadian pilot communities: Fredericton, New Brunswick; Montreal; Ottawa, Kingston, Toronto, Hamilton, and Windsor, Ontario; Winnipeg, Manitoba; and the rural region of southwest of Manitoba (SW Manitoba). These communities were selected by Health Canada professionals in the context of the HRP in order to represent different
local climates, sizes, and populations. The extreme temperature indices analyzed in this study were also defined directly by Health Canada professionals, based on a previous temperature–mortality analysis: the indices characterize extreme temperatures and the occurrence of hot weather events that could lead to an increase of the heat-related mortality significant in the perspective of public health impacts. The indices are based on both multiple absolute thresholds, to embrace the diversity of the pilot communities, and temperature quantiles, to account for the different climates characterizing the different communities. The indices are defined to represent the intensity, frequency, and duration of extreme heat events as these three characteristics are expected to increase with climate change (Solomon et al. 2007). Finally, multiple observation sites are considered within each community in order to account for local effects: one of the key findings of this study relates to the assessment of the uncertainty associated with local effects.

The extreme temperature indices, and their evolution with climate change, are evaluated by using temperature projections from the Canadian Regional Climate Model (CRCM). To reduce model biases and account for the representativeness error, the CRCM temperatures are statistically corrected by performing a quantile–quantile mapping between model values and station observations (Panofsky and Brier 1968; Déqué 2007). Several studies have compared different calibration, bias correction, and downscaling strategies for climate model projections (e.g., Maraun et al. 2010; Fowler et al. 2007; Teutschbein and Seibert 2012a; Chen et al. 2013; Lafon et al. 2013; Themeßl et al. 2010; Ho et al. 2012) and discuss their benefits and limitations. In this study the quantile–quantile mapping approach is favored with respect to other bias correction and downscaling approaches because of its relative simplicity yet high performance at high quantiles (Themeßl et al. 2010). Bias correction and downscaling functions that are calibrated on present climate values are by construction bounded to limit future temperature extremes, since these are expected to achieve very hot values, beyond the range of the present climate values. Already a few studies (e.g., Themeßl et al. 2011; Boé et al. 2007) have underlined the need of extrapolating the quantile–quantile mapping correction function beyond the present calibration range. Piani et al. (2010a,b) apply the quantile–quantile mapping by fitting the data with theoretical distributions and idealized transfer functions, which enable such extrapolation. In this study, the extrapolation of the quantile–quantile mapping is performed by using extreme value distributions.

Extreme value theory (EVT) provides a well-established and robust statistical framework, suitable for analyzing the behavior of extreme events for the present and future climate (Katz et al. 2002; Naveau et al. 2005). Theoretical distributions from EVT are widely used in climate studies to analyze the evolution of extreme temperatures: most studies adopt a block maxima approach and fit annual extremes with generalized extreme value distributions (e.g., Kharin and Zwiers 2005; Kharin et al. 2007; Zwiers et al. 2011), whereas a smaller number of studies consider peaks over thresholds and fit those with generalized Pareto (GP) distributions (e.g., Nogaj et al. 2006; Brown et al. 2008). In this study, GP distributions (Coles 2001) are used to extend the temperature distribution upper tails and infer the behavior of extremes not observed in the present, but which might occur in the future. This enables the extrapolation of the quantile-based statistical correction to temperature extremes beyond the range of the present climate values. The second major aim of this study is to introduce this innovative application of the peaks-over-threshold approach to climate projections of temperature extremes, and hopefully contribute in promoting the use of EVT in climate-driven health impact studies.

The article is structured as follows: the analysis of the temperature–mortality relationship and consequent definition of the extreme temperature indices are presented in section 2. The CRCM simulations providing the temperature projections and the station observations used to perform the quantile-based statistical correction are described in section 3. Some data preprocessing performed to the station observations, the quantile–quantile mapping used to perform the bias correction and downscaling, and the GP distributions fitted to extend the upper tails of the temperature distributions are described in section 4. The evolution of the extreme temperature indices with climate change is presented in section 5. The sources of uncertainties for the climate model temperature projections are discussed in section 6. A summary and some concluding remarks are presented in section 7.

2. Health temperature indices

a. Temperature–mortality relationship

The purpose of this section is to illustrate an analysis of the temperature–mortality relationship that was performed prior the analysis of the extreme temperature indices shown in this study and that motivates the selection of the thresholds for the definition of the extreme temperature indices. This association between temperature and mortality can provide also a sense of the potential health impacts of extreme heat and could be used as a basis for quantifying future health impacts, which are expected to worsen as shown by several papers in the literature (Cheng et al. 2008a,b; Doyon et al. 2008; Martin et al. 2012; Huang et al. 2011; Gosling et al. 2009a).
Figure 1 shows the association between mortality and daily maximum temperatures in Windsor, Winnipeg, Hamilton, Toronto, Ottawa, and Fredericton for the period of 1986 to 2005. A generalized additive model with a Poisson distribution for the dependent variable (mortality) and a logarithmic link function to represent the effect of the predictor (daily maximum temperature) on the predictand (mortality) was used to model the relationship between daily mortality and daily maximum temperature (Hastie and Tibshirani 1990). Only nontraumatic deaths were selected, and mortality data were first analyzed to determine an average (or normal) for the summertime (June–August) of each year: this normal was set as each year’s reference value. Then, a mortality rate was calculated for each summer day as the percentage of deaths occurred during that day relative to this reference value: this percentage can be interpreted as mortality anomaly. Mortality rate (or excess mortality) is often used in health studies (see Gosling et al. 2009a, and references therein) instead of the absolute number of deaths because it reduces interannual differences and helps the comparison of communities characterized by different climate, population size, and level of vulnerability. The mortality rate calculated here represents the departure of the observed mortality from the summer normal/average, and it allows quantifying the change in mortality associated with an increase of temperature (e.g., Fig. 1). For example, a mortality rate of 125% at a given temperature indicates that there is a likelihood of 25% more deaths at this temperature than what should be the normal value.

The analysis of Fig. 1 indicates that the relationship between mortality and temperature varies from one community to another and that there is a community-based temperature threshold (in Fig. 1, where the 95% confidence interval of the relative mortality curves crosses the 100% reference value) beyond which an increase of mortality is observed. As an example, in Fredericton, Toronto, and Windsor mortality increases when daily maximum temperatures exceed a value of 30°C, whereas in Hamilton, Ottawa, and Winnipeg an increase of mortality is observed at lower maximum temperature values (between 27°C and 28°C). The different sensitivity of the different communities to heat events can be explained by several factors related to the local climate, the population size, and the level of vulnerability associated with extreme temperatures. These findings outline the need of using several extreme temperature indices, based both on multiple absolute thresholds, in order to embrace the diversity of the pilot communities, and also on temperature quantiles, to account for the different local climates characterizing each community.

Several health studies highlighted the importance to consider nighttime temperatures in addition to daytime temperatures to respond to hot weather conditions (Robinson 2001; Basu and Samet 2002; Schwartz 2005; McGregor et al. 2007; Ibrahim et al. 2012; Kravchenko et al. 2013). For example, in Montreal, a heat alert is called when maximum and minimum daily temperatures reached 33°C and 22°C, respectively, over three consecutive days; or when minimum daily temperature reached 25°C for two consecutive days (ASSSM 2012). Exposure to high nighttime temperatures has been considered as a risk factor that may exacerbate the health impacts of extreme heat due to the lack of relief from hot conditions, especially among vulnerable population such as seniors and individuals with chronic medical conditions (Health Canada 2012). These findings outline the need of defining extreme temperature indices that account for both daytime and nighttime heat events.

Following the results of the temperature–mortality analysis, the definition of the threshold-based extreme temperature indices was carried out conditioning on daily maximum temperatures of 30°C. Although Fig. 1 shows some variability of heat threshold ranging from 27°C to 30°C, a daily maximum temperature at the higher end of this range was selected because, given the expected increase of temperatures with climate change and given the expected acclimatization and adaptation of the Canadian population to such increase, this choice was considered more appropriate in the perspectives of future health impacts. Table 1 shows the 99th quantiles of daily minimum and maximum temperatures for the 1961–2000 days when maximum daily temperature exceeds 30°C, for the same six communities shown in Fig. 1. The 99th percentile of minimum daily temperatures varies between 22°C and 25°C, whereas the 99th percentile of maximum daily temperature varies from 35°C to 37°C. These daily minimum and maximum temperatures are used to define the threshold-based extreme temperature indices analyzed in this study.

b. Definition of the extreme temperature indices

Climate model projections of daily minimum (Tmin) and maximum (Tmax) temperatures are considered in this study, as these are associated with night and day temperatures, respectively. Six threshold-based indices associated with the occurrence of hot days and warm nights have been defined and analyzed in the context of a changing climate:

- index 1: number of days per year when Tmin > 22°C;
- index 2: number of days per year when Tmin > 25°C;
- index 3: number of days per year when Tmax > 30°C;
- index 4: number of days per year when Tmax > 35°C;
Fig. 1. Mortality curves of (a) Winnipeg, (b) Windsor, (c) Hamilton, (d) Toronto, (e) Ottawa, and (f) Fredericton, during the summertime (June–August) of 1986–2005. The solid line corresponds to the relationship between relative mortality (y axis) and maximum daily temperature (x axis) and the dashed lines represent the 95% confidence interval.
The thresholds of 22°C events, have been also evaluated: temperature values of Tmin and Tmax during hot weather in adverse health outcomes for Canadian communities. To characterize the occurrence of hot weather events that can result in adverse health outcomes, absolute temperature thresholds were used in a mortality analysis and rationale outlined in the previous section: these absolute temperature thresholds characterize the occurrence of hot weather events that can result in adverse health outcomes for Canadian communities. Health Canada professionals, following the temperature–mortality analysis and rationale outlined in the previous section: these absolute temperature thresholds characterize the occurrence of hot weather events that can result in adverse health outcomes for Canadian communities.

Two additional indices, associated with the actual temperature values of Tmin and Tmax during hot weather events, have been also evaluated:

- index 5: number of days per year when Tmin > 22°C and Tmax > 30°C;
- index 6: number of events per year of 3 consecutive days when Tmin > 22°C and Tmax > 30°C.

The thresholds of 22°C and 25°C for night temperatures and 30°C and 35°C for day temperatures were selected by Health Canada professionals, following the temperature–mortality analysis and rationale outlined in the previous section: these absolute temperature thresholds characterize the occurrence of hot weather events that can result in adverse health outcomes for Canadian communities. Two additional indices, associated with the actual temperature values of Tmin and Tmax during hot weather events, have been also evaluated:

- index 7: the 95% quantile of the daily Tmin annual distribution;
- index 8: the 95% quantile of the daily Tmax annual distribution.

The use of temperature quantiles, rather than (exceedance of) absolute temperature thresholds, for these two additional indices 1) informs about the intensity of the extreme temperatures (as opposed to frequency of occurrence of extreme heat events, for the threshold-based indices 1–6) and 2) accounts for the different climatologies associated with the different geographical locations of the communities analyzed. Note that communities characterized by different climate regimes exhibit differences not only in vulnerability, but also in the long-term response through acclimatization and/or adaptation to changes in temperature extremes. The 95% quantiles of the annual Tmin and Tmax distributions were chosen because they were found to be suitable thresholds for defining the GP distributions fitting the upper tails of the Tmin and Tmax temperature distributions (see section 4d). These distributions are commonly used to describe the behavior of extreme values belonging to the distribution upper tails (Katz et al. 2002; Naveau et al. 2005; Nogaj et al. 2006; Brown et al. 2008). The GP distributions are used in this study to extend the temperature distribution upper tails and infer the behavior of extreme temperatures beyond their present range. This enables the extrapolation of the quantile-based statistical correction to future extreme temperatures, which are expected to achieve very hot values, beyond the range of the present climate values (see section 4d).

### 3. Climate data

#### a. Climate model simulations

Climate projections of daily minimum and maximum temperatures are obtained from five simulations of the Canadian Regional Climate Model (Caya and Laprise 1999; Laprise 2008), version 4.2.3 (Music and Caya 2007; de Elia and Côté 2010). The CRCM simulations were driven at the domain boundaries by the Canadian Coupled Atmosphere–Ocean Global Climate Model (CGCM), version 3.1.2 (Scinocca et al. 2008; Flato and Boer 2001). The regional and global models both follow the Intergovernmental Panel on Climate Change (IPCC) observed twentieth-century greenhouse gas emission scenario for the years 1961–2000, and the Special Report on Emissions Scenarios (SRES) A2 GHG emission scenario for years 2001–2100 (Nakicenovic et al. 2000). The five simulations provide projections over a large domain covering the whole of North America (192 × 200 grid points) with a horizontal grid size mesh of 45 km (true at 60°N).

The five CRCM simulations analyzed were produced by driving the same CRCM, version 4.2.3, with five realizations of the CGCM, which differ from each other solely for their initial conditions (these realizations are hereafter called CGCM members). The use of this ensemble of simulations enables us to account for the inherent uncertainty in climate projections due to the natural climate variability. Other sources of uncertainty in climate model projections (e.g., model parameters, modeling physical assumptions and model structure, and future emission scenarios) are not explored in this study but will be discussed in section 6a.

Regional climate model projections are mostly produced over time slices (usually 1961–2000, representing the present climate, and 2041–70, representing the future climate), and continuous simulations are less often available. In our study, two of the five CRCM simulations analyzed cover the entire 1961–2100 period, whereas the other three cover the time windows 1961–2000 and 2041–70 solely. The use of continuous simulations, alongside the time-slice simulations, enables us to analyze climate projections for the near and distant future (i.e., 2011–40 and 2071–2100, in addition to 2041–70), which are important for the public health sector in the planning of

### Table 1. The 99th percentile of daily minimum and maximum temperatures (°C) for the 1961–2000 days when maximum daily temperature exceeds 30°C.

<table>
<thead>
<tr>
<th>Location</th>
<th>Station code</th>
<th>Tmax 99th percentile</th>
<th>Tmin 99th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fredericton (airport)</td>
<td>8101500</td>
<td>35</td>
<td>22</td>
</tr>
<tr>
<td>Hamilton (airport)</td>
<td>6153194</td>
<td>36</td>
<td>24</td>
</tr>
<tr>
<td>Ottawa (airport)</td>
<td>6106000</td>
<td>35</td>
<td>23</td>
</tr>
<tr>
<td>Toronto (Pearson Airport)</td>
<td>6158733</td>
<td>37</td>
<td>24</td>
</tr>
<tr>
<td>Windsor (airport)</td>
<td>6139525</td>
<td>37</td>
<td>25</td>
</tr>
<tr>
<td>Winnipeg (airport)</td>
<td>5023222</td>
<td>37</td>
<td>24</td>
</tr>
</tbody>
</table>

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both immediate and long-term adaptation strategies. The analysis is therefore performed by considering the time window 1961–2000 for the present, and the time windows 2011–40, 2041–70, and 2071–2100 for the future. Note that only two simulations cover the periods 2011–40 and 2070–2100, whereas five simulations cover the 1961–2000 and 2041–70 time windows; results obtained for the 2011–40 and 2070–2100 time windows are therefore expected to be statistically less robust than those for the 1961–2000 and 2041–70 time windows because of the reduced sample size (i.e., because they are calculated by using projections from only two simulations, rather than five). The choice of the present and future time windows, the use of time-slice and continuous, rather than five). The choice of the present and future time windows, the use of time-slice and continuous simulations, and the effects of different sample sizes on the results will be further discussed in section 6d. Table 2 shows the names of the simulations, along with the periods they cover and the CGCM pilot member.

### Observations

Station observations from Environment Canada have been used to perform a statistical correction of the CRCM temperatures. Thirty-three representative stations located in the Canadian communities analyzed have been selected (Table 3). The selection was based on the length of the time series and the amount of available data (excluding missing values) within the time series, the representativeness of the station location (e.g., stations on the water have been excluded), and whether or not the station belongs to the stations adjusted and homogenized by Vincent and Mekis (2006). While performing the station selections it was found that there are more data available for 1961–90 than for 1971–2000. This is due to a reduction of manual stations that happened after the 1990s. The whole period 1961–2000 has been selected to analyze present temperatures in order to maximize the number of observations available while including the most recent observations. Only one of the stations listed in Table 3 (station 6159520, located in Windsor, Riverside) has a poor observation record (less than 20% data coverage in 1961–2000): this station has been retained in our analysis because we want to consider at least two observation records for each community in order to quantify possible local effects; however, results associated with this station should be considered with caution.

Each station has been associated with the nearest neighbor among the CRCM land grid points. Figure 2 shows the CRCM grid points (empty circles and gray boxes) and their collocated stations (gray and black dots; black dots are associated with the stations with the historically most reliable recording procedure for the locations of interest and correspond to the stations in boldface text in Table 3).

### 4. Statistical method

#### a. Observation roundoff correction

Station roundoff recording procedures cause the observed temperatures to have discrete values. Discreteness in the data can affect the evaluation of rank-based statistics and statistical graphical displays (such as the cumulative probabilities and quantile–quantile plots). The effects due to the data discreteness have been eliminated by *dithering* the observed data (i.e., adding a small random noise that eliminates the discreteness). The dithering performed was different, depending on the recording procedure of the station. For two stations (Kingston 6104175 and Windsor 6139520) the temperatures are recorded every 0.5°C; a noise uniformly distributed with range [−0.25, 0.25]°C is applied to these stations. Note that in this case the original temperature values can be re-obtained by rounding the dithered data to the nearest 0.5°C. For approximately half of the stations, the temperatures are recorded every 0.1°C, with a larger number of recordings clustered every 0.5°C: a noise normally distributed with standard deviation of 0.15°C is applied to these stations. Finally, the approximately remaining half of the stations have temperature values clustering irregularly approximately every 0.5°C: a noise normally distributed with standard deviation of 0.25°C is applied to these stations. These slightly different dithering distributions have been calibrated on the station observations in order to obtain the most continuous (and less clustered) data, while not distorting the results.

Figure 3 shows the upper tail (summer) of the quantile–quantile plot for the CRCM versus observed daily maximum temperatures for one of the Kingston station, before and after dithering. Because of the rounding off to the nearest 0.5°C, the observed temperatures in Fig. 3a results as discrete clusters. Multiple values of the CRCM
temperatures are then associated to a single observed value (e.g., 30°C), which can affect the quantile-based statistical correction (section 4c). Dithering (Fig. 3b) eliminates the discreteness and facilitates the quantile–quantile mapping.

b. CRCM biases and representativeness error

Modeled temperatures can exhibit cold or warm biases. The biases affecting the CRCM simulations at the locations analyzed are identified by using quantile–quantile plots of the CRCM versus observed 1961–2000 temperatures (Figs. 4 and 5). Note that the upper-right and lower-left portions of the curves in Figs. 4 and 5 correspond to the upper and lower tails of the Tmin and Tmax annual distributions and are therefore associated with summer and winter temperatures, respectively. The CRCM simulations exhibit a mild cold bias for the summer night temperatures (Fig. 4, upper right) for all locations. For winter night temperatures (Fig. 4, lower left), on the other hand, the CRCM simulations exhibit a large cold bias for Windsor, Hamilton, and Toronto, a less severe cold bias for Ottawa, Kingston, Montreal, and Fredericton, and again a mild cold bias for Winnipeg and SW Manitoba. For all locations, the night temperature biases seem to change regime as Tmin decreases below 0°C possibly due to some physical process associated with freezing temperatures that is misrepresented by the CRCM. For the winter day temperatures (Fig. 5, lower left) the CRCM simulations exhibit again a cold bias for Toronto, Hamilton, and Windsor; a milder cold bias for Ottawa, Kingston, Montreal, and Fredericton; and almost no bias for Winnipeg and SW Manitoba. For the summer day temperatures (Fig. 5, upper right) the CRCM exhibits a warm bias: the quantile–quantile plot curves seem to change regime beyond a critical temperature threshold and increase more steeply as the temperature increases, for all locations. Biases in extreme hot temperatures have been attributed most commonly to the...
atmosphere and soil–moisture interaction, but also to other physical feedbacks, which play a key role in enhancing hot temperature extremes and which are often misrepresented by the current generation of climate models (Seneviratne et al. 2010; Fischer et al. 2007a,b; Clark et al. 2006; Sterl et al. 2008; Fischer and Schär 2009).

Model temperatures can differ from observed temperatures also because of the scale and representativeness mismatching between the CRCM grid mesh and the observation at a specific station location. In fact, model values in general represent an average over a grid box (45 × 45 km²), whereas the station “point” observation is representative of the climatology at a specific location, and can be potentially affected by local factors not accounted for in the model. As an example, Fig. 6 shows the quantile–quantile plots of the CRCM versus observed daily minimum temperature for two Montreal stations collocated into the same CRCM grid box. The temperatures measured at the McGill station, which is...
located downtown, are systematically warmer than those measured at St. Hubert Airport: the difference between the two stations is due solely to the urban heat effect and illustrates an example of representativeness error. Note that the representativeness error is much larger than the spread within different CRCM simulations, and that its magnitude is of the same order as the bias.

c. Statistical correction according to the observations

To reduce the CRCM biases and to account for the representativeness error, a statistical correction according to the observed values has been performed. Several

FIG. 4. Quantile–quantile plot of the CRCM vs observed daily minimum temperature for (a) Windsor, (b) Ottawa, and (c) Winnipeg. Different gray shadings and line types correspond to different CRCM simulations. The horizontal and vertical lines indicate the CRCM and observation 95% quantiles, respectively.

FIG. 5. As in Fig. 4, but for daily maximum temperature for (a) Toronto and (b) SW Manitoba.
with different line types. and Mount St. Bruno. Different CRCM simulations are plotted (gray), located on the south shore between the St. Lawrence River town, is systematically warmer than the St. Hubert Airport station same CRCM grid box. The McGill station (black), located down-
minimum temperature for two Montreal stations located in the
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calibration, bias correction, and downscaling strategies for climate model projections exist [see Maraun et al. (2010) and Fowler et al. (2007) for reviews; see also Teutschbein and Seibert (2012a), Lafon et al. (2013), Chen et al. (2013), Themeßl et al. (2010), and Ho et al. (2012) for comparison studies]. In this study, an empirical quantile–quantile mapping approach is chosen because of its relative simplicity yet high performance at high quantiles (Themeßl et al. 2010). The empirical quantile–quantile mapping was first proposed by Panofsky and Brier (1968) and has been applied in several studies, mainly to bias-correct and downscale climate model outputs for hydrological applications (e.g., Wood et al. 2004; Boé et al. 2007; Déqué 2007; Themeßl et al. 2010). In this section we briefly describe the method and its application in the evaluation of the extreme temperature indices. A discussion on the assumptions behind the quantile–quantile mapping and uncertainty deriving from different methods will follow in section 6b.

The quantile–quantile mapping is applied in this study to relate model grid values to station observations at a point location. The quantile–quantile mapping therefore acts both as bias correction and downscaling technique, so that it simultaneously reduces the biases and accounts for the representativeness error. Moreover, in this study the quantile–quantile mapping is performed for each CRCM simulation individually, to assess the natural climate variability, and for each station and its corresponding CRCM grid point, to account for local effects.

The empirical quantile–quantile mapping transfer function is obtained by matching model ($Y$) and observed ($X$) quantiles with the same empirical cumulative probability in the reference (1961–2000) period. The quantile–quantile mapping transfer function therefore corrects the model value $y$ with the observed value $x$ such that

$$x = F_X^{-1}[F_Y(y)],$$

where $F_X$ and $F_Y$ are the observation and model empirical cumulative probabilities in the reference period, respectively. Note that the distribution of the statistically corrected model values in the reference period, by construction, is identical to the observation distribution. The transfer functions used to correct the CRCM temperature projections are, de facto, the curves in the quantile–quantile plots, as those shown in Figs. 4 and 5.

The extreme temperature indices 1 to 6 inform on the frequency of exceedance of absolute temperature thresholds, which were defined based on observations ($u_X = 22^\circ$ and $25^\circ$C for Tmin; $30^\circ$ and $35^\circ$C for Tmax). To evaluate these indices, the observation-based thresholds $u_X$ are transformed reversing Eq. (1) as

$$u_Y = F_Y^{-1}[F_X(u_X)],$$

and then these new CRCM thresholds $u_Y$ are used to evaluate the indices 1 to 6, from the model projections in the present and future time windows. This much simpler procedure leads to results identical to those from correcting the model with Eq. (1) and then calculating the indices with the original observation-based thresholds $u_X$. Figure 7a shows an example of quantile–quantile mapping of observation-based thresholds ($u_X = 30^\circ$, $35^\circ$C) to the corresponding CRCM thresholds ($u_Y$), for the daily maximum temperatures for a station in Hamilton.

The extreme temperature indices 7 and 8 inform on the evolution of the Tmin and Tmax 95% quantile in the context of the changing climate. To evaluate these indices, the CRCM temperature values corresponding to the 95% quantile in the present and future time windows ($y$ and $y'$, respectively) are statistically corrected by Eq. (1); then the changes between their statistically corrected values ($x$ and $x'$, respectively) are considered. Figure 7b shows an example of quantile–quantile mapping of the CRCM 95% quantile in 1960–2000 ($y$) and 2041–70 ($y'$) to their corresponding statistically corrected values ($x$ and $x'$, respectively). Note that the quantile–quantile mapping affects the climate change signal ($\Delta$), so
that in Fig. 7b the $\Delta_Y = y' - y$ is reduced to $\Delta_X = x' - x$ by a factor $\Delta_X/\Delta_Y$, given by the slope of the quantile–quantile plot curves. This property of the quantile–quantile mapping was already discussed by Haerter et al. (2011) and Hagemann et al. (2011). Haerter et al. (2011) use an idealized example with normally distributed observation and model values $N(\mu_X, \sigma_X)$ and $N(\mu_Y, \sigma_Y)$, respectively, and show that the quantile–quantile mapping stretches the climate change signal of a factor equal to the ratio of the observed and model standard deviations ($\sigma_X/\sigma_Y$), which is the slope of the transfer functions. Similarly, Hagemann et al. (2011) show that a linear transfer function $a + bT$ for temperature bias correction leads to a corrected climate change signal $b\Delta T$. The quantile–quantile mapping in this fashion corrects both mean and variability of the modeled distribution, both in the present and future projections. Furthermore, the quantile–quantile mapping enables to adjust all moments of the probability density function (Hagemann et al. 2011).

The temperatures analyzed in this study exhibit nonnormal distributions and the quantile–quantile mapping transfer functions result highly nonlinear (as shown in Figs. 4 and 5). A key advantage of empirical quantile–quantile mapping is that it can be defined for variables with complex nonparametric distributions. The quantile–quantile mapping approach accounts hence for biases which differ (sometimes in a nonlinear fashion) for low and high quantiles. As an example, in the case of the Hamilton daily maximum temperatures shown in Fig. 7b, the quantile–quantile mapping corrects the larger model variability in the Tmax distribution upper tails (and reduces consequently the climate change signal associated with these tails). These complex characteristics of our data partially motivated the choice of the empirical quantile–quantile mapping for the statistical correction.

d. Extended analysis by using the generalized Pareto distribution

Not all station measurements exceed the absolute temperature thresholds defining indices 1 to 6. In particular, the thresholds were not exceeded for the daily minimum (night) temperatures and for stations located in relatively cold climates, such as Fredericton or Manitoba. When the observed temperatures did not exceed the predefined thresholds, the upper tails of the temperature distributions for the observation and CRCM simulations were fitted by GP distributions (Coles 2001, chapter 4). This enables the extrapolation of the temperature distribution upper-tail behavior, beyond the present observed and modeled empirical values.

The GP distributions are commonly used to describe the behavior of the extreme values belonging to the distribution upper tails (Katz et al. 2002; Naveau et al. 2005; Nogaj et al. 2006; Brown et al. 2008). The cumulative probability density function of the GP distribution is given by
\[
\text{Pr}(X > x | X > u) = 1 - \left( 1 + \frac{y}{\sigma} \right)^{-\frac{1}{\xi}} \left( 1 + \frac{\xi y}{\sigma} \right) > 0
\]

where \( y = x - u > 0 \) is the exceedance of the value \( x \) over the threshold \( u \), and \( \sigma \) and \( \xi \) are the scale and shape parameters characterizing the GP distribution. The scale parameter characterizes the spread of the distribution, whereas the shape parameter defines the behavior of the extreme temperature tails: negative \( \xi \) correspond to light-tail beta distributions, \( \xi = 0 \) corresponds to an exponential distribution, and positive \( \xi \) corresponds to heavy-tailed Pareto distributions. Note that the beta distributions have an upper limit \( (x < u - \sigma/\xi) \), whereas the exponential and heavy-tail GP distributions have no upper bound.

The fitted GP distributions enable us to extend the observed and CRCM temperature distribution upper tails, and hence to extrapolate the quantile-quantile mapping beyond the range of the present climate values: the empirical quantiles used for the statistical correction are replaced with the theoretical quantiles provided by the fit. Figure 8 shows an example in which one of the stations located in SW Manitoba did not record (in the whole period 1961–2000) any daily minimum temperature exceeding 22°C. The quantile–quantile plot of the modeled versus observed temperatures has been extended by fitting a GP distribution to the tails of the observed and CRCM distributions, respectively. The quantile–quantile mapping for the 22°C threshold could then be obtained from the values of the GP fitted distributions.

To fit the upper tails of the temperature distributions with a GP distribution, for each location and CRCM simulation, a suitable threshold for the GP distribution needs to be defined (Coles 2001, chapter 4.3). This threshold must be sufficiently large to meet the asymptotic criteria of extreme value theory, but cannot be too large and possibly lead to instabilities in the estimates of the GP distribution parameters because of the too small sample size. The thresholds used in this study to fit the GP distribution correspond to the 95% quantile of the annual marginal distributions of the observations and each individual CRCM simulation, for each station and its corresponding CRCM grid point. Stability plots of the modified scale and shape parameters were used to verify that this quantile belongs to the range of suitable thresholds for the GP distributions. The goodness of fit of the GP distribution was assessed by probability and quantile plots of the empirical values versus the fitted ones. For a detailed description of this statistical analysis the reader is referred to chapter 4 of Coles (2001).

Figure 9 shows the GP distribution fitting the upper tail of the Fredericton Tmax distribution, along with its corresponding goodness of fit and stability plots used to define the range of suitable thresholds. The stability plots (Figs. 9e,f) show that modified scale and shape parameters are stable for thresholds ranging between 26°C and 30°C. The 95% quantile of the whole distribution (vertical line in Fig. 9a) is approximately 28°C, which belongs to the range of suitable thresholds. The almost perfect overlapping to the diagonal of the cumulative probability and quantile plots corroborates the goodness of the fit.

5. Results

a. Statistically corrected CRCM thresholds

Figure 10 shows the CRCM thresholds obtained by applying the quantile–quantile mapping [Eq. (2)] to the absolute observation-based thresholds defined by Health Canada, and which are used to evaluate the extreme temperature indices 1–6, as described in section 4c. The CRCM thresholds exhibit some consistent behaviors common to most of the analyzed locations. For warm night temperatures (Figs. 10a,b), most of the CRCM thresholds are colder than the observation thresholds (Tmin = 22°C and 25°C). On the other hand, for warm day
temperatures (Figs. 10c,d), most of the CRCM thresholds are warmer than the observation thresholds ($T_{max} = 30^\circ$ and $35^\circ$C). These results are consistent with the cold and warm biases found for $T_{min}$ and $T_{max}$ summer temperatures, respectively (section 4b).

For the stations in SW Manitoba, the spread of the CRCM values for the warm night temperatures (Figs. 10a,b) is larger for the $25^\circ$C threshold than for the $22^\circ$C threshold. This larger spread indicates larger uncertainty associated to the $25^\circ$C threshold statistics. This behavior is expected, since more extreme and rare values belonging to the very upper tail of the distribution are less physically predictable and more affected by sampling errors. Moreover, most of the CRCM quantiles corresponding to the $25^\circ$C threshold were obtained from the GP distributions solely (represented by crosses on the plot) because the observations in SW Manitoba do not exceed very often the $25^\circ$C threshold: the extended analysis performed by fitting the GP distributions introduces inevitably an additional source of uncertainty.

For some of the largest cities (e.g., Montreal for $T_{min} > 22^\circ$C and Toronto for $T_{max} > 30^\circ$C), the CRCM thresholds exhibit large variability from one station to another. These differences are usually due to some peculiarity in the station location and reflect the diversity between the individual station climatologies due to specific local effects. As an example, station 6158665 in Toronto is located at the Harbour Airport, between Lake Ontario and downtown: this station has a cooler climatology than the other Toronto stations because it is affected by the proximity of the lake. Station 7025280 in Montreal is located on the McGill campus downtown, and it has therefore a much warmer climatology than the other two airport-based stations, due to the urban heat. The spread of the CRCM thresholds due to the different station climatologies enables one to quantify the uncertainty associated to the representativeness error.

The CRCM thresholds for $T_{max} > 35^\circ$C are better clustered than those for $T_{max} > 30^\circ$C (cf. Figs. 10c,d) for stations within the individual communities (e.g., Toronto). The higher $35^\circ$C temperature threshold seems to better characterize the behavior of the extreme hot day temperatures, beyond the differences in local climatologies.

b. Projections of the occurrence of warm nights and hot days

Figure 11 shows the warm night indices (number of days per year with daily minimum temperatures exceeding $22^\circ$C...
and 25°C) evaluated for each station and its corresponding CRCM grid point, for the present and future periods. Figure 12 shows the same indices, but with the results from the individual stations grouped for each community. The occurrence of warm nights increases with climate change. The indices are particularly large for Windsor, Hamilton, Toronto, Kingston, and Montreal: these communities are characterized by a humid climatology, which strongly enhances night temperatures. Ottawa, Fredericton, Winnipeg, and SW Manitoba, on the other hand, are characterized by drier weather, and the nights tend therefore to be cooler.

For some of the largest cities, the indices associated with the different stations exhibit large differences. These differences are due to the diversity in the local climatologies of the different stations due to specific local effects. As an example (Fig. 11a), the Montreal station 7025280 (McGill, located downtown) is warmer than the 7025250 (Trudeau Airport) and 7027320 (St. Hubert Airport) stations on account of the urban heat; similarly, station 6158665 located at the Toronto Harbour Airport is cooler than the other Toronto stations since it is affected by the lake proximity. This large diversity in the index values (quantified by the span of the box plots in Fig. 12) provides information on the variability of the index due to local effects. Note that such variability is significantly larger that the CRCM natural variability, quantified by the span of the projections from the different CRCM simulations (segments in Fig. 11).

For a large number of stations in SW Manitoba, and for Winnipeg, Fredericton, and Ottawa (i.e., locations characterized by a drier and cooler climate), night temperatures often do not exceed 25°C. For these stations, index 2 was evaluated by extending the upper tail of the Tmin distribution with the GP distributions (empty bars in Fig. 11). When both dithered temperatures and the GP fit failed to reach the selected threshold, the index could not be calculated (missing bars in Fig. 11). For the locations where the indices can be evaluated from both the dithered temperatures and by fitting the GP distributions, the results obtained are similar (e.g., compare top and bottom panels of Fig. 12 for Tmin > 22°C). Extending the temperature distribution upper tail with the GP distributions seems therefore to provide a valid alternative for the calculation of the indices, for the cases in which the dithered temperatures do not exceed the selected thresholds (e.g., Ottawa, Fredericton, and Winnipeg in Figs. 12b,d). However the index estimates obtained by the GP distributions are less robust than those obtained from the dithered temperatures directly because fitting the GP distributions adds a level of complexity to the index evaluation, with some inherent uncertainties. Moreover, for some stations (e.g., Ottawa and Fredericton for Tmin > 25°C) the GP fit does not extend the temperature distribution sufficiently, so that the sample size of values used for the index estimate is reduced. Finally, larger uncertainty is associated with temperatures belonging to the very upper tail of the distribution because they are more extreme, and therefore intrinsically less predictable, and rarer, and therefore characterized by a reduced sample size. As an example, index 2 shown in Fig. 12b is obtained from a reduced and more scattered sample of values than index 1 (Fig. 12a), and therefore a larger uncertainty (quantified by the span of the box plots) is associated with this index.

Figure 13 shows the hot day indices (number of days per year with daily maximum temperatures exceeding 30°C and 35°C), for each pilot community. The occurrence of hot days increases with climate change, by a factor of 3 (or even larger). As an example, the number of days per year with daily maximum temperature exceeding 30°C (Fig. 13a) increases from 10–20 in the present to 40–60 by the end of the twenty-first century, over all the communities analyzed. The indices are particularly large for Windsor and Hamilton (the two locations most southward) and for Winnipeg and SW Manitoba (characterized by a dry climate, and therefore possibly affected by an uncontrolled enhancement of extreme hot temperatures due to the lack of soil moisture); they are moderate to high for Montreal, Ottawa, Kingston, and Toronto and remain relatively small for Fredericton. These differences are more evident for the index associated with the 35°C threshold, which is higher and is therefore capable of better discriminating the different climatologies of extreme hot-day temperatures for the analyzed communities. Again, for some of the largest cities the indices exhibit a large variability due to the local effects associated with the different stations, and such variability is larger than that due to the different CRCM simulations (not shown).

Figure 14 shows the indices associated with consecutive warm nights and hot days (number of annual occurrences of 1 day or 3 consecutive days with daily minimum temperatures exceeding 22°C and daily maximum temperatures exceeding 30°C) for each pilot community. The behavior of these indices follows that of the warm night indices (Fig. 12), with greatest occurrences of heat wave events in Windsor, Hamilton, Toronto, Kingston, and Montreal. This implies that the humidity (associated with the occurrence of warm nights) plays a dominant role with respect to the solar radiation (associated with the occurrence of hot days) in characterizing heat wave events and their evolution with climate change.
FIG. 10. Statistically corrected CRCM thresholds corresponding to the observation-based thresholds of (a) 22°C and (b) 25°C for the daily minimum temperatures (Tmin), and (c) 30°C and (d) 35°C for the daily maximum temperatures (Tmax). Estimates obtained with the dithered observations are indicated by circles, whereas estimates obtained from the fitted GP distributions are indicated by symbols. The different gray shadings for the symbols indicate the different CRCM simulations. For the stations where both the dithered temperatures and the GP fit failed to reach the selected threshold, the statistically corrected CRCM thresholds could not be calculated, and symbols are missing.
c) CRCM quantiles for observed T$_{\text{max}}$ = 30 $^\circ$C

![Graph showing CRCM quantiles for observed T$_{\text{max}}$ = 30 $^\circ$C.]

d) CRCM quantiles for observed T$_{\text{max}}$ = 35 $^\circ$C

![Graph showing CRCM quantiles for observed T$_{\text{max}}$ = 35 $^\circ$C.]

FIG. 10. (Continued)
FIG. 11. Warm night indices (indices 1 and 2) evaluated for each station and its corresponding CRCM grid point: number of days per year with Tmin (a) $>22^\circ$C and (b) $>25^\circ$C. The bars of different colors show the index value for the present period and the future time window, as indicated in the legend. The bar length indicates the average of the index values found for the CRCM simulations available within each period, whereas the segments at the bar end indicate the index range. This range can be interpreted as the uncertainty associated to the future projections from the different CRCM simulations. The filled bars display the indices evaluated from the dithered temperatures, whereas the nonfilled bars display the indices evaluated by fitting the GP distributions. When both the dithered temperatures and the GP fit failed to reach the selected threshold, the index could not be calculated, and the bars are missing.
c. Projections of extreme night and day temperatures

The extreme temperature indices 7 and 8 provide information on the evolution of the 95% quantile of the daily minimum and maximum temperatures, respectively. These indices quantify the changes of warm-night and hot-day temperatures directly, thus characterizing the intensity of future extreme temperatures. Figure 15
FIG. 12. Warm night indices (indices 1 and 2), where the stations and corresponding CRCM grid points have been grouped for each community: number of days per year with Tmin (a),(c) $>22^\circ$C and (b),(d) $>25^\circ$C. (top) The filled bars display the indices obtained from the dithered temperatures solely, whereas (bottom) the nonfilled bars display the indices calculated by fitting the GP distributions. When the dithered temperatures failed to reach the selected threshold, the index could not be calculated, and the bars are missing. The bars of different shades show the index value for the present and future time windows, as indicated in the legend. The bar length corresponds to the median of the index values found for the CRCM simulations available in the period considered and for the stations available at the location of interest. The number of index values used in this calculation is displayed along the right-hand vertical axis. The box plots show the distribution and range of these index values. The span of the box plots can be interpreted as the uncertainty of the index associated with both the different CRCM simulations and the diversity in the different station climatologies due to local effects.
shows these extreme temperature indices (95% quantile of the daily minimum and maximum temperatures) for each pilot community. We recall that the 95% quantiles shown in Fig. 15 are statistically corrected with the quantile–quantile mapping as described in section 4c. The 95% quantiles of both daily minimum and maximum temperatures increase with climate change, with a range for all the communities analyzed spanning from 3.5°C to 6°C century−1.

The warm night extreme temperatures (Fig. 15a) increase linearly with time, and homogeneously across the different communities, with a range from 3.5°C to 4.5°C.

**FIG. 13.** As in Fig. 12, but for the hot day indices (indices 3 and 4): number of days per year with Tmax (a) >30°C and (b) >35°C.

**FIG. 14.** As in Fig. 12 (top), but for the consecutive warm night and hot day indices (indices 5 and 6): (a) number of days per year with Tmin > 22°C and TMax > 30°C; and (b) number of consecutive 3 days per year when Tmin > 22°C and TMax > 30°C.
The unique exception is Windsor, which exhibits a large increase (6°C century\(^{-1}\)) relative to the other communities. However, the climate change signal for Windsor was similar to (if not smaller than) that of the other communities prior to performing the quantile-based statistical correction (not shown). The statistically corrected climate projections in Windsor are heavily affected by the observations at station 6159520, which has a poor observation record (less than 20% data coverage in 1961–2000). The strong increase of index 7 for Windsor is therefore not entirely trusted.

The hot day extreme temperatures (Fig. 15b) increase mildly in Montreal, Ottawa, and Fredericton (from 3.5°C to 4°C century\(^{-1}\)) and faster in Kingston, Toronto, Hamilton, and Windsor (from 4.5°C to 5°C century\(^{-1}\)). The largest increase occurs in Winnipeg and SW Manitoba (6°C century\(^{-1}\)), and such increase is nonlinear with time. The Manitoba communities are characterized by a dry climate and a lack of soil moisture, as opposed to the humid climate characterizing the eastern Canada communities. Hot day extreme temperatures in humid climates are controlled by the cooling effect of the soil moisture evaporation: in fact, as the temperatures increase, they trigger the soil moisture evaporation, which in its turn acts as a physical limiting factor on the temperature increase itself (Clark et al. 2006; Fischer and Schär 2009). In dry climates, on the other hand, the lack of soil moisture disables this negative feedback, and can therefore result in an uncontrolled enhancement of hot day temperatures (Clark et al. 2006; Fischer and Schär 2009).

The nonlinear large increase of index 8 in the Manitoba communities is possibly due to these physical mechanisms. Projections associated with indices 7 and 8 exhibit a smaller uncertainty than indices 1–6 (cf. the spread of the box plots in Fig. 15 with the same spread in Figs. 12–14). This is due to the index definition: indices 7 and 8 quantify a change of temperatures directly, whereas indices 1–6 quantify the change of the number of days that exceed a given temperature. The count of the annual occurrence adds a degree of complexity to these indices, with an inherent new layer of uncertainty. The indices associated with the occurrences of warm nights and hot days are therefore considered weaker than the indices associated with the extreme warm night and hot day temperatures directly, for assessing the expected changes of warm weather events with climate change.

6. Discussion: Sources of uncertainty

a. Uncertainties in climate and mortality projections

Uncertainties in climate model projections can rise from possible future GHG emission scenarios (Nakicenovic et al. 2000), differences in the modeling physical assumptions and model structure, parameterization schemes and model physical parameters, and natural climate variability. For regional climate models, the nesting technique and dynamical downscaling provide additional
sources of uncertainty to those of the driving model. Multimodel datasets (Meehl et al. 2007a; Christensen and Christensen 2007) and perturbed physic ensembles (Murphy et al. 2004) have been used to explore the contribution of each of these modeling component to the uncertainty in climate model projections. Hawkins and Sutton (2009) show that the uncertainty in GCM projections for the next few decades is dominated by the model uncertainty and natural variability, whereas for larger time scales the emission scenarios provide the largest contribution. Déqué et al. (2007) and de Elía and Côté (2010) shows that the GHG emission scenario and driving GCM provide the largest sources of uncertainty in regional climate model projections.

Understanding and managing uncertainty in projections of future heat-related mortality under climate change adds a degree of complexity and presents a few additional challenges (Huang et al. 2011; Gosling et al. 2009a). In fact, uncertainties in the projection of heat-related mortality under climate change arise from climate models and scenarios but also from the temperature–mortality relationship and how this will be affected by future socioeconomic developments (e.g., infrastructure improvements), demographic change (e.g., aging population), and population acclimatization (Huang et al. 2011; Gosling et al. 2009a). Peng et al. (2011) estimate the association between heat waves and mortality in Chicago using a Poisson regression model. They analyze seven GCMs, forced by three IPCC scenarios, and found that the largest source of uncertainty in the mortality projections derives from the GCMs. Gosling et al. (2012) use a perturbed physics ensemble of HadCM3 to assess the impact of climate model physics uncertainty on heat-related mortality projections, for six U.S. cities. They found that the physics uncertainty is larger than the uncertainty deriving from different scenarios, and that both these uncertainties are larger than the uncertainty due to the dynamical downscaling.

The five CRCM simulations analyzed in this study differ solely for the driving CGCM member, and inform therefore solely as to the inherent uncertainty in climate projections due to the natural climate variability. Uncertainties rising from differences in the model physical parameters, driving GCM and emission scenarios, are expected to be larger than the natural variability and can possibly lead to larger uncertainties in heat-related mortality projections. The analysis of these different sources of uncertainty is beyond the scope of this study but could be considered in later work. In general, for health-impact studies it is recommended to consider a large ensemble of simulations in order to account for the effects of these uncertainties on the projections of extreme heat events and heat-related mortality.

b. Uncertainties in the bias correction approaches

Several statistical calibration, bias correction, and downscaling strategies for climate model projections exist [see Maraun et al. (2010) and Fowler et al. (2007) for reviews; see also Teutschbein and Seibert (2012a), Chen et al. (2013), Lafon et al. (2013), Themeßl et al. (2010), and Ho et al. (2012) for comparison studies]. All these approaches rely on different assumptions, have benefits and limitations, and add a source of uncertainty in climate model projections. Sophisticated bias correction and downscaling strategies (e.g., based on weather types, analogs, or multiple linear and nonlinear regression) are often not feasible in service-oriented institutions, which need to respond to a large demand of climate scenarios for user-specific indices in short times and with relatively small resources. In this study, therefore, only simple statistical calibration, bias correction, and downscaling approaches have been considered. In this section we review some of the characteristics of these simple statistical calibration approaches, and provide some further reasons that have led us to choose the quantile–quantile mapping.

Simple statistical calibration approaches for climate model projections can be divided in two families (e.g., Ho et al. 2012; Chen et al. 2013):

1) **bias correction** approaches, which evaluate a model–observation relationship in the present and then apply it to the future model projections, and

2) **change factor** approaches, which evaluate a climate change signal from the future–present model projections and then apply it to the observations in the present.

Ideally, a change factor and bias correction approach based on the same principle should lead to the same results.

The simplest calibration approaches one can consider are the following:

1) **constant bias correction**, which corrects the future model projections \( Y' \) with a constant mean bias \( B = \mu_{Y'} - \mu_X \), where \( Y \) and \( X \) denote again model and observations in the present period and \( \mu_Y \) and \( \mu_X \) denote their averages, and

2) the **delta method**, which applies a constant (average) climate change signal \( \Delta = \mu_Y - \mu_X \) to the present observations \( Y \).

These approaches lead to the same result solely if the bias and climate change signal (or delta) are constant for the whole distribution values. These approaches do not account for the differences in variability (or differences in any higher moment of the distribution beyond the
mean) between observations and model present values, and between present and future model values. They fail therefore to account for the fact that climate models exhibit biases in both mean and variability, and that climate projections exhibit changes in both mean and variability. This is particularly crucial for future temperature extremes, which are strongly affected by changes in the distribution variability (Seneviratne et al. 2012; Della Marta et al. 2007; Della Marta and Beniston 2007; Sterl et al. 2008; Clark et al. 2006; Fischer et al. 2007a).

Consequently, these calibration approaches have been shown to be too simplistic and inadequate (e.g., Hagemann et al. 2011; Gosling et al. 2009b).

A further step in the calibration approaches is taken when the bias correction or the change factor is applied to higher moments (parameters) of the distribution, beyond the mean. As an example, Gosling et al. (2009b) apply the delta method to the location and scale parameters of logistic distributions fitted to the temperature projections: in this fashion they account for changes in both temperature mean and variability. A bias correction method can be defined based on this same principle (e.g., Chen et al. 2011): observed and present and future modeled temperatures are fitted with theoretical distributions [e.g., the Gaussian distributions $N(\mu_X, \sigma_X)$, $N(\mu_Y, \sigma_Y)$, and $N(\mu_Y, \sigma_Y)$, respectively]; then the parameters of the future model distribution are corrected with the difference (or ratio) between the distribution parameters of the present observed and modeled distributions, such that

$$\begin{align*}
\mu_X' &= \mu_Y - (\mu_Y - \mu_X) \quad \text{and} \\
\sigma_X' &= \sigma_Y \frac{\sigma_X}{\sigma_Y}.
\end{align*}$$

This approach accounts for both biases and changes, in both mean and variability. Note that these parameter-based bias correction and change factor approaches (when defined on the same theoretical distributions and with the same type of transformation for the parameters) lead to the same results. However, for both the bias correction and change factor methods, the nature of the transformation applied to the parameters (e.g., additive or multiplicative) changes the results and constitutes a source of uncertainty.

The quantile–quantile mapping extends this concept and enables to adjust all moments of the probability density function (Hagemann et al. 2011). From Eq. (1) it is easy to show that the cumulative distribution function (CDF) obtained by applying the bias correction based on the quantile–quantile mapping is $F_X(u) = F_Y[F_Y^{-1}[F_X(u)]]$. The bias correction based on the quantile–quantile mapping therefore accounts for both biases and changes in the whole distribution, since involves all the three CDFs $F_Y$, $F_Y$, and $F_X$. Haerter et al. (2011) show that for the idealized case of normally distributed values, the bias correction based on quantile–quantile mapping leads to

$$\begin{align*}
\mu_X' &= \mu_X + \frac{\sigma_X}{\sigma_Y} (\mu_Y - \mu_X) \quad \text{and} \\
\sigma_X' &= \sigma_Y \frac{\sigma_X}{\sigma_Y}.
\end{align*}$$

The correction for the variability is identical to Eq. (4) and shows that the bias correction based on quantile–quantile mapping accounts for both biases and changes in the distribution variabilities (since it involves $\sigma_X$, $\sigma_Y$, and $\sigma_Y$). Michelangeli et al. (2009) use the change factor based on quantile–quantile mapping: the observed value $x$ is adjusted with the value $x' = F_Y^{-1}[F_Y(x)]$, so that the CDF obtained by applying the change factor based on the quantile–quantile mapping is $F_X(u) = F_X[F_Y^{-1}[F_Y(u)]]$. If for the bias correction, the change factor based on the quantile–quantile mapping accounts for both biases and changes in the whole distribution, since it involves all the three CDFs $F_Y$, $F_Y$, and $F_X$. The bias correction and change factor approaches based on the quantile–quantile mapping, however, act differently: Ho et al. (2012) compare these approaches for the idealized case of normally distributed values. They find that the change factor based on quantile–quantile mapping leads to

$$\begin{align*}
\mu_X' &= \mu_Y + \frac{\sigma_Y}{\sigma_Y} (\mu_X - \mu_Y) \quad \text{and} \\
\sigma_X' &= \sigma_Y \frac{\sigma_X}{\sigma_Y}.
\end{align*}$$

The variability obtained with the change factor [Eq. (6)] is identical to that obtained from the bias correction [Eq. (5)]; however, the mean values differ. Ho et al. (2012) show that change factor and bias correction approaches based on quantile–quantile mapping lead to different results, and that the path for the calibration (i.e., bias correction versus change factor) introduces a further source of uncertainty.

Daily translation and daily scaling (Chen et al. 2013) are different quantile-based bias correction and change factor approaches. In these approaches, the bias (delta) obtained for a specific quantile $q_p$, associated with the cumulative probability $p$, is applied to the future (observed) quantile with same cumulative probability. Then, for the additive and multiplicative bias correction one obtains
These temperature-dependent biases, the model projections fer function of the quantile–quantile mapping captures biases associated with similar temperatures. As the trans-
also misrepresented in the future climate, with similar
soil moisture), it is likely that the same process would be
estimation of extreme hot temperatures due to lack of
a physical process in the present climate (e.g., over-
mapping some physical basis. If the model misrepresents
information, providing then to the quantile–quantile
dependence and incorporates some of this process-based
the quantile–quantile mapping preserves this temperature
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is represented by the transfer functions shown in the
quantile–quantile plots (Figs. 4 and 5), and that such re-
lation is maintained in the future. In section 4b, we show
that CRCM biases are often associated with temperature-
dependent physical processes misrepresented by the
model: as an example, the transfer functions in Fig. 4
show that Tmin exhibits a peculiar bias associated with
the freezing process; the transfer functions in Fig. 5
show increasing biases for extreme Tmax, possibly asso-
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fer function of the quantile–quantile mapping captures
these temperature-dependent biases, the model projections
associated with that process can be improved by the
quantile–quantile mapping. The quantile–quantile map-
ing approach, on the other hand, cannot correct biases
associated with new physical processes that might occur
in a changing climate but that are not observed in the
present climate.

All bias correction approaches rely on the assumption
of stationary bias: they are calibrated for present climate
conditions and are then applied to future climate pro-
jections. This underlying assumption is still a main
concern and subject of current research. Maraun (2012)
assessed the assumption of stationary bias and the ef-
effectiveness of bias corrections in the context of a
changing climate by using a pseudoreality experiment
with future climate model projections from a subset of
the RCMs of the “ENSEMBLES” dataset, over Europe.
He found that in general biases are stable, such that bias
correction on average improves scenarios for impact
studies. However, significant changes in the biases were
found for Tmin in the Alps and ice-covered oceans,
associated with changes in the albedo (possibly caused by
future loss of snow cover and sea ice), and for Tmax in
arid regions in central Europe (affected by future soil
moisture depletion and changes in cloud cover). For
these regions where the future physical processes are
significantly changed the bias correction is ineffective
(or even deteriorates future climate scenarios). Teutschbein
and Seibert (2012b) test the stationarity bias assumption
on the ENSEMBLES RCMs temperature and precip-
itation projections by dividing their sample into cold and
warm, and wet and dry, years. These two half samples
represent two different climate regimes. They then cali-
brate the bias correction on one half sample and apply
it on the other half. They found that more advanced
correction methods such as distribution (or quantile–
quantile) mapping performed relatively well, whereas
simpler approaches such as the delta method resulted in
the least reliable corrections for changed conditions.
These finding strengthen our choice of the quantile–
quantile mapping as a bias correction and downscaling
approach.

Other calibration approaches, which have not been
explicitly analyzed here, have been proposed. As an
example, Leander and Buishand (2007) and Leander
et al. (2008) use a power transformation $X = aY^b$ to bias-
correct precipitation values; Li et al. (2010) propose new
quantile-based bias corrections that account for distrib-
ution changes between the projection and baseline
periods. There exists a very large body of literature
dedicated to calibration approaches for climate model
projections, but no technique has yet emerged to be op-
timal, and it is in general recognized that calibration,
bias correction, and downscaling techniques introduce

\[
x'_p = y'_p - (y_p - x_p) \quad \text{and} \quad x'_p = y'_p y_{p}^{x_p} \quad (7)
\]

and for the additive and multiplicative change factor
one obtains

\[
x'_p = x_p + (y'_p - y_p) \quad \text{and} \quad x'_p = x_p y_{p}^{y'_p} \quad (8)
\]

These equations show that the daily scaling and daily
translation lead to the same values in the distribution
$F_X$, independent of the calibration path (i.e., bias cor-
rection or change factor) chosen. Moreover, these ap-
proaches do not need extrapolation of the tails behaviors,
since high quantiles are paired based on their cumulative
probability, independent of their values. However, given
the projected increase of temperatures with climate
change, the daily translation by construction applies the
bias correction associated with present near-zero tem-
peratures to future warmer temperatures, above freez-
ing level. Biases mirror the model misrepresentation of
physical processes, which often are related to specific
temperatures, as for example freezing and thawing
around zero. The daily translation and daily scaling ap-
proaches do not preserve this temperature dependence
and physical link and hence have not been considered in
this study, since they seem lacking physical coherence.

The underlying assumption of the quantile–quantile
mapping bias correction performed in this study is that
the discrepancy between model and observations
is represented by the transfer functions shown in the
quantile–quantile plots (Figs. 4 and 5), and that such re-
lation is maintained in the future. In section 4b, we show
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These finding strengthen our choice of the quantile–
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Other calibration approaches, which have not been
explicitly analyzed here, have been proposed. As an
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periods. There exists a very large body of literature
dedicated to calibration approaches for climate model
projections, but no technique has yet emerged to be op-
timal, and it is in general recognized that calibration,
bias correction, and downscaling techniques introduce
Finally, approaches based on analogs and weather types combined with simple bias correction and downscaling techniques, such as the quantile–quantile mapping, have shown improvements (e.g., Maurer et al. 2010; Boe et al. 2007). Quantile–quantile mappings, which account for the physical dependence between different variables, have been also recently introduced (e.g., Piani and Haerter 2013; Hoffmann and Rath 2012). The use of a multivariate quantile–quantile mapping, conditioning on weather types, analogs, or different physical processes, or simply performing the quantile–quantile mapping separately for different seasons, strengthens the physical coherence of the statistical correction. Although the present study did not use these types of approaches, they could be considered in future work.

c. Uncertainty due to the GP distribution fit

The fit of the GP distributions performed to the upper tails of the annual temperature distributions and described in section 4d enables to extrapolate the quantile-based statistical correction beyond the present temperature range; however, they add a level of complexity and a source of uncertainty to future climate projections. Wehner (2010) shows that the uncertainty due to the parameter estimation of the EVT distributions is similar to the natural GCM variability, and that both these uncertainties are small compared to the uncertainty associated with the intermodel variability. In this study the parameters of the GP distributions are estimated by using a maximum likelihood estimation, which is probability based and hence enables direct inference as to the parameter estimations. The uncertainty derived by the GP fit is quantified by 95% confidence intervals, evaluated from the maximum-likelihood estimation (MLE) variance–covariance matrix, under the assumption of a multivariate and approximately normal log-likelihood surface (Coles 2001, chapter 2.6). We also find that the uncertainty associated with the GP fit is comparable to that of the natural variability (not shown), and that both these uncertainties increase as the temperature values become more extreme (e.g., in Fig. 8 the dashed curves separate the more the temperatures increase).

d. Uncertainty associated with the experimental design and data constraints

This study considers a 40-yr-long reference period (1961–2000) for the present and three 30-yr-long future periods (2011–40, 2041–70, and 2071–2100) for characterizing the near, middle-range, and distant future. The choice of this slightly longer reference period, as explained in section 3b, is dictated by the change in the station recording procedures in 1990 and aims to maximize the amount of available observations while including the most recent observations. The quantile–quantile mapping transfer function calibrated in 1961–2000 is expected to be more robust than if it were calibrated on a 30-yr reference period (because of both the observation nature and the sample size). The choice of a different reference period could affect our results. The statistics evaluated on the 30-yr future windows are expected to have a larger sample uncertainty than those evaluated in the 40-yr-long reference period. However, the different lengths of the present and future periods are not expected to affect significantly the nature of our results.

The choice of the future time periods (2011–40, 2041–70, and 2071–2100) was dictated by the time windows covered by the CRCM available simulations. As explained in section 3a, continuous simulations are rarely produced, and most of the CRCM simulations cover the time slices 1961–2000 and 2041–70. In our analysis, only two simulations cover the whole period 1961–2010, and the other three simulations cover the 1961–2000 and 2041–70 time windows solely. Results obtained for the 2011–40 and 2070–2100 time windows (evaluated using two simulations) are therefore expected to have a larger sample uncertainty than those for the 1961–2000 and 2041–70 time windows (evaluated using five simulations) because of the reduced sample size. These sample size differences are, however, not expected to affect significantly the nature of our results.

It is worth noting that, independent of the sample size, as we consider time windows in the more distant future (e.g., 2071–2100 vs 2041–70, or 2041–70 vs 2011–40) the climate change signal is stronger. However, also the uncertainty associated with this climate change signal, originated by all the sources mentioned in this section, is growing with the future time periods.

7. Summary and conclusions

This study quantifies the evolution of several extreme temperature indices in the context of a changing climate. The analysis is performed on a community level, for nine pilot communities located in Manitoba and eastern Canada. The indices were defined in collaboration with Health Canada professionals, based on a temperature–mortality analysis, in order to characterize extreme temperatures and the occurrence of hot weather events that can result in adverse health outcomes. The analysis is performed by using temperature projections from five
simulations of the Canadian Regional Climate Model. The CRCM temperature projections are bias corrected and downgraded by a quantile–quantile mapping performed with station observations.

Extreme hot temperatures and the occurrences of hot weather events are expected to increase with climate change. Extreme temperatures associated with hot days are expected to increase from 3.5 to 6°C century⁻¹, whereas extreme temperatures associated with warm nights are expected to increase from 3.5 to 4.5°C century⁻¹. The largest temperature increase occurs in southern Manitoba, where the lack of soil moisture can possibly lead to an uncontrolled enhancement of hot day temperatures. The occurrence of warm nights (when the daily minimum temperatures exceed 22°C and 25°C) is already large and increases substantially in communities characterized by a humid climatology, such as cities over the Great Lakes or Montreal. Communities characterized by a dryer weather (e.g., Winnipeg) exhibit a smaller increase in the occurrence of warm nights. The occurrence of hot days (when the daily maximum temperatures exceed 30°C and 35°C) increases by a factor of 3 (and even more) by the end of the century. The occurrences and increase of heat waves (i.e., the occurrence of consecutive warm nights and hot days) is similar to those of the warm nights because of the dominant role played by humidity in characterizing such events.

The CRCM simulations exhibit warm biases for the extreme temperatures associated with hot days and cold biases for the extreme temperatures associated with warm nights. To reduce these biases, the CRCM temperatures have been statistically corrected by an empirical quantile–quantile mapping (Panofsky and Brier 1968; Déqué 2007; Themeßl et al. 2010). Moreover, generalized Pareto distributions (Coles 2001) are used to extend the temperature distribution upper tails and infer the behavior of extremes not observed in the present, but which might occur in the future. This enables to extrapolate the quantile–quantile mapping and to perform the statistical correction of temperature extremes beyond the range of the present climate values.

Temperatures and indices were found to vary significantly due to the diversity of local climates represented by different stations. The impact of these local effects on the projections of extreme temperatures and occurrence of hot weather events is accounted for by providing the index span for the different stations belonging to each individual community. The variability due to the local effects is larger than the CRCM natural variability. For impact and adaptation studies it is fundamental to account for the variability due to local climatologies, since it can affect significantly the impact and adaptation strategies from one location to another.

The five CRCM simulations analyzed in this study differ solely for the driving CGCM member, and therefore provide information solely on the inherent uncertainty in climate projections due to the natural climate variability. Uncertainties rising from model physical parameters, modeling physical assumptions and model structure, and possible future GHG emission scenarios are expected to be larger than the natural variability, and are therefore expected to have larger impacts on heat-related mortality projections. Déqué et al. (2007) and de Elía and Coté (2010) show that the largest uncertainties in regional climate projections derive from different GHG emission scenarios and driving GCMs. Gosling et al. (2012) and Peng et al. (2011) show that physical parameters and different GCMs have larger effects on the uncertainty of heat-related mortality projections than the emission scenarios. Future work could consider a larger ensemble of simulations in order to include these different sources of uncertainty and analyze their effects on the projections of extreme heat events and heat-related mortality, in Canada.

Bias correction and statistical downscaling approaches are an additional source of uncertainty in the climate model projections. The empirical quantile–quantile mapping has been chosen in this study for several reasons:

1. The quantile–quantile mapping is relatively simple and fast to apply, it has been shown outperforming several (even more complex) techniques, and it exhibits high performance at high quantiles (e.g., Themeßl et al. 2010).
2. The quantile–quantile mapping accounts for both biases and future changes in the temperature variability, in addition to averages (section 6b). More generally, the quantile–quantile mapping enables us to adjust all moments of the probability density function (Hagemann et al. 2011).
3. The temperatures analyzed in this study exhibit nonnormal distributions that result in highly nonlinear transfer functions (Figs. 4 and 5). The empirical quantile–quantile mapping can be defined for variables with such complex nonparametric distributions, and accounts for biases (and climate change signals) that differ in a nonlinear fashion for low and high quantiles.
4. The quantile–quantile mapping is temperature dependent and hence retains the physical link between the temperature and physical processes misrepresented by the model.
5. The quantile–quantile mapping, despite relying on the stationary bias assumption, outperforms other bias correction approaches when applied to changed climate conditions (Teutschbein and Seibert 2012b).
It is recognized, however, that the quantile–quantile mapping has drawbacks: as an example, there is the need to extrapolate the distributions’ upper tails, which introduce an additional source of uncertainty; moreover, a change factor approach based on quantile–quantile mapping leads to different results than does bias correction (Ho et al. 2012). Future climate and statistical research should continue focusing on the better understanding and improvement of calibration, bias correction, and downscaling techniques. The technique physical coherence (e.g., by using multivariate bias corrections; conditioning on weather types, analogs, and physical processes; considering seasonality) should be retained as a key factor for advancements in this field.

The quantile-based statistical correction performed in this study considers each CRCM member individually in order to quantify the effects of the natural climate variability on the bias correction and downscaling. However, we expect the biases to be independent of the ensemble member since they are caused by model deficiencies, rather than the natural variability. Future analyses should consider aggregating the members of the same climate model for statistical correction purposes.

Humidity has been identified as a key factor for characterizing hazardous hot weather events, such as warm night temperatures and heat waves. Moreover, soil moisture has been associated with the enhancement of hot day extreme temperatures. Future work could consider heat metrics that explicitly account for the joint occurrence of hot and humid (night) events [such as the Humidex developed by Masterton and Richardson (1979)] and indices that explicitly relate hot (day) temperatures to soil moisture.

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